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From Accession to Abatement: EU Membership, the EU ETS, and Romania's Electricity CO_2 Emissions

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Abstract: The EU's Emissions Trading System (EU ETS) has been widely studied for early members, yet evidence for late joiners that accede to the EU and ETS simultaneously is scarce. We study Romania's 2007 entry to disentangle the instrument-specific effect of the ETS from accession-wide forces on CO_2 emissions in the electricity sector. We implement a three-stage causal design: (i) Synthetic Control (SCM) using a donor pool of non-treated countries to estimate the joint EU+ETS effect; (ii) Generalized Synthetic Control (GSCM) exploiting within-Romania sectoral coverage to isolate the ETS effect; and (iii) trade-adjusted SCM based on an original dataset linking generation, trade flows, and partner emission intensities to test for carbon leakage. The stages yield consistent annual abatement magnitudes—6.7% (joint), 5.2% (ETS-only), and 2.7% (trade-adjusted)—revealing complementary channels and underscoring the need to account for imports when assessing net gains. These findings help guide accession policy, ETS design, and carbon leakage risk.

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List of Abbreviations

CAGR	Compound Annual Growth Rate
CATT	Cohort Average Treatment Effect on the Treated
CBAM	Carbon Border Adjustment Mechanism
DiD	Differences-in-Differences
EDGAR	Emissions Database for Global Atmospheric Research
ETS	Emissions Trading System
GSCM	Generalized Synthetic Control Method
IEA	International Energy Agency
IFE	interactive fixed effects
JRC	European Commission Joint Research Centre
MSPE	Mean Squared Prediction Error
SCM	Synthetic Control Method
tCO_2e	Tonnes of Carbon Dioxide Equivalents

1 Introduction

Climate policy increasingly relies on explicit carbon prices to make high-carbon production less profitable and accelerate decarbonization. The EU introduced its carbon pricing scheme, the EU Emissions Trading System (EU ETS), in 2005 as one major building block in confronting the current climate change challenge. Among others, it covers the electricity sector, the highest emitting sector worldwide (IEA 2025a). The effect of the ETS introduction on EU Member States—and particularly on their power sectors—has been studied extensively (see Bayer and Aklin (2020)). However, these findings may have limited applicability for assessing the impact of EU ETS adoption in the context of future EU enlargement: The current nine EU candidate countries—most of them post-communist Eastern European states—differ both economically and institutionally from the original ETS members. Moreover, the effects of adopting the ETS at its inception may not be the same as those associated with joining at a later phase.

More relevant proxies for prospective ETS entrants are countries that joined after the scheme's launch, namely Romania and Bulgaria (2007) and Croatia (2013), which entered the EU and the EU ETS simultaneously. Examining these cases provides valuable insights into potential differences between early and late adopters, benchmarks expected emission reductions, and helps assess risks of carbon leakage. These insights offer concrete guidance for post-accession green-transition policy design. Yet the literature remains sparse, in part because late joiners are often excluded: the simultaneity of EU and ETS accession makes the separate effects more difficult to identify.

This thesis addresses the gap by estimating the causal effect of late EU ETS entry on emissions. We focus on Romania, whose institutional and industrial features make it well suited to our identification strategy. To isolate the EU ETS effect from the broader consequences of EU accession, we compare emissions in the ETS-covered power sector (treated) with a synthetic counterfactual constructed from non-covered industries (control). Romania's relatively diversified industrial base supports credible counterfactual construction. In addition, its electricity sector combines deepening cross-border integration with a border location exposed to imports from both ETS and non-ETS countries, offering a compelling setting to examine potential carbon leakage.

Specifically, our objective is to answer three causal questions. First, at the country level we implement the Synthetic Control Method (SCM) to estimate the combined effect of EU accession and ETS participation on CO_2 emissions of the electricity sector by constructing a synthetic counterfactual electricity sector from a donor pool of non-treated countries. Second, at the sectoral level we apply the Generalized Synthetic Control Method (GSCM) to sector-disaggregated emissions within Romania to isolate the ETS effect by comparing ETS-covered (treated) and non-covered (control) industries, extending the mapping in Bayer and Aklin (2020). This stage exploits the identifying assumption that accession affected all sectors while the ETS directly covered only a subset of sectors. Third, to broaden the scope and capture emissions embodied in cross-border electricity trade, we assemble an original harmonized dataset linking domestic electricity generation, electricity trade flows, and country-level emission intensities. Using this trade-adjusted SCM, we test for carbon leakage and provide an updated country-level estimate on the EU and EU ETS accession effect. Together, these complementary strategies triangulate causal mechanisms and magnitudes of the changes in CO_2 emissions in Romania's electricity sector.

Our stage one results indicate that EU and EU ETS accession led to a causal compound annual reduction of emissions in the electricity sector of 6.7 %. The pure ETS effect, estimated in the second stage, corresponds to 77 % of this yearly reduction. When potential carbon leakage is incorporated in the third stage, the initial causal reductions from the first stage fall by two-thirds in absolute terms. The comparison between the first and second stages highlights the need to distinguish the EU accession effect from the specific EU ETS effect, while the third stage underscores the importance of accounting for emissions from electricity imports.

In our first stage SCM, causality relies on the ability of the Synthetic Control Method to reproduce Romania's pre-2007 path in electricity CO_2 emissions using a weighted combination of donor countries. The key assumption is that only units that are similar in both observed and unobserved characteristics would have followed comparable trajectories prior to treatment, which means that post-2007 deviations are plausibly attributable to the joint effect of EU accession and ETS participation rather than to pre-existing differences. In practice, this requires a long pretreatment window with a good pretreatment fit and a donor pool that excludes incompatible countries. Thus, our outcome variable is based on emissions data (specifically IEA-EDGAR data) from 1993 to 2019 and we filter out unsuitable control countries according to multiple criteria. Additionally, to assess the validity of our results for the SCM, we report in-space and in-time placebo permutations, leave-one-out donor sensitivity tests, and alternative predictor sets to assess how exceptional the estimated post-treatment gap is and how sensitive it is to modeling choices. For our posttreatment period, we find a causal yearly compound annual growth (CAGR) of emissions of negative 6.7 %. The stage-one results provide an order of magnitude, however the in-space placebo tests indicate that the effect is modest compared to some placebo countries.

The causal identification of the pure ETS effect in stage two via the Generalized Synthetic Control Method uses variation in ETS coverage across industries within Romania. GSCM is an interactive fixed-effects framework that models latent common factors that generate economy-wide dynamics while allowing heterogeneous loadings across sectors. Under this specification, the remaining systematic difference between covered and non-covered sectors can be interpreted as the pure ETS effect. This approach therefore relies on two related assumptions: (i) the latent factors capture relevant economy-wide forces (including accession-induced shocks) and (ii) absent ETS coverage treated and control sectors would follow the same factor-driven evolution. To make these assumptions transparent, we map pretreatment fit, latent factors and their loadings, select factor numbers with information criteria, run placebo treatments on control sectors, alternative timings, and perform leave-one-out robustness checks. The sector-split emission data from 1993 to 2019 is available through the UNFCCC. As one would expect, the pure ETS effect is lower than the joint EU and ETS accession effect. The stage two GSCM model estimates on average yearly reductions of 5.2 % between 2007 and 2019.

Our third stage relies on the same SCM methodology as the first stage to identify causal effects of the EU and ETS accession. To capture potential carbon leakage, we construct an original dataset that covers 2000 to 2019, using UN Comtrade, Ember, and IEA-Edgar data. This allows us to expand the SCM outcome variable from domestic generation emissions to include also emissions embodied in imports, while being coherent with our stage one dataset. Because of data availability we have a smaller, but still robust set of comparators for the carbon leakage SCM analysis. Accounting for potential carbon leakage with the

SCM model reduces the stage-one emission reductions by two-thirds in absolute terms, yielding yearly reductions of 2.7 % relative to the estimated counterfactual scenario.

While all stages come with some caveats, the consistent and plausible pattern of results across all stages supports the interpretation of multi-channel effects. This highlights the importance of considering all three stages together when assessing the net impact and proposing policies to reduce emissions.

Overall, this thesis contributes on three fronts: Methodologically, it combines SCM, GSCM and a trade-adjusted SCM in a single, coherent framework that relates the different effects. Empirically, it includes Romania, a late entrant, often omitted from prior work to the literature of the EU ETS effects. By disentangling the EU and the EU ETS effect, we go a significant step further than previous research. Moreover, it expands on existing literature using an original dataset for our third stage. Policy-wise, the results illustrate how the EU ETS, accession-related channels, and carbon leakage jointly shape net emission outcomes, highlighting the importance of disentangling their separate effects. Additionally, being able to specifically quantify the ETS effect helps policy makers to evaluate the cost-effectiveness of the policy. Although the external validity of our findings may be limited, they still provide useful guidance for assessing the expected emission impacts of future EU accession countries. Furthermore, it informs the current discussion around frameworks to avoid carbon leakage such as the Carbon Border Adjustment Mechanism (CBAM) that will take effect in 2026.

The paper is organized as follows: Chapter 2 provides background on the EU Emissions Trading System and the Romanian electricity sector. This is followed in Chapter 3 by a review of the relevant literature. The methodological framework and data are introduced in Chapter 4, while Chapter 5 presents the results together with placebo tests. A discussion of the findings and their implications is offered in Chapter 6, and we conclude in Chapter 7.

2 Background

This chapter explains the evolution of the EU ETS and major reforms in Romania's electricity sector during and around our pre- and post-treatment period. It helps to better understand the context in which the EU and ETS accession occurred and to recognize potential confounding factors in our analysis.

2.1 Evolution of the EU ETS

As the EU ETS is an essential part of our analysis, this section outlines the concept, evolution, and different phases of the system.

The EU Emissions Trading System (ETS) is a cap-and-trade system where companies have to surrender one allowance (either bought or allocated) for each tCO_2e emitted. There is a fixed cap of total allowances that cannot be exceeded. Today, the EU ETS is the largest cap-and-trade system by volume and countries involved. It got approved in 2003 and the system started in 2005. While our posttreatment period from 2007 to 2019 only overlaps with the first three phases of the EU ETS, the system is in total divided into four phases: Phase I from 2005 to 2007, phase II from 2008 to 2012, phase III from 2013-2020, and phase IV from 2021 to 2030. Therefore, Romania joined the EU ETS at the end of phase I. Along these phases more sectors and gases got covered by the EU ETS. Simultaneously, the limit on the total allowed emissions shrank, and some market mechanisms changed. From phase I onward, CO_2 emissions from power stations with more than 20 MW thermal rated input had to have certificates to cover their emissions. Also, from the beginning, the iron and steel, refinery, cement, ceramic and glass, and paper sectors were covered. In 2013, among others, the chemical sector was added (World Bank 2015). The revenue of the first three phases of the EU ETS is mainly directed towards national budgets and could be used to partly compensate electricity-intensive industries for the price increase in electricity (International Carbon Action Partnership (ICAP) 2024). The price for EU ETS allowances has fluctuated with a strong upward trend since 2017 (Sitarz et al. 2024).

Meanwhile, in phases I and II most of the emission certificates (between 90 and 100 %) got allocated for free based on historical emissions. Romania started auctioning a part of the emission allowances in November 2012 (European Commission 2025b). In phase III electricity producers were obliged to buy all their emission certificates (European Commission 2025d). However, Romania, together with ten other member states, made use of a derogation to give out free allowances to the sector of up to 70 % of companies' investments in clean technologies (European Commission 2025a).

2.2 Development of the Romanian Electricity Sector

As Romania underwent a market liberalization, it is important to understand how it unfolded in the electricity sector. Therefore, our aim is to provide in this section the context for understanding the institutional and market conditions in Romania under which the EU ETS was introduced and potentially influencing factors.

Romania experienced an uprising in 1989 that marked the end of the authoritarian communist regime of Ceaușescu. Following a new constitution in 1991 and economic reforms in November 1992, Romania resembled other emerging markets (Turnock et al. 2025).

This also marks the starting point from which Romania's electricity sector evolved. From the early 1990s until today, its electricity sector transformed from a centrally planned state monopoly into an EU-integrated competitive market.

Up until 1998, Romania's electricity sector remained under the complete control of RENEL (Romanian Electricity Authority), a state-owned monopoly that controlled all aspects of electricity generation, transmission, and distribution. RENEL was the successor to CONEL (The National Company of Electric Energy) and managed virtually all electricity production in Romania. Between 1998 and 2001, reforms introduced an independent regulator ANRE (National Energy Regulation Authority). Furthermore, the electricity generation got separated from the transmission and distribution. This created a dedicated transmission system operator (Transelectrica), a wholesale market platform (OPCOM), and split the distribution network into multiple regional entities. From 2002 to 2007, these regional distributors were progressively sold to (foreign) investors, while market rules and infrastructure were aligned with EU requirements, including steps toward price liberalization.

Romania joined the EU and the EU ETS simultaneously on the first of January 2007 (Gores et al. 2021; European Commission 2025e). After EU accession in 2007, the generation sector became more decentralized. Transmission remained under a dedicated national operator (Transelectrica), distribution was largely under foreign ownership, and electricity supply was opened to competition but weakly supervised by ANRE. Although all consumers formally gained the right to choose their supplier in 2007, regulated tariffs for households persisted until 2018, following a staged liberalization calendar set by ANRE. From 2012, the Electricity and Gas Law aligned the sector with the EU's Third Energy Package, banning bilateral power purchase agreements outside the centralized market platform OPCOM to improve transparency. While renewable capacity expanded rapidly under generous subsidies, frequent policy shifts created some regulatory uncertainty (Bădileanu 2014; Diaconu et al. 2009; Rotaru 2013; European Commission 2016).

2.3 Trends in the Romanian Electricity Sector

To get a first impression of the characteristics and trends of the Romanian electricity sector, we provide a selection of different descriptive graphs and figures. This includes the historical development of the Romanian power sector's electricity mix, its carbon emissions, and the trade balance between electricity im- and exports. These descriptive graphs underscore the relevance of our research question by pointing out important changes after the introduction of the EU ETS.

Historically, coal was the biggest contributor in electricity generation in Romania. While coal became less important after 2008, other energy sources like nuclear and wind increased their production levels leading to coal being only the fourth biggest source in electricity generation in 2023 (see Figure 2.1). This illustrates a shift toward lower emitting electricity production during our treatment period which suggests potential responsiveness of the electricity sector in Romania to being exposed to the EU ETS.

The resulting emissions from Romania's electricity sector are central to this analysis, since the ETS was specifically designed to reduce them. Figure 2.2 clearly shows that Romania's CO_2 emissions from the electricity sector fell very rapidly in the second part of the 1990s and, albeit at a lower pace, continued to trend downwards in most years afterwards.

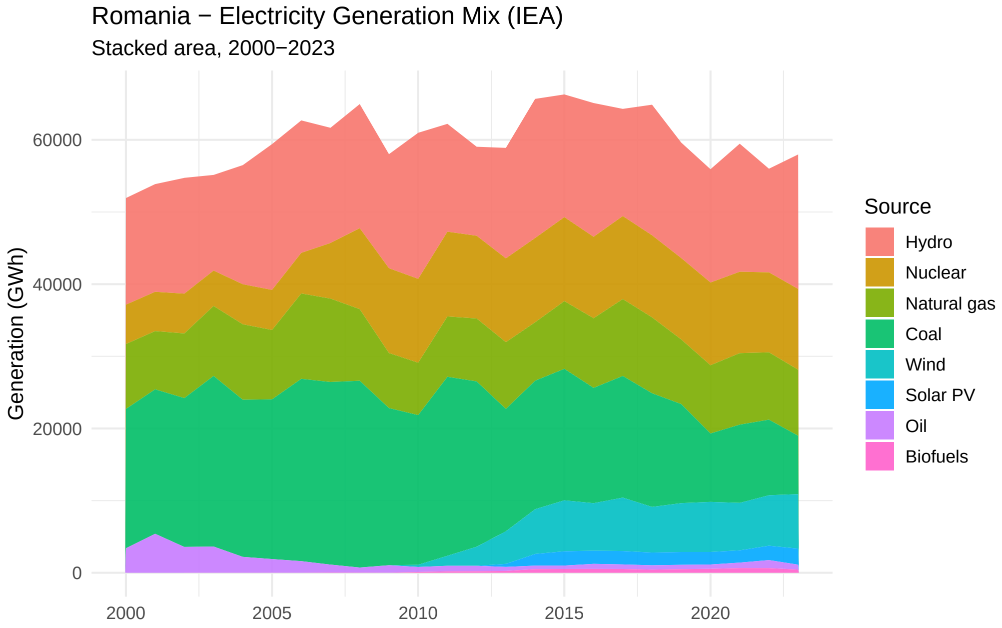

Figure 2.1: Electricity generation per source in GWh in Romania, 2000–2023 (IEA 2025b)

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These big changes in emissions underscore the importance of trying to disentangle the causal effect of the EU ETS on CO_2 emissions amid the sizable reductions of that time. It remains to show that the decline in carbon emissions after 2007 can be attributed to the introduction of the ETS in Romania and would not have occurred otherwise.

Looking at the electricity trade is relevant for the third stage of our analysis. The ETS would not fulfill its purpose if emission reductions made in the ETS-covered area were offset by carbon intensive imports from non-covered trade partner countries. Its geographical position bordering EU and non-EU countries makes Romania especially interesting to expand the analysis on potential carbon leakage in electricity trade. Since 1993, Romania's power grid has transformed from an isolated system into an integrated part of the European network. Following the early 1990s, Romania (together with neighboring Bulgaria and ex-Yugoslav countries) operated in a separate synchronous zone until reconnection with Western/Central Europe in 2004. This reintegration required huge infrastructure investments such as upgrading and building high-voltage links to neighbors, significantly boosting cross-border transmission capacity. Thus, in 2007, Romania was already directly connected to Serbia and Montenegro, Bulgaria, Ukraine, Hungary, and Macedonia (SYSTINT 2007).

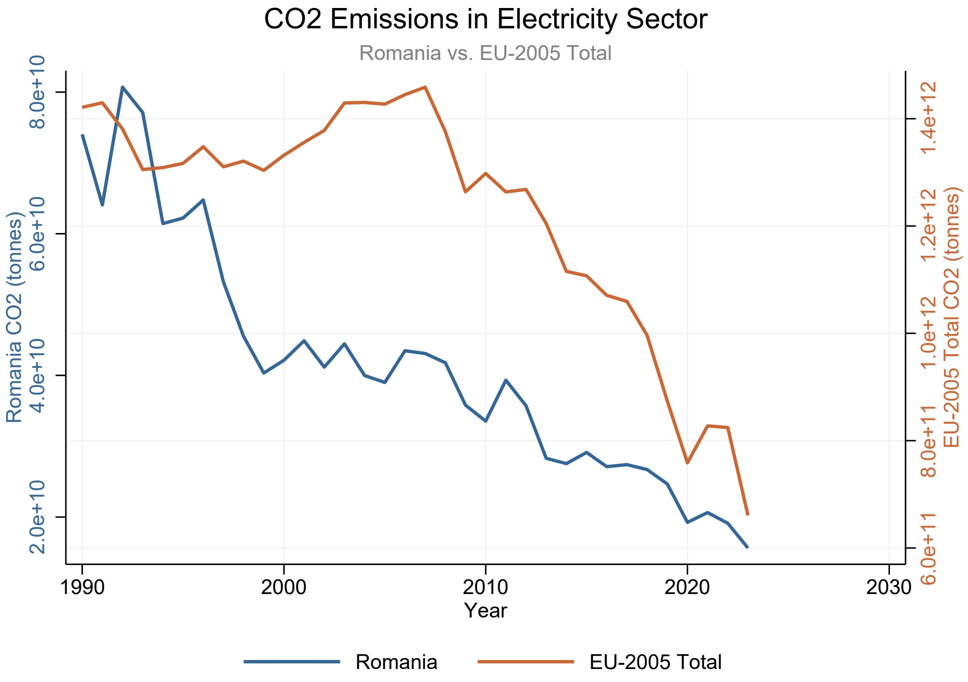

Figure 2.2: Romania's and the EU's (2005 member countries) electricity production CO_2 emissions 1990-2023 (Crippa et al. 2024)

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These infrastructure investments and the integration into the European network enabled Romania to largely expand its international electricity trade. Both imports and exports grew substantially since 2000 while Romania remained a net exporter in most years except from 2019 to 2022 (see Figure 2.3).

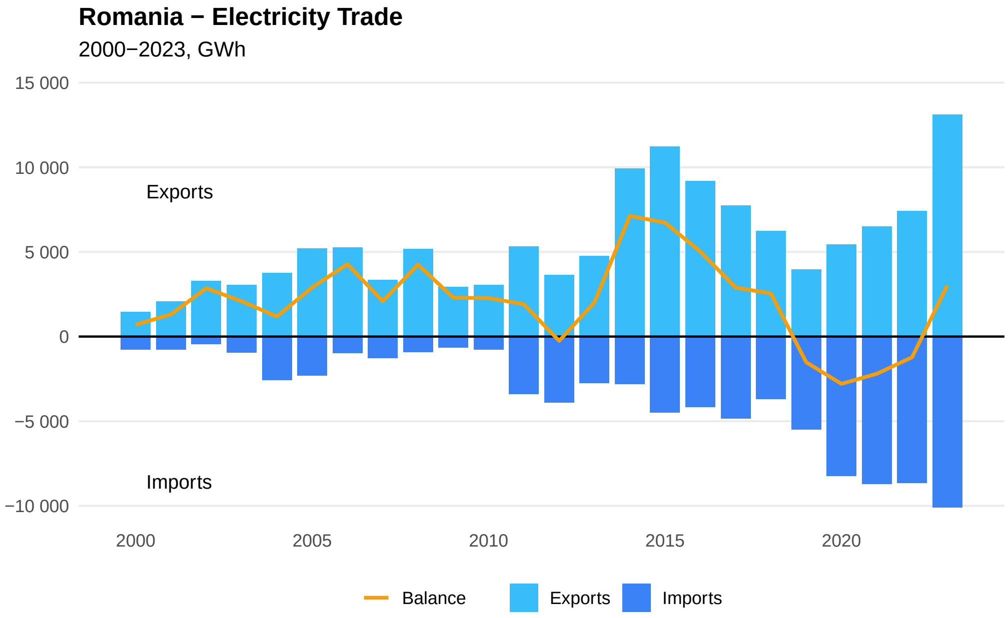

Figure 2.3: Romania's electricity trade balance, 2000–2023 (IEA 2025b)

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3 Literature Review

In line with our chosen methodology, we provide an overview of the use of the Synthetic Control Method (SCM) and the Generalized Synthetic Control Method (GSCM) in the broader context of carbon pricing. Additionally, through the results of this chapter, we can set a benchmark to evaluate our findings against and provide an intuition on the expected effects based on the existing literature.

3.1 Carbon-Pricing Effects

In order to link the carbon content of goods to their prices and thus internalize the social cost of carbon, many countries have introduced carbon taxes or established an emissions trading system. Both measures are intended to make "greener" products more affordable than products that heavily contribute to polluting the environment. It is meant to incentivize companies to reduce their carbon footprint. Research on the effect and effectiveness of both carbon taxes and ETSs up to this point is mixed with most showing emission reduction effects of varying degrees. A systematic literature review by Döbbeling-Hildebrandt et al. (2024) finds average emission reductions of carbon pricing schemes of 4 to 15 % after controlling for publication bias. They note that studies over longer time periods, such as ours, find more pronounced effects.

The use of the Synthetic Control Method to estimate the effect of carbon taxes is widespread. For example, Andersson (2019) uses it to analyze the effect of Sweden introducing a carbon tax on transport fuels in the early 1990s. He finds that Sweden's policy was highly effective, with the carbon tax causing the CO_2 emissions to decline by 6 % in an average year.

In the same vein as our approach in stages one and three, Leroutier (2022) applies the SCM to the electricity sector. She finds an annual reduction of 20.5 % to 26.0 % of CO_2 emissions through the Carbon Price Support mechanism on electricity generation in the United Kingdom between 2013 and 2017. On the same topic, contributions from Gugler et al. (2023) and Abrell et al. (2022) apply regression-discontinuity-in-time and a combination of economic theory and machine learning, respectively, to investigate the effect of the same policy. They also find significant emission reductions, although not at the same level as Leroutier.

An example for a paper that uses GSCM in the context of carbon prices, is the work by Rafaty et al. (2025). They aim to investigate the effect that changes in carbon price levels have on CO_2 emissions in 39 countries. Using Generalized Synthetic Control, Two-Way Fixed Effects, and Interactive Fixed Effects methodologies, the authors differentiate between an initial introduction of and a change of levels in a carbon price. On average, they report an effect of 0.6 to 1.5 percentage point reduction in CO_2 emission growth compared to the counterfactuals through carbon pricing instruments. The majority of the reduction stems from the electricity and heating sectors. Moreover, the introduction of a carbon price seemed effective (1 percentage point reduction in emissions growth compared to counterfactual) while an increase in carbon price led to only small effects. A second paper by Heiaas (2021) uses the GSCM for air travel emissions under the EU ETS, but fails to find conclusive findings because of data limitations.

Importantly, Martinsson et al. (2024) bridge the gap between national carbon taxes and the EU ETS by looking at both the effect of the Swedish carbon tax and the EU ETS on manufacturing between 1990 and 2015. Their estimate is that without carbon taxes, the emissions from this sector would have been 30 % higher during that time. Using variation in marginal tax rates, the study finds that a 1 % increase in the marginal cost share of emissions reduces carbon intensity per deflated sales by about 2 % over three years with significant heterogeneity across firms. This relationship is stable even when the ETS is introduced in parallel to the national carbon tax. It shows that results from other carbon taxes can be indicative for the EU ETS as well and vice-versa. We will therefore use the results on carbon taxes as well, when comparing our findings to previous literature.

3.2 Specific Impact of the EU ETS

In addition to the results from carbon taxes in general, we want to narrow down on the effect of the EU ETS specifically, presented in this section. The above-mentioned literature review by Döbbeling-Hildebrandt et al. (2024), calculates an average treatment effect of the EU ETS of 7.3 %.

Two papers that build the basis for an important part of our methodology in stage two focus as well on the causal change in emissions under the EU ETS: First, Bayer and Aklin (2020) use the Generalized Synthetic Control Method to estimate the effect of the EU ETS on CO_2 emissions. They construct panel data on sector-level emissions across 25 EU countries that were part of the EU in 2005 (therefore not including Romania, Bulgaria, and Croatia). Aggregated ETS and non-ETS sectors per country serve as treated and control groups (thereby having two data points per country per year). Through the GSCM method, they account for unobserved confounders and heterogeneous reactions for example to the financial crisis in 2008. Measures of per country GDP serve as covariates. They find additional aggregated emission reductions of 8.1 % (95 % CI: 1.7 %, 13.2 %) in the sectors covered by the EU ETS compared to sectors not covered by the EU ETS. They also brush upon sectoral reductions across Europe using slightly less aggregated data as controls. Overall, the authors argue that low permit prices do not rule out policy effectiveness if firms expect future stringency. There is some overlap between our paper and their paper as the second stage of our paper uses GSCM as well and, with some modifications, we base our sector specification on the methodology of this paper. However, Bayer and Aklin (2020) do not try to disentangle the EU accession effect from the EU ETS effect and simply exclude the late comers. Additionally, they only offer a very limited sector analysis and do not look at all at country-specific effects per sector. Therefore, we build upon, but significantly expand on their paper. The second paper, by Basaglia et al. (2024) follows the same GSCM methodology to look at positive spillovers from the EU ETS for other greenhouse gases besides CO_2 emissions. They find emission reductions for all tested pollutants. These two studies that look at similar aspects, support that the GSCM is suitable for our setting.

Related to our topic, a paper by Müller and Teixidó (2021) uses SCM on the share of wind and lignite electricity production for the free allocation program of EU ETS allowances. They do not find any significant difference compared to their counterfactual scenario with full auctioning. This suggests that free allocation is not a factor we have to take into account specifically.

To provide further concrete estimates on EU ETS emission reductions, we present two papers using the Differences-in-Differences methodology that shares some characteristics with the SCM. Petrick and Wagner (2014) find through matched Differences-in-Differences (DiD) that German manufacturing firms covered by the EU-ETS reduced CO_2 emissions by 20 % from 2007 to 2010, predominantly through fuel switching and energy-efficiency. In a similar set-up with matched DiD for French manufacturing firms, Colmer et al. (2025) find CO_2 emission reductions of around 15 % for companies in phase I and phase II. The matched DiD estimation for different sectors in selected EU countries from Dechezleprêtre et al. (2023) show a significant emission reduction of 15 % for the second phase of the EU ETS. The first phase does not yield any significant reductions.

To complement in general terms the intuition behind the impact of the EU ETS, a paper by Tian et al. (2016) examines whether the system also exerts an additional incentivizing effect on electricity companies through their stock market valuations. The authors look at the relationship between the price of EU ETS certificates and stock returns. For phase I of the EU ETS, they do not find significant results. However, for phase II, they find that low-carbon electricity producers experience a positive relationship between rising certificate prices and their market valuation, whereas carbon-intensive producers see a negative relationship. According to the authors, this underscores that the EU ETS incentives energy companies to reduce emissions, but that phase I was likely less effective than phase II. Bernardini et al. (2021) support this, by finding a low-carbon premium on stock returns for European energy utilities. These results are significant for phase III of the EU ETS until 2016 and more weakly, depending on the specification, from 2006 to 2016 as well.

Unfortunately, there are no causal emission reduction effects through the EU ETS available for Romania specifically. However, Purcel (2023) finds in her firm-level analysis for Romania for 2014-2015 that the EU ETS increases (short-term) current environmental spending, but that it does not influence (long-term) investments on environmental protection. However, the author acknowledges the short time period covered and sector-specific sensitivity to the results as caveats. In a dynamic general equilibrium model for Romania, Loisel (2009), looks, among other aspects, at a permit scheme with similar function, but stricter caps than the EU ETS. The author predicts for Romania emission reductions and economic growth.

This lack of studies on Romania illustrates how most of the existing literature focuses on countries with high-quality micro-data. However, as Känzig and Konradt (2023), Mangiante (2024), and Känzig (2023) highlight, the effects of the EU ETS on economic variables can vary significantly depending on country-specific characteristics. This leads us to assume that there could also exist heterogeneity in the effect of the EU ETS on CO_2 emissions. This stresses again the importance of examining Romania more closely to uncover potential country-specific effects that provide additional insights for Romania *and*, thereby, countries with similar characteristics.

3.3 Effects of EU Accession

A central element of our research strategy involves disentangling the effects of Romania's simultaneous accession to the European Union and the EU ETS. Since both institutional shifts occurred concurrently, isolating the specific impact of EU ETS participation requires a clear understanding of the broader economic, ecological, and structural transformations associated with EU membership. As such, it is essential to examine in this part the literature on the effects of EU accession to gain an understanding of the expected effects from EU accession. In particular, this section relates how most studies find that joining the EU has a negative effect on the carbon emissions in a country but do not take into account the simultaneous effect through the EU ETS.

Xiao et al. (2022) and Jorgenson et al. (2017) deliver valuable insights to our analysis. Xiao et al. (2022) analyze carbon emissions, energy consumption, and economic development in the 10 countries that joined the EU in 2004 through their index decomposition and mitigation scenario analysis. They state that while those countries grow faster economically, they are slower in decreasing their CO_2 emissions compared to the other EU members. Moreover, additional emissions through economic growth are offset by a decline in carbon intensity. Using multilevel regressions, Jorgenson et al. (2017) focus on the effects that economic and political integration had on power plants' carbon emissions in post-Soviet transition nations. Their results indicate that average carbon emissions per plant are lower in countries that joined the EU. Additionally, this effect is even more pronounced for countries entering the EU in 2004 compared to Bulgaria and Romania who joined in 2007.

Because the results on the development of carbon emissions after EU accession are limited, we also include the economic growth of countries after accession. This is only indirectly connected to our research proposal but illustrates the effect on other variables and the use of the SCM methodology.

Cieślik and Turgut (2025) analyze the effect of Romania's and Bulgaria's EU accession on their respective economic developments using the Synthetic Control Method. Overall, they find that Romania's real GDP per capita exceeded that of its synthetic counterpart by an average of 644 USD per year between 2007 and 2019. This translates to a 4.6 % larger annual GDP per capita growth rate. However, the positive effects only became noticeable from 2014 onward, seven years after accession, suggesting that EU membership benefits require significant time to materialize. Hagemejer et al. (2021) also use an SCM approach to estimate the effect on GDP. They include more countries (Poland, Estonia, Latvia, Lithuania, Romania, Czech Republic, Slovenia, and Bulgaria) in their scope of analysis but find a comparable effect for Romania. Like Cieślik and Turgut (2025), Hagemejer et al. (2021) observe a growing gap of GDP per capita between the actual and counterfactual

Romania that widens over time resulting in a 30–40 % higher GDP per capita in the 6 to 12 years after EU accession.

Using Structural Decomposition Analysis (SDA) based on input–output tables augmented with environmental indicators, Duarte and Serrano (2021) offer a more nuanced analysis of the effects of Central Eastern European countries' EU accession on particulate matter emission. They examine structural changes through three distinct lenses: scale, composition, and technology effects. While not all countries show equal results, Romania's advances in technology and shifts to less particulate-intensive industries more than offset additional emissions through economic growth. This finding, albeit for different types of emission, is in line with the above mentioned paper of Xiao et al. (2022) who report analog effects for the ten countries that joined the EU in 2004.

3.4 Carbon Leakage Findings

The findings above mostly present the effects of one or multiple policy introductions within the policy's sphere. However, carbon leakage represents a significant risk to the reliability of these estimates. Potentially, the introduction of a carbon price can cause an increase in imports with a higher carbon footprint resulting in a smaller effect than originally measured. As this part of our literature review indicates, carbon leakage is still discussed among researchers. Depending on the exact specification and context of the research question, reported effects are significant, weak, or non-existing. This highlights the importance of including carbon leakage in future research to gain more insight into the mechanisms of this important concept.

In a simple gravitational model, Wang and Kuusi (2024) analyze potential carbon leakage due to the EU ETS. Their results indicate an increased carbon content of EU imports, while the carbon content of EU exports decrease. A counterfactual scenario without the EU ETS shows that there has been slight carbon leakage, but due to the two countering effects, the net carbon balance is close to zero compared to overall emissions embedded in trade. This simple model shows that there is a theoretical risk of carbon leakage. Bistline and Rose (2018) find in their version of the US Regional Economy, Greenhouse Gas, and Energy (US-REGEN) model that carbon leakage in between US states is determined by electricity price differences between regions and relative regional CO_2 intensities of power generation. Furthermore, according to a Garch-model by Guo et al. (2019), the unilateral British carbon tax altered the electricity trade patterns with its partners by increasing imports to the UK. In a later study, again using a Garch-model, Guo (2023) estimate that between 12.7 % and 19.8 % of the emission reduction through the British Carbon Price Support in the UK between 2015 and 2020 have been upset by carbon leakage to France and the Netherlands.

On the other hand, Colmer et al. (2025) find no evidence of carbon leakage in French manufacturing firms covered by the EU ETS between 2005 and 2012 by controlling for changes in the supply-chain through value-added and employment figures of companies. Additionally, they control for within-firm leakage, i.e. reallocating production to non-covered facilities, by looking at the firm-level effects. A decomposition of the emission reduction in the Swedish manufacturing sector by Martinsson et al. (2024) shows that 10 percent of the reduction is due to lower scale, 32 % is caused by a changing composition towards other sub-sectors and the majority – 58 % – due to improved technology and production methods. In the bigger picture, the literature review by Verde (2020) shows that only weak evidence has been found of widespread carbon leakage due to the EU ETS. However, they note that more research on long-term effects and sector-specific effects is needed.

3.5 Overall Findings and Gap in Literature

Overall, the literature presents emission reduction effects from carbon taxes and the EU ETS. These vary in magnitude depending on the country, the sector, and the phase of the EU ETS. EU ETS phases II and III mostly show significant CO_2 emission reductions, while phase I often yields negative but insignificant results. In line with these findings, we expect similar dynamics in our analysis. As the EU ETS evolved, particularly from Phase III onward, with the introduction of stricter caps and annually declining emissions allowances, firms were increasingly incentivized to internalize the cost of emissions, leading to more pronounced abatement responses over time.

The simultaneous timing of EU accession and ETS participation further complicates inference and remains unexplored. There is inconclusive evidence on carbon leakage, with many papers seeing only small or no effects. Moreover, despite substantial literature evaluating carbon pricing, most studies focus on countries with rich microdata (Petrick and Wagner 2014) or report cross-country averages, leaving important heterogeneity unexplored (Rafaty et al. 2025).

This reveals a significant gap in the literature, namely the lack of evidence on how the EU accession-related effect and the introduction of carbon pricing through the ETS jointly shape electricity-sector emissions in late-joiners, and whether the domestic effect is influenced by potential carbon leakage through cross-border electricity trade. A thorough search on existing papers lets us conclude that our research question is still open and needs to be answered.

4 Methodology and Data

The goal of this thesis is to answer three causal questions on the example of Romania: did the EU ETS lower domestic electricity CO_2 emissions; how large is the pure ETS effect relative to broader EU accession effects; and were domestic emissions reductions offset by imports, thereby resulting in carbon leakage? To achieve this goal, we introduce in this chapter a three-stage setup that aims to provide a holistic overview, allowing to compare magnitudes of different effects on the CO_2 emissions in the Romanian power sector.

4.1 Stage 1: SCM Effect of the EU and the ETS Accession

The first step in our methodology assesses the overall effect of Romania's simultaneous EU and EU ETS accession on carbon emissions in its power sector. We use the Synthetic Control Method (SCM). Our outcome variable is the annual emissions generated by domestic electricity production.

4.1.1 Introducing the Synthetic Control Method

The Synthetic Control Method allows us to create a counterfactual control for Romania's electricity sector that has never been affected by an ETS, carbon tax or EU accession. Given this control, we can compare the development of the synthetic twin to the one of its actual counterpart.

Its logic is similar to the differences-in-differences (DiD) method as it compares the evolution of the treated unit to a control group. However, unlike DiD, the control group does not have to be a single entity or simple average. The synthetic control is a weighted average of units that were not affected by the intervention. These are supposed to be similar in relevant characteristics to the treated unit. The goal is to create a weighted comparison group that is a better match for the treated group than any one unaffected unit would be on its own (Abadie 2021). As already seen in our literature review, this method, introduced in Abadie and Gardeazabal (2003) and expanded in Abadie, Diamond, et al. (2010) has been widely applied to evaluate public policy.

Following the notation and approach by Cunningham (2021), the treatment effect in any post-intervention year $t > T_0$ for the treated unit $j = 1$, is given by

$$Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}, \quad \forall t > T_0 \tag{4.1}$$

with Y_{1t} being the actual outcome of Romania's electricity sector and the right part of the expression being the counterfactual synthetic control group outcome. The units $j = 2$ until $J + 1$ are the control units and w_j^* is the weight associated with each unit. The weight therefore indicates how strong a unit j enters into the linear combination that makes up the synthetic control group. Therefore, the weights can as well be interpreted in a straightforward way.

Ultimately, the SCM method minimizes the Mean Squared Prediction Error (MSPE) for the pretreatment period between the synthetic control group and the treated unit.

$$\min \sum_{t=1}^{T_0} \left(Y_{1t} - \sum_{j=2}^{J+1} w_j^*(V) Y_{jt} \right)^2 \tag{4.2}$$

This ensures that the weights w^* are chosen to represent a good pretreatment fit between the treated unit and the control group. The weights w^* are restricted to:

$$\sum_{j=2}^{J+1} w_j^* = 1, \quad w_j^* \geq 0 \, \forall j \in \{2, \ldots, J+1\} \tag{4.3}$$

This restriction leads to the desirable property that the synthetic control group, if any is found, lies in the convex hull of the control group units. This means that there is no extrapolation, which increases the validity of the results (Abadie, Diamond, et al. 2010).

Finding the optimal vector of weights $\mathbf{W}^*$, comprised of the individual w^*, involves two steps:

In a first step $\mathbf{V}$ is optimized to minimize the MSPE as in equation 4.2.$\mathbf{V}$ is a symmetric and positive semi-definite matrix that the optimal weights w^* depend upon.

The synthetic control group is constructed to replicate the behavior of the treated unit's outcome variable in the absence of treatment. Accordingly, the weights v^* indicate how strongly the covariates predict the outcome.

In a next step, $\mathbf{W}^*$ is chosen to minimize the following equation:

$$\|X_1 - X_0 W\| = \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)} \tag{4.4}$$

where $\mathbf{X_j}$ are covariates.

As the matrix $\mathbf{V}$ is diagonal with main diagonal entries $v_1, v_2, \ldots, v_k$, this is simplified to:

$$\sum_{m=1}^{k} v_m \left(X_{1m} - \sum_{j=2}^{J+1} w_j X_{jm} \right)^2 \tag{4.5}$$

The term X_{jm} is the value of the m^{th} covariate for unit j, and v_m is the weight that reflects the relative importance of the m^{th} variable.

The SCM method also accounts for unobserved factors. When the number of pre-intervention periods is large, matching on pre-intervention outcomes effectively controls for unobserved factors and their heterogeneous effects. The key assumption is that units similar in both observed and unobserved characteristics would have followed comparable trajectories prior to treatment (Cunningham 2021).

To assess the statistical significance of the estimated treatment effect, Abadie (2021) proposes an in-space placebo test. This permutation-based procedure involves iteratively applying the synthetic control method to each control unit in the donor pool, thereby generating a distribution of placebo effects. He uses the ratio of the post-intervention Root Mean Squared Prediction Error (RMSPE) to the pre-intervention RMSPE as the test statistic for each unit j:

$$r_j = \frac{\text{RMSPE}_{\text{post}}}{\text{RMSPE}_{\text{pre}}} \tag{4.6}$$

A large value of r_j for the treated unit relative to the distribution of r_j values for the placebo units suggests a significant treatment effect.

Additionally, as described in Abadie, Diamond, et al. (2015), one can conduct in-time placebo tests. The core idea is to apply the SCM to time periods before the actual intervention occurred. If the method produces large estimated effects during these placebo periods, it suggests that the estimated effect for the true intervention may be unreliable and not genuinely attributable to the intervention itself. Conversely, if the method shows no significant effect during the placebo periods but a large effect during the real intervention, it increases confidence in the validity of the original findings.

Lastly, one can test the validity of the results through leave-one-out placebo tests as in Abadie, Diamond, et al. (2015). This procedure systematically re-estimates the model, each time removing one of the control group units. This visualizes whether the original results are heavily reliant on any single donor unit. If the results remain consistent despite the exclusion of different units, it increases confidence that the findings are robust and not merely an artifact of a particular control group unit.

4.1.2 Assumptions and Choices of the SCM for the Romanian Electricity Sector

After the general introduction of the stage one method, this section describes the main SCM assumptions applied to our case.

Abadie, Diamond, et al. (2010) lists two main assumptions for the SCM:

1. "We assume that outcomes of the untreated units are not affected by the intervention implemented in the treated unit."
2. "We assume that the intervention has no effect on the outcome before the implementation period"

Assumption one is straightforward for most countries. It is very likely that the EU and EU ETS accession of Romania did not have any effect on the emissions of the electricity sector of most donor countries as the ETS only applies to the domestic production of the participating countries. There could be, however, some effect in neighboring non-EU countries exporting electricity to Romania. This could be the case if the EU ETS in Romania had an effect on the emissions of the electricity production of these donor countries, e.g., through higher electricity demand of electricity from donor countries from Romanian consumers trying to avoid the ETS cost, resulting in higher emission of these donor countries. If this were the case, by increasing pollution from electricity production in the donor countries, our estimate would be an upper bound estimate, as the counterfactual emissions would be higher than without the treatment.

Assumption two holds with some caveats. The EU ETS and EU accession took effect from one day to the other and producers only had to take emission costs into account from the 1st of January 2007. Therefore, there was no direct incentive for fuel switching before the treatment. Gugler et al. (2023) assume the introduction or a hike in a carbon tax on electricity to be a sharp change without anticipation effect, because electricity cannot be stored economically. However, some electricity producers might have prepared beforehand and changed behavior as both the date of the EU accession and the start of the EU ETS was known and a major event. This would lead our treatment effect to be a lower bound estimate as emissions would already have declined in preparation of the start of the EU ETS or investment could have increased in anticipation of changed demand through the EU accession.

For the general parameters of our SCM set-up, we choose, given the history of Romania and its economic reforms in 1992, to start our synthetic control pre-treatment period in 1993. As Romania joined the EU and the EU ETS in 2007, this is the treatment year. The COVID-19 pandemic marked a break for many aspects of the economy, therefore we restrict our post-treatment period to before 2020, shortly before the end of Phase III. The post-treatment period is thus from 2007 to 2019. As recommended by Abadie, Diamond, et al. (2015), we chose a long post-treatment period to see potential gradually emerging effects or changing effects in different EU ETS Phases. For example, phase three of the EU ETS took effect in 2013 and brought with it changes to the EU ETS. Any potential change in the treatment effect would be visible due to our long post-treatment period.

4.1.3 Data

Through this section, we describe how our donor pool was built to ensure similar characteristics as Romania's power sector and which variables are of importance to our stage one analysis.

The most important variable for our stage one SCM analysis is CO_2 emissions from electricity production per country per year. This is our outcome variable. We use as a data source, the Emissions Database for Global Atmospheric Research (EDGAR) compiled by the European Commission Joint Research Centre (JRC) (Crippa et al. 2024). Specifically, we use the IEA-EDGAR values that harmonize the CO_2 emissions across countries globally. The IEA-EDGAR CO_2 values are available from 1970 until 2023.

As described above, the SCM method allows to add additional variables that could potentially have predictive value. Therefore, similar to Bayer and Aklin (2020), we include GDP (constant 2015 US$, World Bank 2025b), population (World Bank 2025c), and a carbon tax indicator based on World Bank (2025a) that indicates whether a country had a carbon price in a specific year. Furthermore, we add to our dataset the energy mix per country per year aggregated by Ember (2025b). From this, we calculate the share of renewable energy per country and year. All variables are available for the period of 1990 to 2019, with the exception of the share of renewable energy, which is available from 2000 to 2019.

In a next step we clean the assembled dataset to create a reliable donor pool for our synthetic control that consists of the electricity sectors of 39 different countries. We remove all countries with missing CO_2, GDP, or population data. This does not affect any relevant countries for our donor pool and leaves 169 countries.[1]

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[1] To ensure that Serbia and Montenegro have continuous data, we calculate all values as if the country had not split and keep it as one unit. We do not see any structural breaks in the data for the Serbia and Montenegro unit after their split in 2006. As GDP data was missing, we took the 1995 value for 1993 and 1994. As it is very early in our dataset, we do not expect that it will have a strong influence while allowing us to include Serbia and Montenegro in our dataset.

As our treatment is the EU ETS and EU accession, we remove all countries that have been part of the EU ETS as these "treated" countries would bias our estimates. This group mainly consists of EU countries. Similarly, we drop all countries that had a carbon price on electricity in any region before 2020 as these countries would not present a valid counterfactual.

To ensure comparability with Romania, we additionally exclude island nations, countries in the Americas, petro-states on the Arabian Peninsula, and all of Sub-Saharan Africa. Our final donor pool consists of 39 countries. The full list of countries can be found in Appendix Table 9.1.

4.2 Stage 2: GSCM Effect of the ETS Accession

Knowing that in our first stage, we cannot distinguish between effects of EU and EU ETS accession, we aim to single out the effect of Romania's EU ETS accession. To achieve this, we compare treated and untreated industries in Romania using the GSC Methodology. This section describes the methods and discusses its assumptions related to our stage two analysis.

4.2.1 Introducing the Generalized Synthetic Control Method

We follow Bayer and Aklin (2020) and Rafaty et al. (2025) to use the Generalized Synthetic Control Method (GSCM), initially implemented by Xu (2017). The idea behind this approach is to compare the development of CO_2 emissions of treated and untreated sectors within Romania. Like a "regular" Synthetic Control Method, GSCM constructs the counterfactual by creating a reweighting scheme. However, in the GSCM setting before these weights are determined, an interactive fixed effects model (IFE) estimates the counterfactuals. Thus, it is possible to model how latent factors affect carbon emissions. One latent factor could be commodity prices and the unit-specific factor loading would capture the exposure to commodity prices, i.e. the influence of commodity prices on carbon emissions. Another example of a latent factor could be macroeconomic shocks such as recessions, and the factor loading would represent how sensitive a sector is to such shocks. While these examples illustrate the idea of latent factors, it is, however, not possible to unequivocally attribute the factors that the model uses to real life trends. One can merely plot the factors and aim to find an interpretation that mimics the factors' course. Additionally, the interactive fixed effects (we use both time and unit fixed effects) allow us to capture, for example, time-varying effects such as during the financial crisis in 2008 (Bayer and Aklin 2020). Another benefit of GSCM over traditional SCM is that, through parametric bootstrapping, it allows to generate 95 % confidence intervals around the treatment effect. In our specification, we set the number of bootstrapping repetitions to 1000.

These features of GSCM allow us to credibly compare the effect of Romania's ETS accession to a counterfactual path based on different Romanian industries. This is crucial as Romania's accession coincides with EU ETS entry in 2007. Any SCM design such as the one we use in stage one and three would conflate accession dynamics with the carbon-pricing effect. These accession dynamic can be important as EU accession is a large, economy-wide policy bundle that simultaneously affects emissions through multiple channels such as scale (output and FDI growth), composition (industry mix), technique (adoption of economy-wide environmental regulation and cleaner technologies), and public investment (cohesion funds), all evolving over time and co-moving with shocks such as the financial crisis and energy-price swings. Thus, the GSCM is needed because it models time-varying unobservables via interactive fixed effects with sector-specific loadings, allowing us to absorb broad accession-related and country-wide shocks while constructing a credible counterfactual for the ETS-covered electricity sector. Moreover, GSCM recovers a dynamic treatment path that captures the evolution of the treatment across time rather than a single shift. This is essential as both accession impacts and ETS stringency evolve. Taken together, these features make GSCM suitable for our analysis and plausible that any remaining post-2007 divergence of covered sectors from their synthetic path reflects the ETS effect and not the accession bundle.

Applied to our case, we assume that the carbon emissions per industry (i.e. our outcome variable) can be explained by the following GSCM specification:

$$Y_{it} = \delta_{it} ETS_{it} + \lambda_i' f_t + \tau_t + \zeta_i + \varepsilon_{it},$$

Accordingly, the variable of interest for us is the treatment effect at time t: δ_{it}. δ_{it} is the difference between the observed outcome of industry i at time t and the respective counterfactual outcome. Thus, δ_{it} is equal to $Y_{it}(1) - Y_{it}(0)$ whenever $t \geq t_i^{ETS}$ with t_i^{ETS} denoting the treatment year (i.e., 2007 for Energy, Minerals, Metals, and Paper and 2013 for Chemicals; World Bank 2015).

Generally, the ATT in periods $t \geq t_i^{ETS}$ is given by $ATT_{t,t \geq t_i^{ETS}} = \frac{1}{N_{tr}} \sum_{i \epsilon \mathcal{T}} \delta_{it}$ with N_{tr} being the number of treated sectors. Although we calculate the treatment effects for all treated industries, for our thesis, we are only interested in the effect the ETS had on the electricity sector. Thus, the sum collapses to $ATT_{t,t \geq t_{electricity}^{ETS}} = \delta_{electricity,t}$ (Basaglia et al. 2024).

To impute the estimates for $Y_{it}(0)$ (which, for treated units, is unobserved by definition), we follow the three-step procedure in Xu (2017) and Bayer and Aklin (2020), with i indexing sectors and t indexing time.

$$Y_{it} = \lambda_i' f_t + \tau_t + \zeta_i + \varepsilon_{it}, \qquad \text{control group data, } t = 1, \ldots, T \tag{4.7}$$

$$Y_{it} = \hat{\lambda}_i' \hat{f}_t + \tau_t + \zeta_i + \eta_{it}, \qquad \text{treatment group data, } t < t_i^{ETS} \tag{4.8}$$

$$\hat{Y}_{it} = \hat{\lambda}_i' \hat{f}_t + \tau_t + \zeta_i, \qquad \text{treatment group data, } t \geq t_i^{ETS} \tag{4.9}$$

In the first step, the IFE model only uses control group data of all available years to retrieve the coefficients on the latent factors, f_t. The second step is used by the GSCM algorithm to determine the factor loadings $\hat{\lambda}_i'$ for each treated unit. This is done by minimizing the mean squared prediction error (MSPE) of the predicted treated outcome in pretreatment periods. Lastly, $Y_{it}(0)$ is imputed by utilizing $\hat{f}_i$ and $\hat{\lambda}_i'$. We use an algorithm to determine the optimal amount of latent factors λ_i (between 0 and 5) for our model. This process, implemented by Xu (2017), allows to capture multiple dimensions while simultaneously preventing overfitting. The chosen factors are constant over time thus the number of factors is fixed (Basaglia et al. 2024; Bayer and Aklin 2020; Xu 2017).

We differ from Bayer and Aklin (2020) in three ways: First, in their main analysis, Bayer and Aklin use aggregated emissions with only one group of combined EU ETS-covered sectors and one group of non-covered sectors, without differentiating between individual sectors. We, on the other hand, make use of the different sectors and report our results in detail specifically for the electricity sector. We also rely on a broader control group. However, using the data on an aggregate level allows Bayer and Aklin to include country-level covariates like GDP which is impossible for us as there is no consistent data for the time frame we are interested in. Second, Bayer and Aklin (2020) only include countries that were already EU members when the ETS was established. Thus, they exclude Romania because of methodological difficulties. Using GSCM on sector level, we can credibly isolate the ETS effect from the effect of the EU accession and augment their analysis. Third, we embed the GSCM in our three stage approach and can compare magnitudes between the different effects of EU and ETS accession.

4.2.2 Assumptions and Choices of the GSCM

To ensure that our case is suitable for the method, we justify and test the assumptions listed in Xu (2017):

Assumption 1: Functional Form The functional form assumption means that a fixed set of factors affects all treated and control units i.e., that there is no structural break in the data (Xu 2017):

$$Y_{it} = \delta_{it} ETS_{it} + \lambda_i' f_t + \tau_t + \zeta_i + \varepsilon_{it}, \tag{4.10}$$

where the treatment indicator ETS_{it} equals 1 if industry i has been in the scope of the EU ETS regulation prior to time t and equals 0 otherwise (i.e., $ETS_{it} = 1$ when $i \in \mathcal{T}$ and $t \geq t_i^{ETS}$, and $ETS_{it} = 0$ otherwise; with $\mathcal{T}$ being the treated industries and t^{ETS} the first year of treatment for industry i).

δ_{it} is the heterogeneous treatment effect on industry i at time t, $f_t = [f_{1t}, \ldots, f_{rt}]'$ is an $(r \times 1)$ vector of unobserved common factors, $\lambda_i = [\lambda_{i1}, \ldots, \lambda_{ir}]'$ is an $(r \times 1)$ vector of unknown factor loadings, τ_t is a vector of time fixed effects, ζ_i is a vector of industry fixed effects, and ε_{it} represents unobserved idiosyncratic shocks for industry i at time t and has zero mean.

Assumption 2: Strict exogeneity This assumption claims that the error term of any unit at any time is independent of treatment assignment, observed covariates, and unobserved cross-sectional and temporal heterogeneities of all units at all periods, i.e. conditional mean independence is implied: $\mathbf{E}[\epsilon_{it}|D_{it}, x_{it}, \lambda_i, f_t] = \mathbf{E}[\epsilon_{it}|x_{it}, \lambda_i, f_t] = 0$ (Xu 2017).

The strict exogeneity assumption is needed to identify the treatment effect even though some unmeasured confounders like industry-specific shocks and other time-varying idiosyncrasies might exist (Rafaty et al. 2025). One example of such a development could be a decrease in investment costs for renewable energies that cannot be attributed to the ETS.

The assumption can be supported by analyzing the pretreatment fit of the estimator as well as in-time placebo tests. If the treatment effect stays close to zero in the pretreatment period and the behavior does not change drastically with the treatment assignment year, the assumption is likely to hold.

Assumption 3: Weak serial dependence on the error terms Strong common trends or persistent patterns should be captured by the latent factors and time fixed effects in the GSCM framework, which mitigates residual serial dependence.

Moreover, as shown in Figure 4.1, the PACF of the residuals shows a spike at lag 1 but no significant autocorrelation at higher lags. This indicates weak short-term serial correlation without strong persistence, consistent with the assumptions of the method.

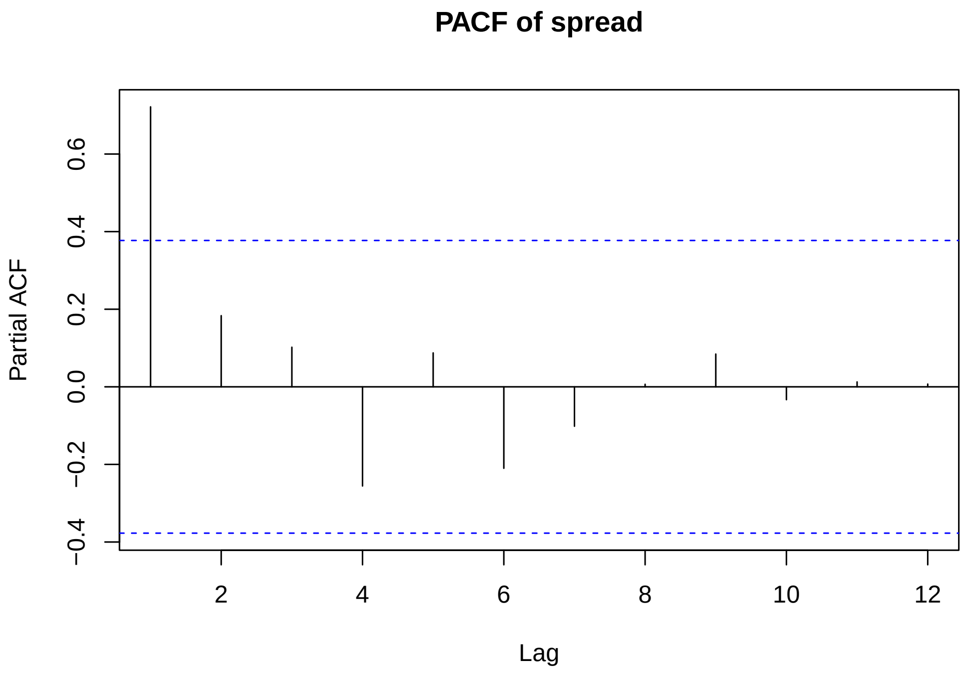

Figure 4.1: PACF Test

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Assumption 4: Regularity conditions This condition ensures the convergence of the estimator. As can be seen in figures 4.2 and 4.3, the factor loadings and latent factors do not show explosive behavior. Furthermore, the error terms are bounded and do not show any strong outliers. Finally, if our estimator converges, we do not have any indication that the assumption is violated.

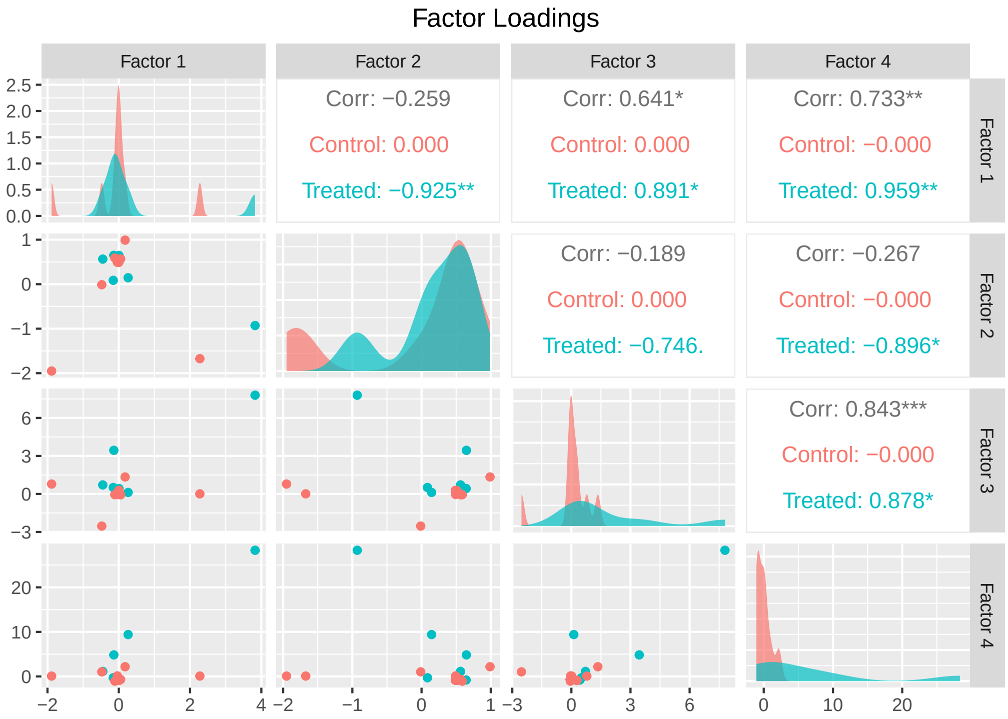

Figure 4.2: Factor Loadings

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Assumption 5: Cross-sectional independence and homoscedasticity of the error terms Transitory shocks in $\epsilon_{i,t}$ are assumed to be cross-sectionally independent, meaning that any unobserved common factors and heterogeneities with a substantive impact on emissions in our model are accounted for by time and industry-sector fixed effects τ_t and ζ_i, or by the multiplicative factor structure, $\lambda_i' f_t$ (Rafaty et al. 2025). As there exists currently no test for this, we assume that through the structure we set up, this assumption holds.

With the same justification as for stage one, we choose as our pretreatment period the time from 1993 to 2006. Our posttreatment period goes from 2007 to 2019.

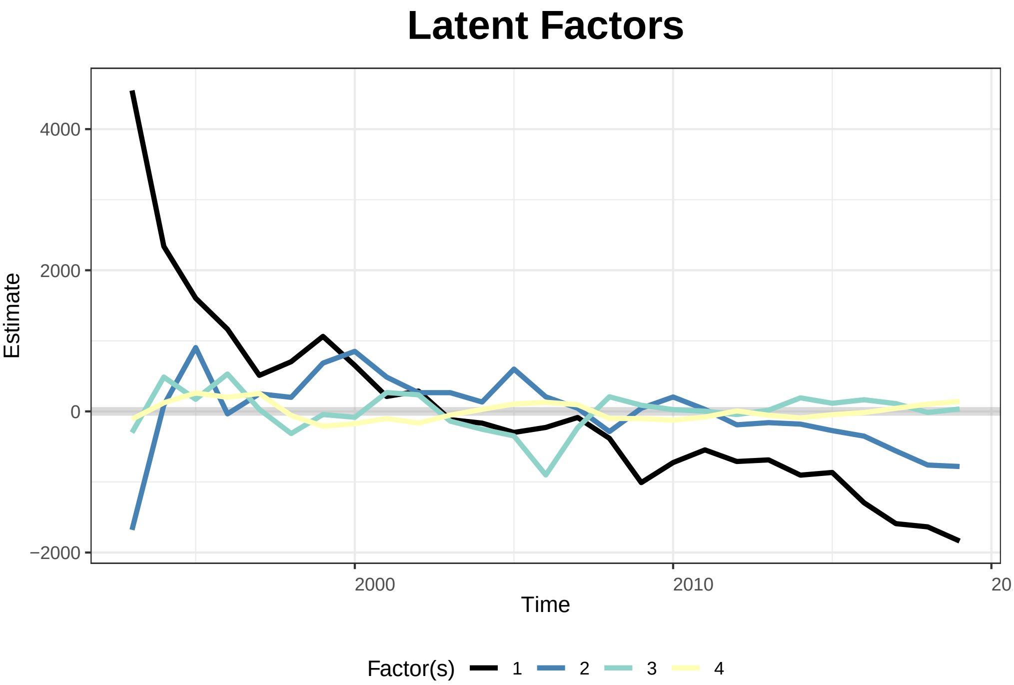

Figure 4.3: Latent Factors

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4.2.3 Data

This section describes the data collection process for stage two and the rationale behind the choices made.

To estimate counterfactual emissions in the absence of the EU ETS, we require data from before the policy's introduction. Specifically, we need emissions data that is disaggregated at the industry-sector level and allows us to distinguish between treated sectors (covered by the EU ETS) and non-treated sectors (not covered). Compared to the other late entrants to the EU, Romania has a larger and more diverse industrial sector. This enhances the robustness of our model by reducing sensitivity to firm-level shocks or idiosyncrasies. The industry-level distinction is essential for applying the generalized synthetic control method, which constructs counterfactual outcomes by comparing trends in treated units to suitable control units over time.

To fulfill these requirements, we build on the approach developed by Bayer and Aklin (2020), who construct a harmonized sectoral dataset by mapping UNFCCC emission categories to EU ETS activity codes. We adopt their sector classification scheme to ensure conceptual consistency in identifying treated industries. Importantly, Bayer and Aklin demonstrate that UNFCCC emissions data closely match the official EU ETS data from the EU Transaction Log (EUTL) for the post-treatment period (2005-2016 in the EU). They report that "the data we use in our main analysis (...) achieve very high accuracy of $\bar{\rho} = 0.954$" when comparing UNFCCC and EU ETS emissions across countries, and that "the data also obtain excellent matches not only in levels but also in trends" with an average $R^2 = 0.997$ in country-level regressions (p. 8809).

In our analysis, we rely solely on the *UNFCCC dataset* (European Environment Agency (EEA) 2025) and apply Bayer and Aklin's sector mapping to the Romanian case. This approach enables us to generate consistent, long-run emissions data from 1993 to 2019 while maintaining compatibility with the EU ETS framework and avoiding inaccuracies from merging multiple reporting systems. We are using absolute CO_2 values per sector and do not relate it to each sector's GDP as, to our knowledge, there is no per sector GDP data available for Romania in the period from 1993 to 2019. Normalizing sector-level emissions by Romania's aggregate GDP is inappropriate, because the resulting intensity measure conflates sectoral performance with economy-wide output dynamics and can decline purely due to GDP growth elsewhere in the economy, even without any emissions abatement in that sector.

After the mapping, we initially end up with five treated and nine untreated sectors. While four of the treated sectors are part of the ETS directly after Romania joined the EU in 2007 (Energy, Metals, Minerals, and Paper), the ETS got expanded for Chemicals in 2013 (phase 3 of the EU ETS). Because we are interested in the emissions from electricity and not the entire energy sector, we split up further the energy sector as it was defined by Bayer and Aklin (2020). We distinguish between Electricity (category 1.A.1.a "Public Electricity and Heat Production" in the UNFCCC data) and Residual Energy (categories 1.A.1.b "Petroleum Refining" and 1.A.1.c "Manufacture of Solid Fuels and Other Energy Industries" in the UNFCCC data). Consequently, we end up with six treated sectors.

As control sectors, we use Agriculture, Food Processing Manufacturing Industries, Fugitive Emissions from Fuel, Non-energy Products from Fuel, Other Energy Not Specified Elsewhere, Other Manufacturing Industries and Construction, Other Sectors Energy Fuel Combustion, Transportation, and Waste.

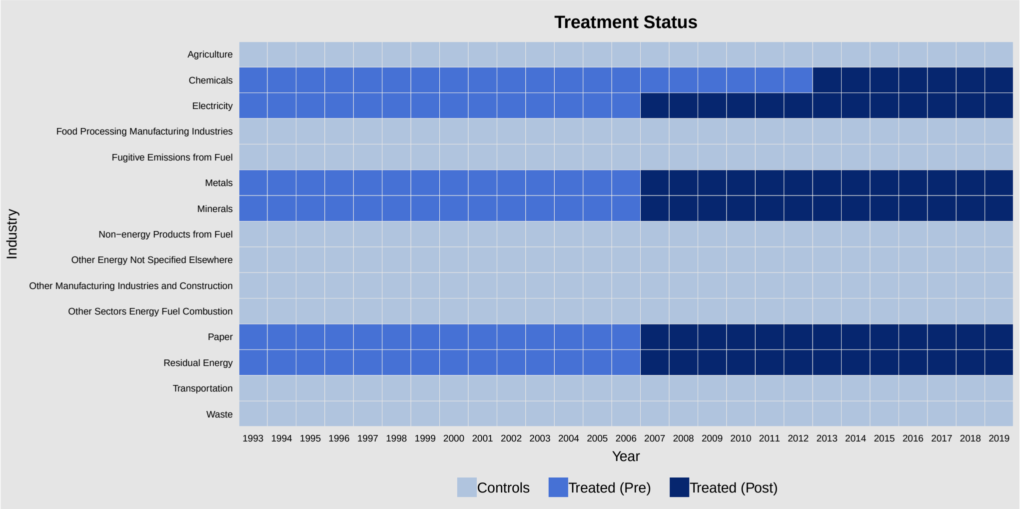

Figure 4.4: Treated and Untreated Sectors and their Treatment Status

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4.3 Stage 3: Expanding SCM to Carbon Leakage

Our third stage uses the same SCM methodology and assumptions as our first stage in chapter 4.1.1, applying it to a different dataset to expand our analysis toward carbon leakage. As in stage one, it estimates the effect of the joint EU and ETS accession. This section proceeds by focusing on the aspects that differ from stage one and the data used for the carbon-leakage analysis.

In our setting, we define carbon leakage as an increase in emissions from electricity imports that partially offset domestic emission reductions. Thus, in the absence of significant carbon leakage, the net treatment effect estimated in stage three should be comparable in magnitude to the stage-one results. Conversely, smaller net emissions reductions would be indicative of carbon leakage.

There is a specificity to take into account for our third stage: An abrupt and drastic increase in average emissions of the electricity production from a country that is exporting to Romania, would increase Romania's emissions through imports without any change in behavior from Romania. Additionally, if this country was entering the synthetic control group, this would increase actual emissions and counterfactual emissions. In this case, both the actual and counterfactual emissions would be directly connected. However, in our data, we do not see big jumps in average emission intensity, so we assume it to be a lesser concern.

As donor pool, we use data of different countries filtered and cleaned as described below. Specifically, our outcome variable is the sum of the emissions from domestic electricity production and emissions attributed to the production of imported electricity. The pretreatment period spans 2000–2006 and the posttreatment period covers 2007–2019.

4.3.1 Data

For our third stage, we create a dataset on the emissions of imported electricity that allows us to expand our analysis. While the OECD Teco2 dataset offers similar data on CO_2 emissions embodied in trade (Yamano et al. 2024), we prefer to assemble our own dataset using the EDGAR CO_2 emissions from stage one. Thereby, we can calculate emissions from both domestic and foreign production based on the same harmonized CO_2 emission data. This way, we can ensure that the emission data is consistent between domestic and foreign production, which leads us to aggregate them in a methodologically sound way.

First, we compile annual UN Comtrade Trade data from 2000 to 2019 for electrical energy (United Nations Statistics Division 2025). The corresponding HS code is 2716 and we choose as reporting country the importer. This is to facilitate a higher data quality as one can more easily assume that a country that reported its imports from one country, reported all its imports, whereas some countries might not report any of their exports in a given year, which would bias downwards the import quantity of the importing country. Nevertheless, there remains some potential for measurement error in international trade statistics. This data provides us with the electricity imports in quantity and value for each country and year individually. However, in some cases, the importing country only recorded the import in value and not in quantity. For these, we impute the quantity based on the average price of imports to this country in this year to fill these gaps.

Afterwards, we combine it with a dataset on electricity production by Ember (2025a). This gives us the yearly total electricity production per country. Using our CO_2 data on emissions from the electricity sector from stage one, we can calculate the average emission intensity per MWh for each country for each year.

Thereby, we now have the emission intensity of electricity production for each country and year *and* the electricity imports (together with the information on the country of origin) into each country for every year. This allows us, in a last step, to calculate the emissions resulting from electricity imports to each country in every year. Combining it with our first dataset on emissions of the domestic electricity production, we capture the full picture of emissions from both domestic production and imported electricity.

Subsequently, to ensure high quality data for the donor pool of countries, we clean our dataset. First, we discard any countries that have missing data (i.e. reported no imports) in any year between 2000 and 2019. Then, we remove the countries where in any year we could not calculate the emissions from imports because of missing data on the emission intensity of the exporting countries. Afterwards, we exclude again island states and countries in South America. This leaves 35 countries in our dataset. After removing all remaining EU countries, we have 13 countries left in our country pool. Although this is fewer countries than in our first step, it is in line with existing SCM papers such as Andersson (2019) that has 14 donor countries. Due to data quality, there is unfortunately, not a perfect overlap between the stage one and stage three SCM donor pool. The full list of countries can be found in Appendix Table 9.2 to compare the donor pools of stage one and stage three in more detail.

5 Results

This chapter presents the results of each stage of our analysis together with the robustness and placebo tests associated with the respective methodology.

5.1 Results First Stage

In figure 5.1, we show the main results for the stage one SCM analysis on the CO_2 emissions[2] of Romania's electricity sector. In the treatment year 2007, Romania joined

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[2] We are using absolute emissions to ensure comparability among all stages of our analysis. As in stage two, there are data limitations regarding GDP per sector data (described in chapter 4.2.3), we also do not normalize the emissions in stage one and stage three. However, for stages one and three, we do run robustness checks including GDP data.

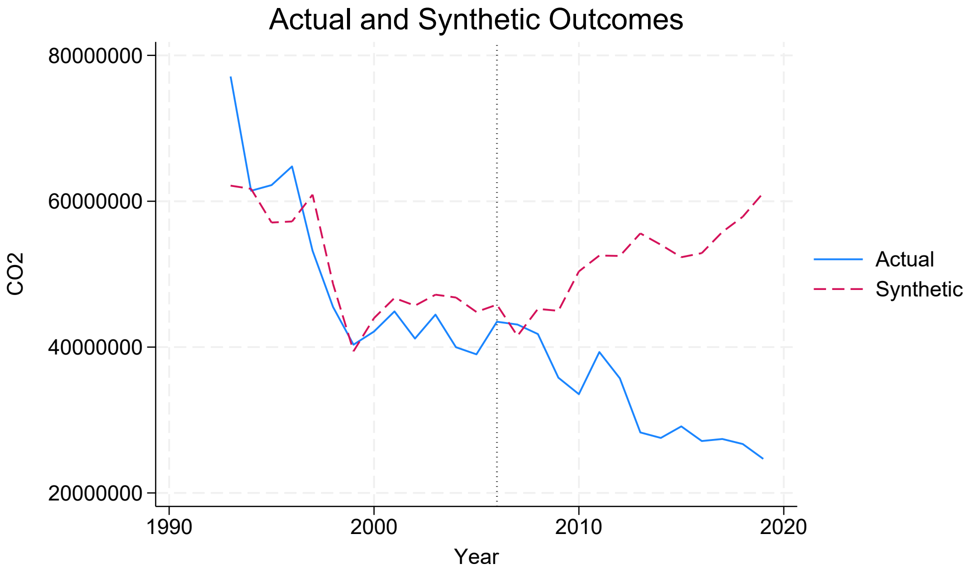

Figure 5.1: SCM Actual and Predicted Counterfactual CO_2 Emissions from Domestic Romanian Electricity Production (tonnes of CO_2).

both the EU and the EU ETS. As will be shown later in chapter 5.1.2 on placebo tests, these stage one results have to be taken with a grain of salt.

The synthetic control unit for Romania, as chosen through the SCM, is composed of 52 % Moldova, 40 % Iraq, 5 % Kazakhstan, and 3 % Russia. During the pretreatment period, the synthetic control group for Romania follows the actual outcome. Especially the decline in the second half of the 1990 and the subsequent rise is mirrored closely. From 2002 to 2005, the synthetic control is slightly higher than the actual unit. However, this gap is reduced to 5 % in the last pretreatment year.

After the treatment in 2007, the CO_2 emissions of the synthetic control group start rising. The emissions of Romania on the other side, start falling. This results in the causal effect, per the SCM, to be even higher than the simple decline in emissions. The actual observed decline in CO_2 emissions in the Romanian electricity sector is of 43 % (CAGR of -4.3 %). The value is calculated by comparing the actual emissions in 2019 to the last pretreatment value of actual emissions in 2006. The SCM indicates a cumulated treatment effect of 60 % (CAGR of -6,74 %). This is the difference between the synthetic counterfactual value after 13 years of treatment, so in 2019, compared to the actual value in 2019. The exact evolution of the treatment effect over the time period can be seen in Figure 5.2. There is no particular structural break in 2013 when the third phase of the EU ETS takes effect.

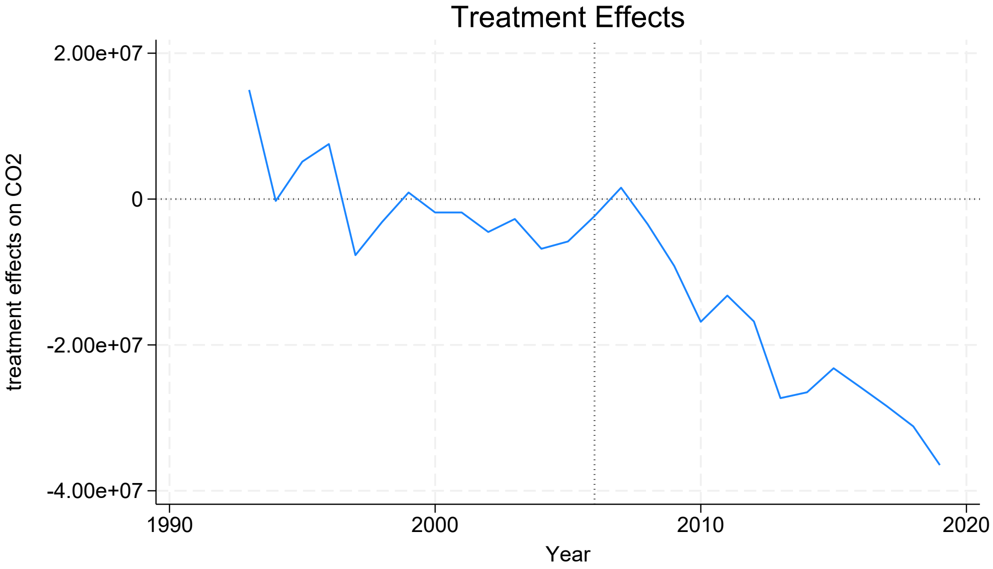

Figure 5.2: SCM Treatment Effect on CO_2 Emissions from Domestic Romanian Electricity Production (tonnes of CO_2).

5.1.1 Robustness Tests

As an additional robustness check, we look at the GDP per capita for the period of 2000 to 2005. The synthetic control group GDP per capita is up to 40 % lower than Romania's. As it could potentially influence the ability to reduce emissions in the electricity sector, we have added a SCM specification with CO_2 emissions per GDP as our outcome variable. You can find the exact results in the appendix (see, for example, Figure 9.1). Additionally, we have included in Figure 9.2, another alternative predictor set with CO_2 emissions per capita. Both show a similar trend as our main specification, indicating that the differences in GDP or population are not an obstacle for our main specification. We want to note as well that the average share in 2000-2005 of renewable electricity production in the synthetic control group is much lower compared to Romania (6.3 % and 28.9 %). However, we assume this to be already reflected in the total emissions of the sector.

The leave-one-out robustness test in figure 5.3 is also promising. No single country drives the treatment effect and the patterns remain similar. Leaving out a country from the donor pool, does not alter the general direction and trend of the results. The results still indicate

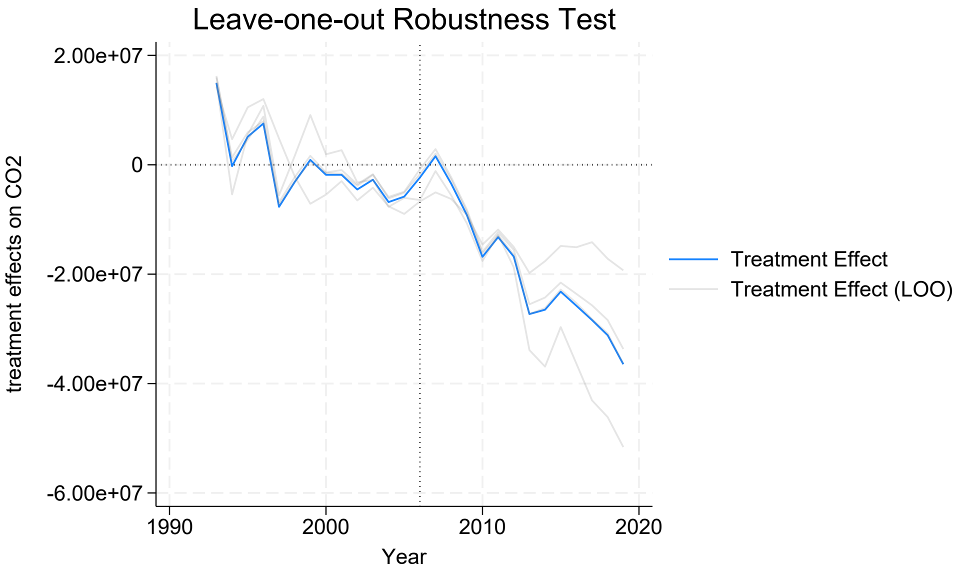

Figure 5.3: SCM Leave-one-out Robustness Test: Treatment Effect on CO_2 Emissions from Domestic Romanian Electricity Production (tonnes of CO_2).

a strong decline in CO_2 emissions of the electricity sector due to joining the EU ETS and EU accession.

5.1.2 Placebo Tests

As explained by Abadie, Diamond, et al. (2010), the in-space placebo tests, allow to evaluate whether the synthetic control's estimated effect on the treated country is large relative to the estimated effect for a random country. Following Andersson (2019), the in-space placebo test result on the left in figure 5.4, shows all countries that have a pretreatment MSPE of up to 20 times larger than Romania's pretreatment MSPE. This excludes the most extreme outliers A graph including only units that have a similar pretreatment fit as Romania (up to two times the pretreatment MSPE) follows the final specification by Abadie, Diamond, et al. 2010 and is shown on the right.

While the main specification and robustness checks, seemed promising, the in-space placebo tests leave some doubt whether the results could be coincidental. One can see that the treatment effect for the Romanian electricity sector is consistent and strong. However, there are multiple other countries that exhibit similar treatment effects without any connection to the EU ETS. As we have excluded any countries with a carbon tax or

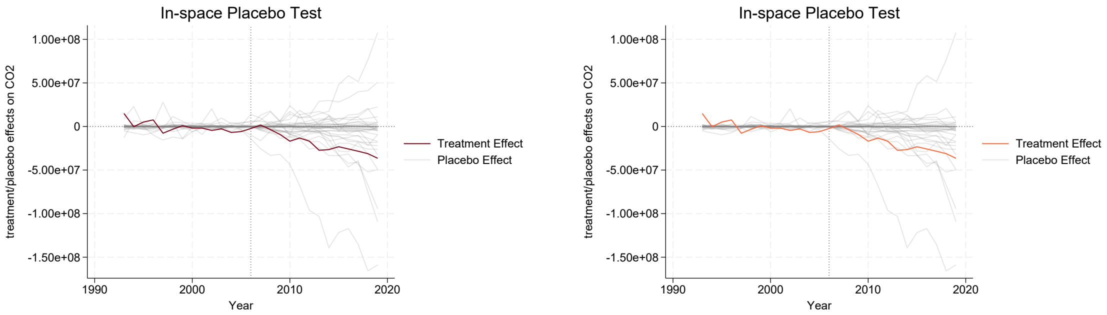

Figure 5.4: SCM In-space Placebo Test: Treatment Effect on CO_2 Emissions from Domestic Electricity Production of respective Countries (tonnes of CO_2). Left: Including units with a pretreatment MSPE of 20 times the pretreatment MSPE of Romania. Right: Units with a pretreatment MSPE multiple of 2.

a cap-and-trade carbon system, we exclude the possibility that the placebo effect is due to other countries introducing such a scheme simultaneously. This does not mean that the effect that we found is void. However, there is quite some uncertainty attached to it, as similar or even stronger results could be found in random countries without specific policies.

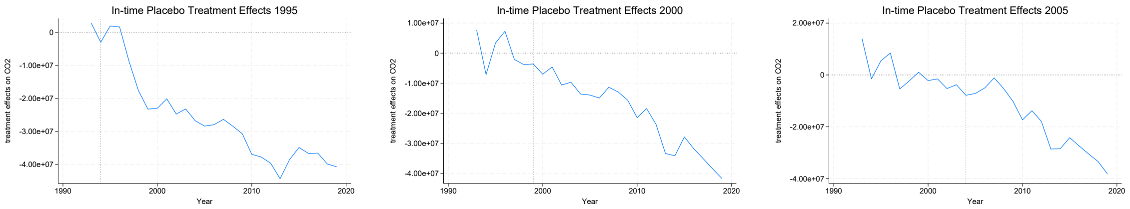

Figure 5.5: In-time placebo tests in 1995, 2000, and 2005 showing the placebo SCM Treatment Effect on CO_2 Emissions from Domestic Romanian Electricity Production (tonnes of CO_2).

Whereas the in-space placebo tests cast doubt on the results of our main specification, the in-time placebo tests slightly support it. The placebo test for 1995 has only two years of pretreatment and the country pool consists of two countries of which 93 % is made up of Bosnia and Herzegovina. This leads us to discard it from further analysis. The composition of the 2000 in-time placebo test control group shows similarities with the main SCM specification, albeit with different weights: It is made up of 50 % Moldova, 27 % Kazakhstan, 20 % Iraq and 3 % Russia. We can see as well a treatment effect, however, already in the three years before the placebo treatment time, the treatment effect is negative. This indicates that there is a poor fit for the actual treatment period and makes it less robust than our actual specification. The synthetic control group for the 2005 placebo test is weighted as 49 % Moldova, 36 % Iraq, 12 % Kazakhstan, and 3 % Russia. This specification confirms our results from our main specification as emissions only fall from 2008 on and we see little treatment effect before. These three in-time placebo tests together indicate that for Romania, only the actual treatment period of 2007 is a valid specification.

5.2 Results Second Stage

The GSC method allows us to show the cohort average treatment effect on the treated (CATT) for the electricity sector and the respective confidence intervals that are based on a parametric bootstrapping procedure (Figure 5.6). Additionally and analogically to stage one, the treated and counterfactual emissions paths can be found in Figure 5.7. The results are based on four latent factors which was the optimal number according to the cross-validation process described in Section 4.2. Latent factors and factor loadings can be found in Figures 4.2 and 4.3.

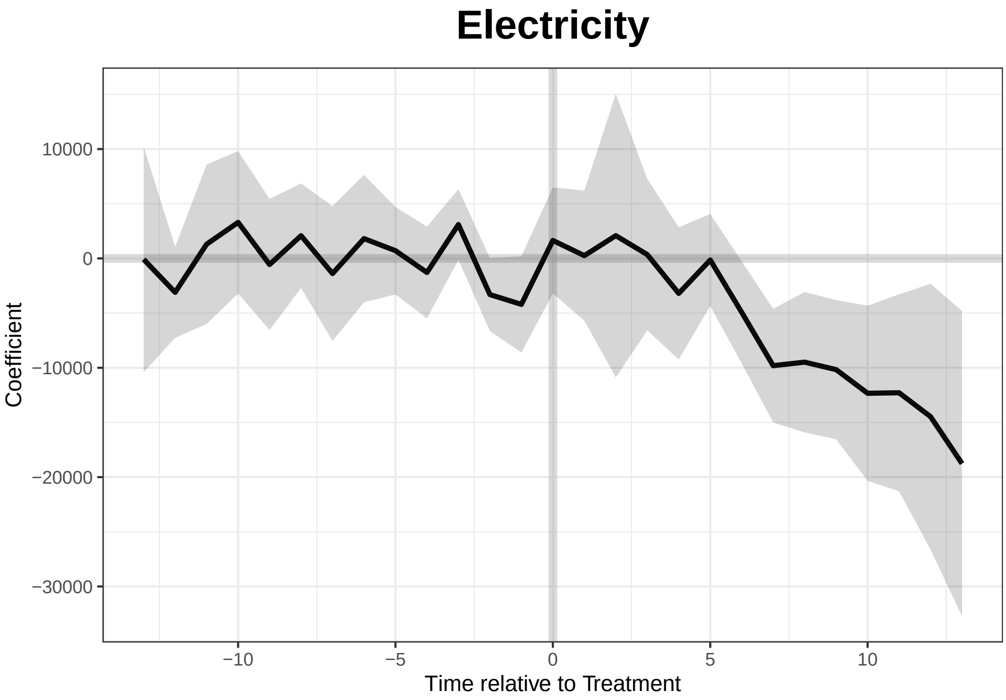

Figure 5.6: GSCM Treatment Effect on CO_2 Emissions from Domestic Romanian Electricity Production (in kilotonnes of CO_2).

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The four factors allow for a close approximation in the pretreatment period. After treatment in 2007, both treated and counterfactual emissions rise for a short period and start declining after 2008. While the actual emissions of the Romanian electricity sector continue to decline, the estimated counterfactual stabilizes and shows a slow incline after 2010. From 2011 onward, the two paths start to diverge. Figure 5.6 shows that the difference becomes significantly different from zero in 2013 (see also in the appendix Table 9.3). In

2019, the estimation indicates a cumulative CO_2 emission reduction of 50.05 % comparing the actual outcome with the synthetic counterfactual. This translates to a CAGR of -5.20 % meaning that, based on our estimate, the EU ETS led to an average annual reduction of CO_2 emissions of 5.20 % compared to a scenario where it would not have been introduced.

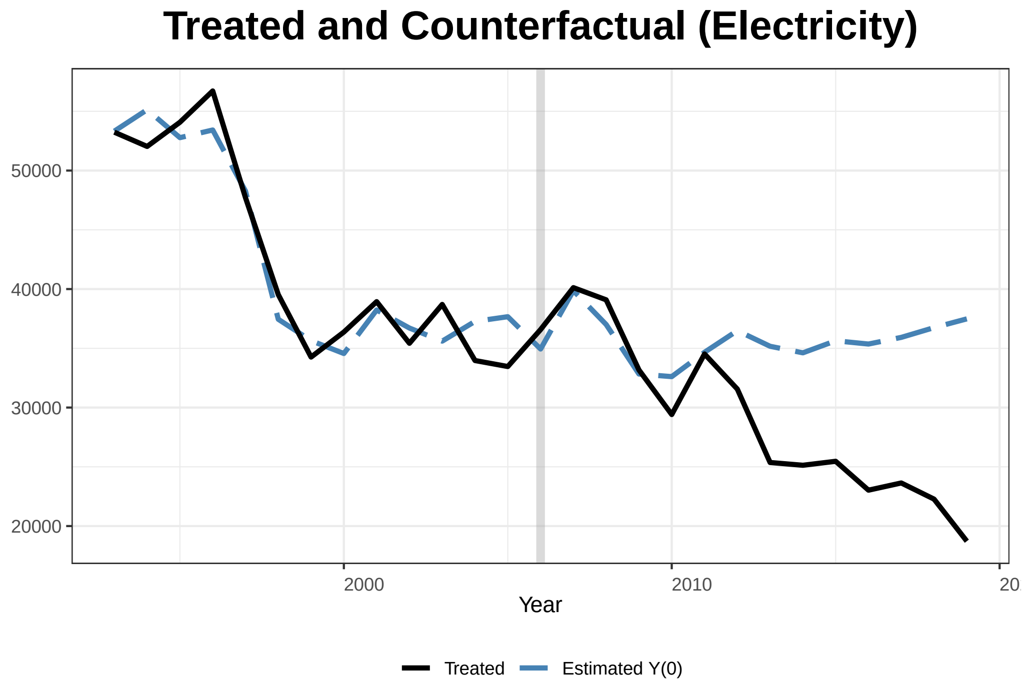

Figure 5.7: GSCM Actual and Predicted Counterfactual CO_2 Emissions from Domestic Romanian Electricity Production (in kilotonnes of CO_2).

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5.2.1 Robustness Tests

Similar to Bayer and Aklin (2020), we perform Leave-One-Out robustness checks. In our case this corresponds to leaving out one untreated sector completely and running our GSCM without it. This check is especially important since our analysis relies on a limited number of untreated sectors. To ensure comparability, we used four latent factors for each of the tests. As Figure 5.8 shows, all Leave-One-Out robustness checks behave roughly like the initial estimation. However, in two tests (without Food Processing Manufacturing Industries and without Other Manufacturing Industries and Construction) the pretreatment fit suffers. Still, we do not see drastically different behavior and conclude that our findings are robust to changes in the underlying data.

Unfortunately, we cannot perform a robustness test with regards to the inclusion of GDP data. To our knowledge, there is no data available that can be sufficiently well matched with our sector split. An inclusion of GDP data on country level, like in Bayer and Aklin (2020), is not possible as we only analyze one country leading to no variation between the treated units in a time period.

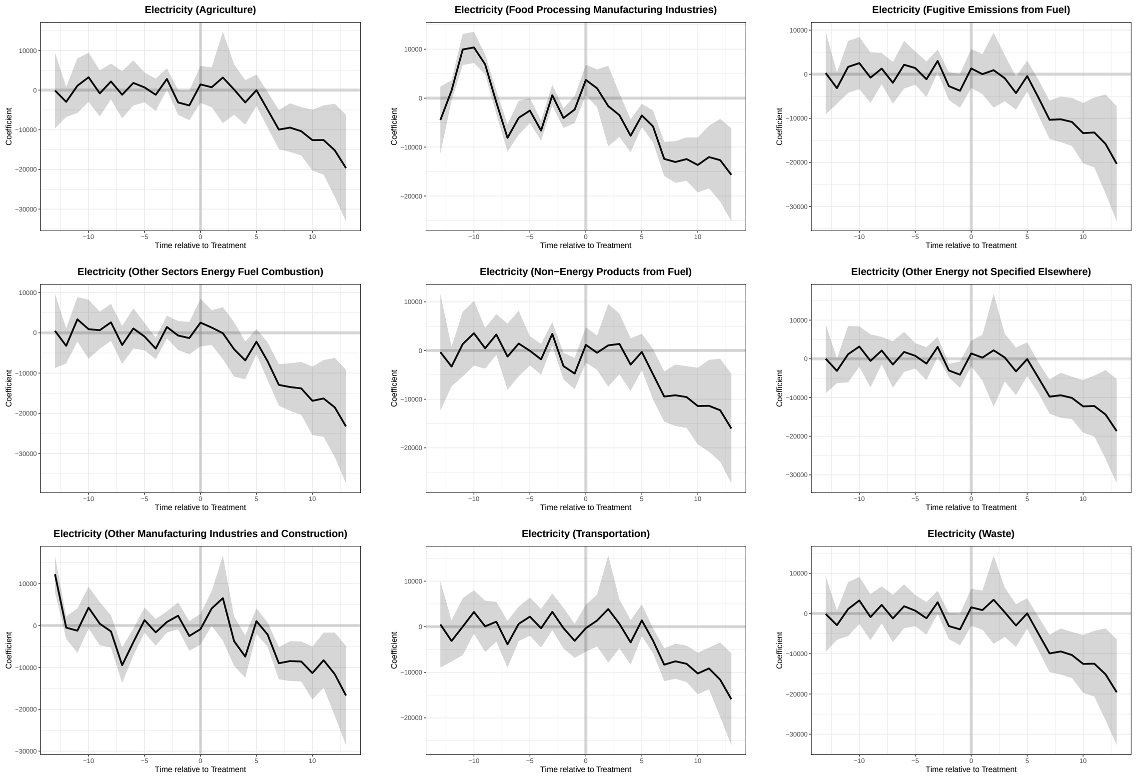

Figure 5.8: Leave-One-Out Robustness Checks with Left-Out Industries in Parentheses. Treatment Effect on CO_2 Emissions from Domestic Romanian Electricity Production (in kilotonnes of CO_2).

5.2.2 Placebo Tests

We conducted multiple in-time placebo tests (see Figure 5.9). In all placebo tests, emissions start dropping around 2013. This suggests that there is no indication for the effect in our main specification being attributable to anything but Romania's EU ETS accession and the start of phase III. If the shape of the graph would change drastically between placebo tests or the beginning or the negative trend would appear at different times, our model would lack robustness. This would indicate that the latent-factor structure would not adequately absorb evolving, economy-wide shocks, attributing unrelated variation to the ETS. Our earliest in-time placebo test simulates treatment in the year 2000. Earlier placebo years introduce practical issues with the GSC method as it needs a sufficiently long pretreatment period to calibrate the results.

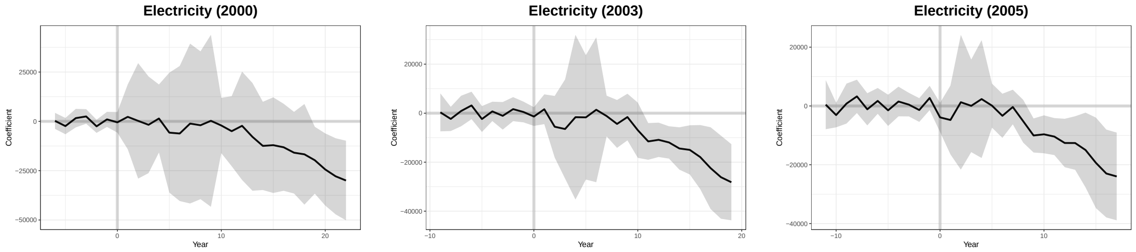

Figure 5.9: In-Time Placebo Tests with Placebo Treatment Year in Parenthesis. Treatment Effect on CO_2 Emissions from Domestic Romanian Electricity Production (in kilotonnes of CO_2).

To conclude the stage two placebo tests, we also investigated the effect, the EU ETS introduction had on non-treated industries, like transportation. If, for example, the transportation sector were to also experience a decline in emissions, our causal estimate for the electricity sector would appear less trustworthy. However, an analysis of the transportation sector does not indicate such behavior (see Figure 5.10). Although not statistically significantly different from zero, the GSCM model for the transportation sector estimates a surplus of actual emissions to a synthetic twin.

Overall, all our robustness checks and placebo tests leave us to conclude that the methodology in stage two is valid and robust. We do not see any behavior that would indicate otherwise or trouble causality.

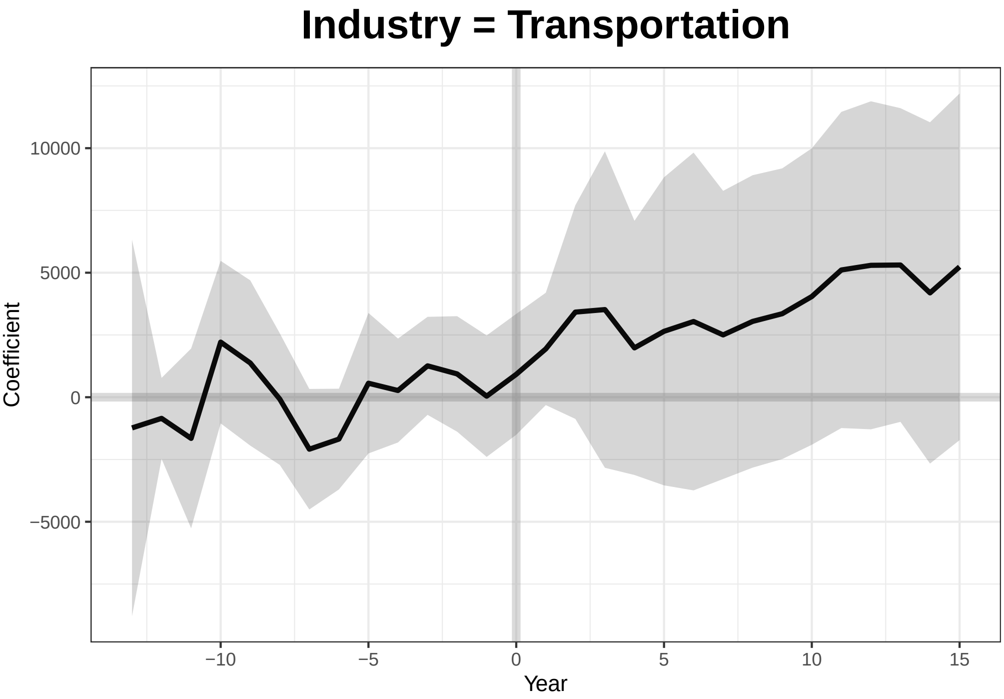

Figure 5.10: Treatment Effect of the Placebo Test for the non-EU ETS covered transportation sector (in kilotonnes of CO_2).

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5.3 Results Third Stage

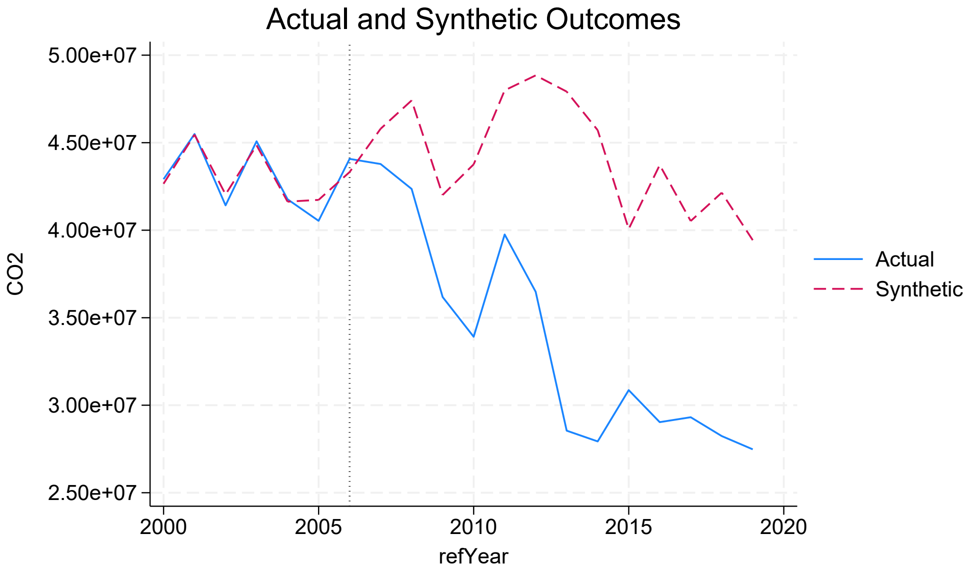

Figure 5.11: SCM Actual and Predicted Counterfactual CO_2 Emissions from Domestic Romanian Electricity Production and Imported Electricity (tonnes of CO_2).

Stage one and two have looked at domestic emissions. However, as Romania has seen a strong increase in electricity trade, it is important to expand the view to include as well CO_2 emissions that can be attributed to imports into Romania. The SCM counterfactual prediction and the actual emissions can be seen in Figure 5.11. As in stage one, the joint effect of the EU and the EU ETS accession is estimated.

The synthetic control group in our third stage is composed of 56 % Armenia, 23 % Ukraine, 14 % Turkey, and 7 % South Africa. During the six year pretreatment period, the fit between the actual emissions and the synthetic control group is very good. At no point it is off by more than 3 percent and on average only by 1 percent, oscillating around zero. After the treatment, the counterfactual emissions vary up and down in a similar pattern to the actual emissions. However, while the counterfactual emissions show a relatively stable mean over the 13 years post-treatment period, the actual emissions trend downward. Between 2006 (the last pretreatment year) and 2019, actual CO_2 emissions from the sum of Romanian electricity sector emissions and emissions attributed to electricity imports, fell by 38 %, corresponding to a CAGR of -3.57 %. When comparing the observed trajectory to the synthetic counterfactual, the SCM attributes as treatment effect a cumulative reduction of 30 % (CAGR of -2.74 %) compared to the counterfactual outcome. The year-by-year development of this treatment effect is illustrated in Figure 5.12. It shows that most of the emission reduction, taking into account both domestic and foreign electricity production, is causally attributed by the SCM model to the EU and ETS accession. In our third stage, one can see a sizable emission reduction in the actual values between 2011 and 2014. This coincides with the start of the third phase of the EU ETS. However, as this reduction, albeit to a smaller extent, is mirrored by the synthetic Romania, the causal reduction according to the SCM is smaller than the actual decline.

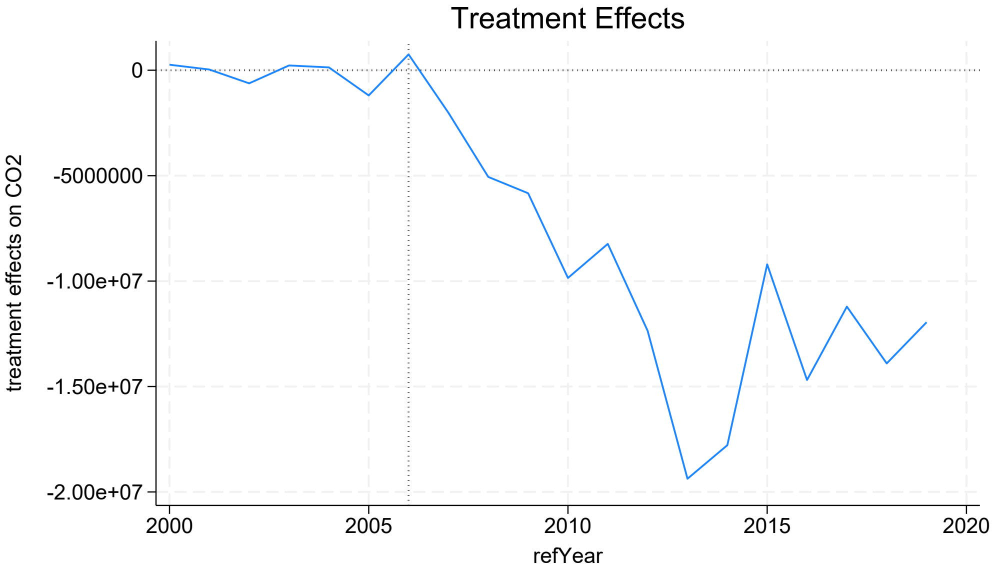

Figure 5.12: SCM Treatment Effect on CO_2 Emissions from Domestic Romanian Electricity Production and Imported Electricity (tonnes of CO_2).

5.3.1 Robustness Tests

Similarly to stage one, we provide the SCM specification with CO_2 emissions per GDP and per capita in the Appendix in Figure 9.3 and 9.4 respectively. As in stage one, both show a similar descending treatment effect at overlapping times as our main specification. This confirms the robustness of our findings in spite of differences in the share of renewable energy and GDP per capita between our synthetic control and the actual Romanian energy sector.

The leave-one-out robustness test in figure 5.13 shows a solid performance of our main specification. Leaving out a country from the donor pool, does not impact the direction of the treatment effect. Although the alternative specifications show smaller treatment effects, they still see a reduction in emissions and follow similar overall patterns. Therefore, no single unit is responsible for all the reduction seen in the treatment effect.

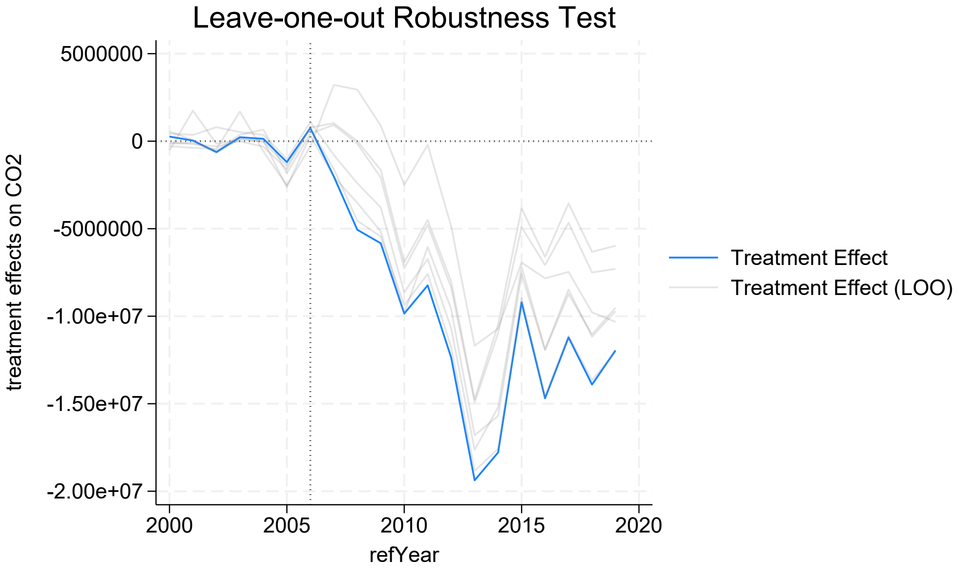

Figure 5.13: SCM Leave-one-out Robustness Test: Treatment Effect on CO_2 Emissions from Domestic Romanian Electricity Production and Imported Electricity (tonnes of CO_2).

5.3.2 Placebo Tests

Figure 5.14, shows the in-space placebo tests for units with a pretreatment MSPE of up to 20 times the pretreatment MSPE of Romania. This is the same threshold as used by Andersson (2019). One country shows an erratic treatment effect and can be discarded. We can see that from the results with normal behavior that Romania presents the most significant treatment effect and is consistent in its direction. It has as well the third highest ratio of posttreatment to pretreatment MSPE of all the countries in the dataset. Therefore, contrary to stage one, the in-space placebo test supports the validity of the results.

The in-time placebo tests also support the results of our main specification. Both times, the treatment effects only start to show a clear direction around the treatment time of our main specification. Before, they only oscillate around zero. For the 2003 in-time placebo

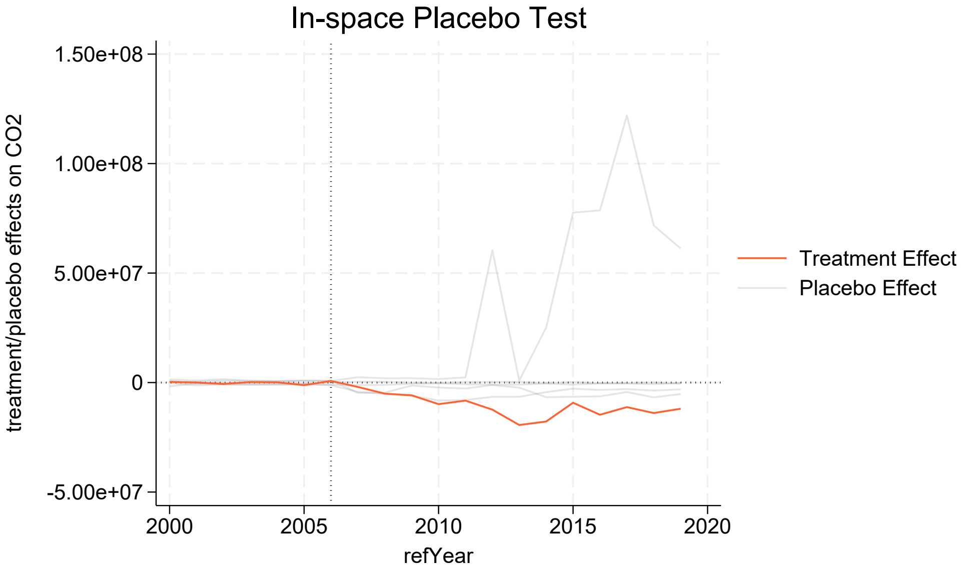

Figure 5.14: SCM In-space Placebo Test: Treatment Effect on CO_2 Emissions from Domestic Electricity Production and Imported Electricity of respective Countries (tonnes of CO_2). Shows countries that have a pretreatment MSPE of up to 20 times larger than Romania's pretreatment MSPE.

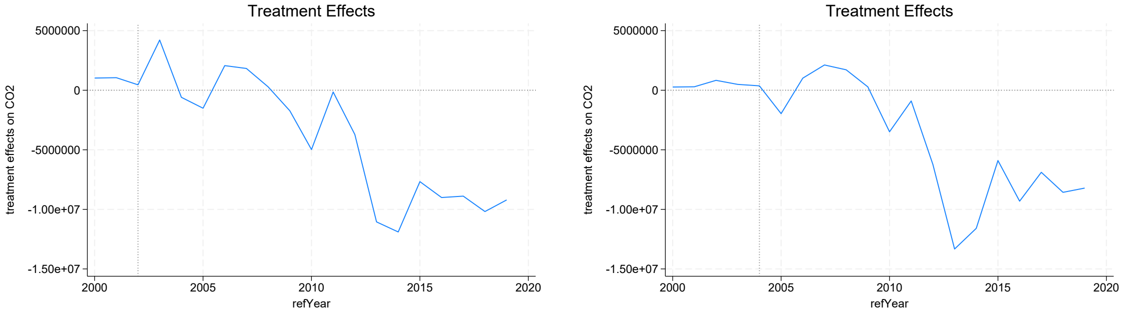

Figure 5.15: In-time placebo tests in 2003 and 2005 Showing the Placebo SCM Treatment Effect on CO_2 Emissions from Domestic Romanian Electricity Production and Imported Electricity (tonnes of CO_2).

test, all countries enter as control group: Armenia with 48 %, Azerbaijan with 37 %, South Africa with 5 % and all other countries with less than 3 %. Similarly, for the 2005 placebo test, all countries except one enter the synthetic control group. 70 % Azerbaijan, 15 % Ukraine, 8 % South Africa, and the rest less than 2 % each.

6 Discussion

This chapter compares and connects the results obtained across the different stages and links them to findings from the literature review. It also discusses the potential policy implications and outlines opportunities for future research that could build upon this study and address some of its limitations.

6.1 Comparison of the Results between Stages

Both stage one and stage three examine the combined impact of EU and ETS accession on emissions. In stage one, the results suggest a very large treatment effect, although the placebo tests raise some concerns about the robustness of these findings. However, when broadening the scope in stage three to also account for emissions linked to electricity imports, the picture changes. Here, the estimated treatment effect is only about one third of the size (in absolute terms) compared to stage one. When comparing the actual development to the corresponding synthetic counterfactual in percentage terms, the effect of stage three also appears considerably smaller. Specifically, the stage three SCM estimates a compound annual growth rate (CAGR) of –2.7 %, compared to –6.7 % in stage one. Over a thirteen-year period, this translates to a total reduction of 30 %, whereas stage one suggests a reduction of 60 % over the same time span. This finding highlights the importance of capturing as many levers as possible. As electricity trade flows become more important, the carbon footprint of imported electricity can play a decisive role when trying to grasp the full picture of policy implications.

Given that this crucial step was missing in stage one, it may have contributed to the stage one placebo tests yielding less favorable results. Therefore, the results of stage three should be taken as the main valid results for the joint effect of the EU and ETS accession.

	Stage 1	Stage 2	Stage 3
Method	SCM	GSCM	SCM
Overall Reduction	-60 %	-50 %	-30 %
CAGR	-6.7 %	-5.2 %	-2.7 %
Pretreatment Period	1993–2006	1993–2006	2000–2006
Posttreatment Period	2007–2019	2007–2019	2007–2019

(a) Estimated causal changes in percentage compared to the respective counterfactual for each stage

	Stage 1	Stage 2	Stage 3
Method	Observed	Observed	Observed
Overall Reduction	-43 %	-49 %	-38 %
CAGR	-4.2 %	-5.0 %	-3.6 %
Posttreatment Period	2007–2019	2007–2019	2007–2019

(b) Actual observed changes in percentage compared to the last pretreatment year 2006 in the respective dataset of each stage.

Table 6.1: Comparison of counterfactual estimates of each stage and observed actual changes in CO_2 emissions of the electricity sector based on each dataset

The results of stage two differ from stage one by trying to disentangle the effect of the EU ETS under our assumptions. Both, stage one and two, do not consider electricity imports. Notably, stage two deviates from the other stages in this paper in methodology. While stage one and three utilize the traditional Synthetic Control Method and have different countries in their donor pools, stage two relies on Generalized Synthetic Control based on different sectors within Romania.

When it comes to the results in stage two, we estimate additional emission reductions through the EU ETS of 50.05 % over the period of Romania's EU accession in 2007 to 2019. Thus, the estimated annual growth rate of CO_2 emissions in the electricity sector is -5.20 %, compared to -6.7 % in stage one. This difference in results aligns with our expectations, since in stage one both EU and ETS accession effects are measured simultaneously. EU accession itself created several enabling conditions in Romania that contributed to emission reductions. These include access to more advanced technologies, eligibility for EU subsidies, such as Cohesion Policy Funds (European Commission 2025c), the LIFE Program (European Commission 2025f), or the European Energy Efficiency Fund (European Investment Bank 2025), as well as facilitated inflows of foreign direct investment, all of which may have accelerated decarbonization.

Interestingly, when analyzing the plotted results for step two (Figure 5.6), one notices that the majority of the decline in CO_2 emissions occurs after 2013. Thus, the GSCM model attributes the biggest share of emission reduction to Phase III of the EU ETS. Generally, Phase III marked the end of free allowances in the electricity sector while in Phase II 90 % of allowances were distributed for free. However, ten lower income EU member states, among them Romania, were exempted from that rule if the free allocation is dedicated to the modernization of the energy sector. These states were allowed to grant free allowances for up to 70 % of their verified emissions in 2013. This figure would gradually decline to 0 % in 2020 (World Bank 2015; European Commission 2025a). Thus, the regulation shift was not as abrupt for Romania as it was for other European countries. Nonetheless, the introduction of Phase III in 2013 represented still a significant change for Romania. Consequently, it seems logical to expect the biggest effect under the most stringent regulation which is what we show in stage two. Conversely, our findings in stage one and three, do find a notable reduction in emissions before 2013 already. Previous papers also reflect these differences in the timing of the treatment effect. While some find the third phase of the ETS to be the most effective (Bayer and Aklin 2020; Bernardini et al. 2021; Eslahi et al. 2025), others also report significant effects in previous stages (Petrick and Wagner 2014). This reflects some of the uncertainty around measuring the effect of complex policy instruments such as the EU ETS.

6.2 Comparison of the Results to Literature

Because the setting of our analysis in stage one is so unique with Romania joining both the EU and EU ETS simultaneously, it is hard to find equivalent papers to compare the effect to. When comparing the magnitude of the effect, our results are broadly in line with previous findings of how carbon pricing schemes can impact carbon emissions (Andersson 2019; Leroutier 2022; Gugler et al. 2023; Rafaty et al. 2025). For example, while we find reductions of annually -6.7 % in stage one, Andersson (2019) reports an effect of -6.3 % annually for the Swedish carbon tax and Gugler et al. (2023) estimate an effect of the UK Carbon Price Support of -7.3 % annually.

With regard to the EU ETS, we specifically relate our findings in stage two to Bayer and Aklin (2020) as our approaches meaningfully overlap. Bayer and Aklin estimate an additional reduction in carbon emissions of roughly 20 % in the energy sector that can be attributed to the ETS. Translated into annual growth rates, our results for Romania's electricity sector suggest a more pronounced decline compared to the EU-wide energy sector estimate by Bayer and Aklin (–5.20 % in our specification versus –2.75 % to –3.53 %). We list two possible, though non-exhaustive, explanations for this difference: First, the sector definitions differ. As described in Section 4.1.3, we split the energy sector in two parts to be able to analyze the electricity sector in particular. Second, our analysis covers a longer time horizon (three additional years) during which the decline is particularly evident, thereby driving our results. Taken together, these differences imply that a direct comparison between the two sets of results may be misleading.

Our stage three results, incorporating imported emissions, show a smaller joint effect of the EU and ETS accession than stage one. This is in line with back-of-the envelope calculations by Leroutier (2022) who finds spillover effects up to 11 % of the total abatement for a UK electricity carbon tax. This includes only a partial spillover on those countries that enter his synthetic control (Ireland and Netherlands). The full effect is therefore likely higher and could be close to our range. This underlines as well the importance of including potential carbon leakage into the methodological design when looking at aggregate emission reductions.

6.3 Policy Implications

Our three-stage analysis yields a clear directional conclusion for policy-makers: Romania's EU accession together with participation in the EU ETS was associated with a marked reduction in electricity-sector CO_2 emissions, but a share of those gains is attenuated once emissions embodied in electricity imports are included. In view of new entrants to the EU, Romania offers an ideal example both through the setting of joining the EU and the ETS simultaneously and of sharing post-communist characteristics with candidate countries at the time of accession. Our estimates provide an order of magnitude to set for example target emission reductions for the candidate countries at the time of accession or to support countries with free emission allowances, taking into account feasible emission reductions in the range of our findings.

Additionally, these findings indicate that policy-makers can choose between a range of instruments to reduce CO_2 emissions. While the ETS effect dominates, our comparative results also reveal a reduction effect through EU accession. This indicates that other non-price measures such as easier access to private capital or increased investor-confidence through trust in institutions because of the EU accession, can be effective as well. Our results do not allow us to draw any conclusion on the efficiency of these instruments. Moreover, and in line with findings by Bayer and Aklin (2020) and Rafaty et al. (2025), carbon prices have a steering effect even when they are low.

Nevertheless, the results imply as well that domestic progress under carbon pricing can be partially offset by trade-related flows. Therefore, policy should be designed and evaluated at the system level and not by looking at domestic generation alone. Proposed policy frameworks such as the EU Carbon Border Adjustment Mechanism (CBAM) start to take this into account. For the electricity sector this is, of course, a more pressing concern for peripheral EU countries rather than for example the westernmost EU countries that have little interconnection with non-EU ETS members.

6.4 Limitations and Future Research

Some caveats qualify the interpretation of our results. For the SCM's cross-country counterfactual our in-space placebo results indicate some uncertainty about the magnitude of the stage-one effect. Additionally, infrastructure projects with a long-time span, planned independently of the EU ETS or EU accession that got completed after 2007 coincidentally, could alter the results. Moreover, the GSCM isolates the price channel but cannot fully rule out sector-specific, contemporaneous policies that mimic coverage. These would be policies that target the exact same sectors as the EU ETS during our treatment phase and make it impossible to distinguish the effects. While we do not identify any major confounding initiatives with the same sectoral coverage as the EU ETS, national and regional regulations in Romania did promote renewable electricity generation during our study period. These schemes were, however, frequently revised, creating substantial regulatory uncertainty (see, for example, Parlamentul României (2008) and European Commission (2016)). Given this instability, we consider it unlikely that national regulation systematically biased our estimated treatment effects. Concerning the limitations of our third stage, the trade-adjusted outcome relies on importer-reported flows and calculated average electricity production CO_2 intensities of the exporters, which potentially introduce measurement error. Finally, due to data availability, the donor pool of stage three differs compared to stage one. We therefore frame our numerical magnitudes as best estimates under transparent assumptions, and highlight that the comparison across stages, rather than any single point estimate, offers consistent results that reveal different influencing factors and channels that are important for policy analysis.

Our findings open the door to several potential extensions. Plant- or unit-level data would allow a direct view on production and technology-switching mechanisms behind the sectoral response. Industry-level GDP data that matches our sector split would enable us to run further robustness checks and enhance our model in stage two. Including price information and higher-frequency long-term trade data could better trace import displacement through the CO_2 emission allowance price. In stage three, our estimates may be biased by factors outside Romania. For example, investments in the electricity sectors of trade partner countries that are not part of the EU or EU ETS, or the construction of new high-capacity electricity lines, could affect the results. Given access to the appropriate data, these investments could constitute valid controls to extend our model. More broadly, comparative work across multiple EU members would test external validity and clarify whether the different effects documented here generalize to other peripheral, trade-exposed EU economies. There remains as well a gap in literature regarding the channels through which EU accession could influence the CO_2 emissions of different sectors. Whereas, our paper finds such an EU accession effect, we cannot distinguish the exact mechanism.

Also, future research could incorporate emissions from indirect carbon leakage through import changes of products of electricity-intensive industries, because of carbon-cost pass-through of electricity in domestic production. Whereas, Aldy and Pizer (2015) do not find strong effects for this phenomenon at a price of 15 $, with rising carbon prices, it could become relevant in the future to add this additional dimension.

Moreover, as an extension to our third stage, one could take into account that the price of electricity can differ substantially from trade partner to trade partner. We suppose that this is at least to some degree connected to some countries delivering rather base load capacities and other countries providing flexible peak load capacities. Base load is usually foreseeable and in advance agreed upon, making it thus cheaper than more flexible peak load capacities. With such data, instead of using the average carbon intensity for a trade partner, one could investigate deeper what technologies are usually used to cover peak loads, which role CO_2 emission pricing plays in the peak load electricity auction price, and what CO_2 footprint is associated with it.

7 Conclusion

This thesis analyzes and disentangles the effect that a simultaneous EU and ETS accession has on the emissions of the electricity sector. This is especially important in view of future EU and ETS accessions of current EU candidate countries that will join, just as Romania did, after the initial inception of the ETS. Romania provides the fitting context to estimate the question to what extent EU accession and EU ETS participation, respectively, caused reductions in electricity CO_2 emissions and which role potential carbon leakage played.

Our three-stage causal analysis finds a clear decline in Romania's electricity CO_2 emissions after EU accession and ETS participation, but the estimated magnitude depends on the counterfactual. The stage one, country-level SCM implies the largest reduction, about -60 % total emission reductions over the thirteen years posttreatment period (CAGR -6.7 %). The sectoral stage two GSCM that isolates the pure ETS channel implies about 50 % (CAGR -5.2 %) emission reduction, thus lower than the joint EU and ETS accession effect. Stage three, the trade-adjusted country-level SCM that adds emissions embodied in imports reduces the net effect of stage one to about -30 % (CAGR -2.7 %). Accounting for imports therefore materially attenuates the reductions. Thus, all three approaches point in the same direction toward strong emission reductions through the EU and EU ETS accession. Our findings indicate that despite different institutional and market characteristics than early EU countries, future EU candidate countries can be expected to show strong emission reductions. These results can serve as a benchmark to help adjust and align transitional policies after EU and ETS accession.

Overall, this thesis contributes in three important ways: i) methodologically, by combining SCM, GSCM and a trade-adjusted SCM in one framework; ii) empirically, by including Romania, a potential role model for future EU countries, as a late entrant to the EU ETS and expanding the analysis with a harmonized dataset that takes into account imported emissions; iii) policy-wise, by showing what magnitude of causal reductions were in the past and potentially are in the future possible for late joiners. It underscores as well that ETS effects and accession channels jointly shaped net outcomes and that imported emissions matter. Some caveats apply, notably the in-space placebo-tests for stage one, the GSCM's limits in excluding contemporaneous sector policies, and for stage three changes in the donor pool and measurement uncertainty in import intensities. Despite these, the consistent pattern across methods supports the conclusion that carbon pricing through the EU ETS was effective, that EU accession contributed also to the reduction effect of the electricity sector, and that trade-adjusted measurements should inform policy evaluation.

8 References

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9 Appendix

Albania	Algeria	Armenia
Australia	Azerbaijan	Bangladesh
Belarus	Belize	Bosnia and Herzegovina
Brunei	Cambodia	Egypt
Georgia	India	Indonesia
Iran	Iraq	Israel
Jordan	Kazakhstan	Kyrgyzstan
Libya	North Macedonia	Malaysia
Moldova	Mongolia	Morocco
Myanmar	Pakistan	Romania
Russia	Serbia and Montenegro	Sri Lanka
Tajikistan	Thailand	Tunisia
Turkey	Turkmenistan	Uzbekistan
Viet Nam		

Table 9.1: Stage 1: SCM Countries Pool

Armenia	Azerbaijan	Belarus
Botswana	China	Kazakhstan
Lesotho	North Macedonia	Romania
Russia	Turkey	Ukraine
United States	Zimbabwe	

Table 9.2: Stage 3: SCM Countries Pool

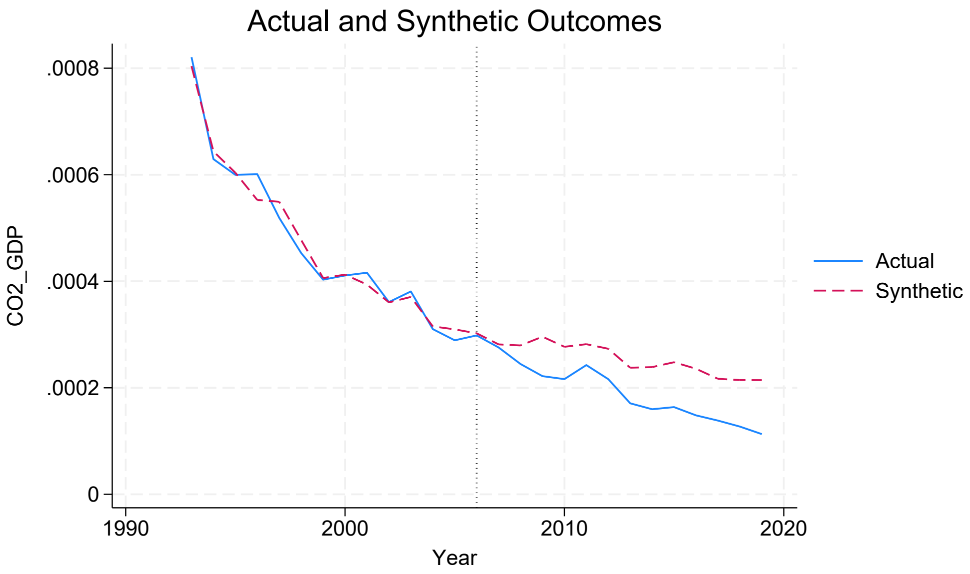

Figure 9.1: Stage 1: SCM Actual and Predicted Counterfactual CO_2 Emissions from Domestic Romanian Electricity Production per GDP.

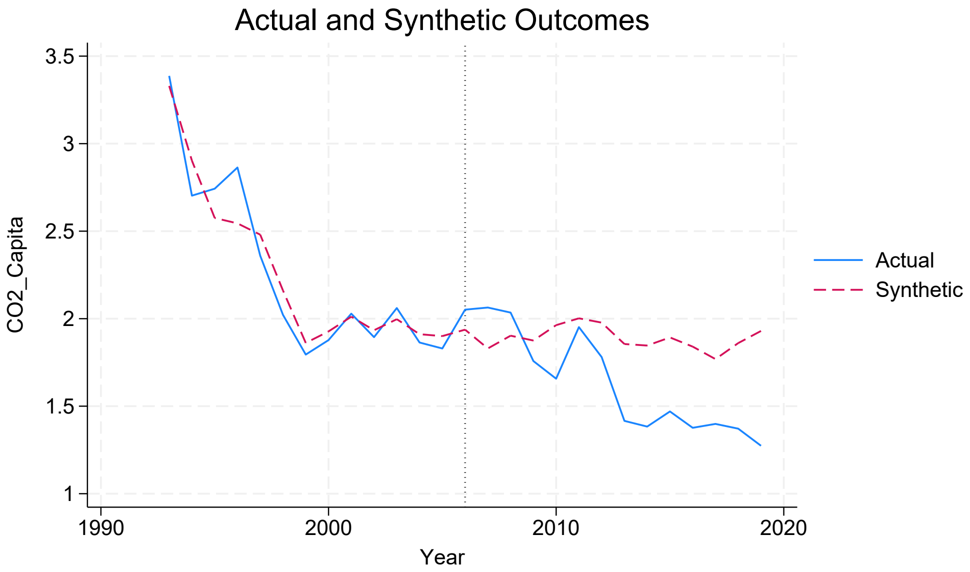

Figure 9.2: Stage 1: SCM Robustness Test: SCM Actual and Predicted Counterfactual CO_2 Emissions from Domestic Romanian Electricity Production per capita

Year	CATT	S.E.	CI lower bound	CI upper bound	p value
2006	1642.1009	2549.8388	-5320.0396	6659.4111	0.32
2007	254.3772	2998.4954	-6324.376	7456.4594	0.566
2008	2083.5444	6572.3071	-13865.9856	14822.9731	0.71
2009	346.1603	3462.5383	-7101.5294	6904.4191	0.894
2010	-3199.1878	3108.5835	-10916.1983	1241.2455	0.13
2011	-145.3185	2178.1347	-5056.1915	3360.3775	0.692
2012	-4931.7781	2363.8235	-7861.7799	1026.4423	0.154
2013	-9807.9871	2571.355	-14080.9853	-4259.5322	0
2014	-9488.4335	3244.8612	-15429.2919	-2926.8009	0.002
2015	-10170.3211	3115.7773	-14503.5759	-2781.308	0.006
2016	-12332.761	3906.7032	-17193.3456	-2620.2753	0.012
2017	-12287.1499	4397.681	-16408.202	-343.817	0.036
2018	-14473.4381	5830.5797	-20471.7534	1748.6498	0.098
2019	-18762.4956	6691.843	-25595.2158	356.6858	0.052

Table 9.3: Stage 2: CATT estimates for the electricity sector, 2006–2019

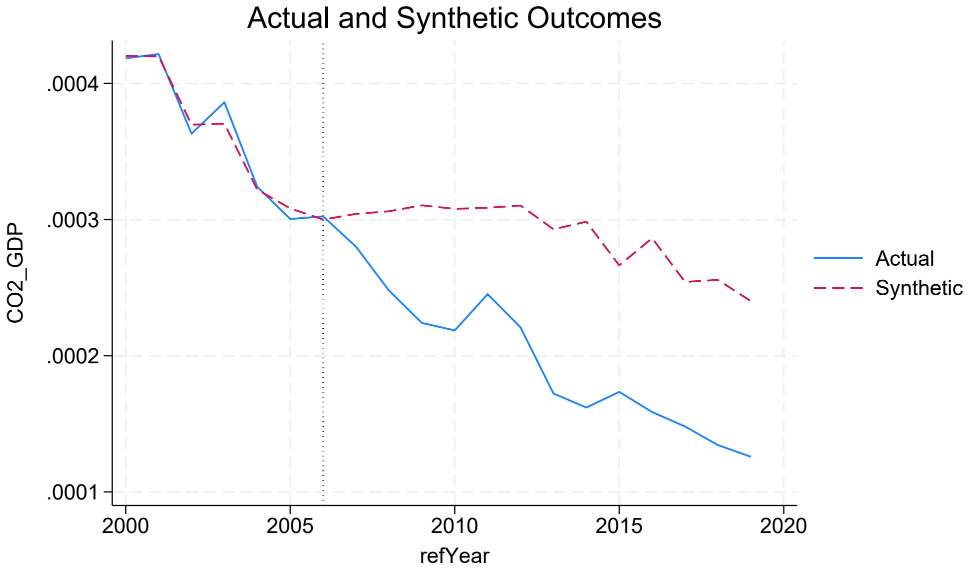

Figure 9.3: Stage 3: SCM Robustness Test: SCM Actual and Predicted Counterfactual CO_2 Emissions from Domestic Romanian Electricity Production per GDP

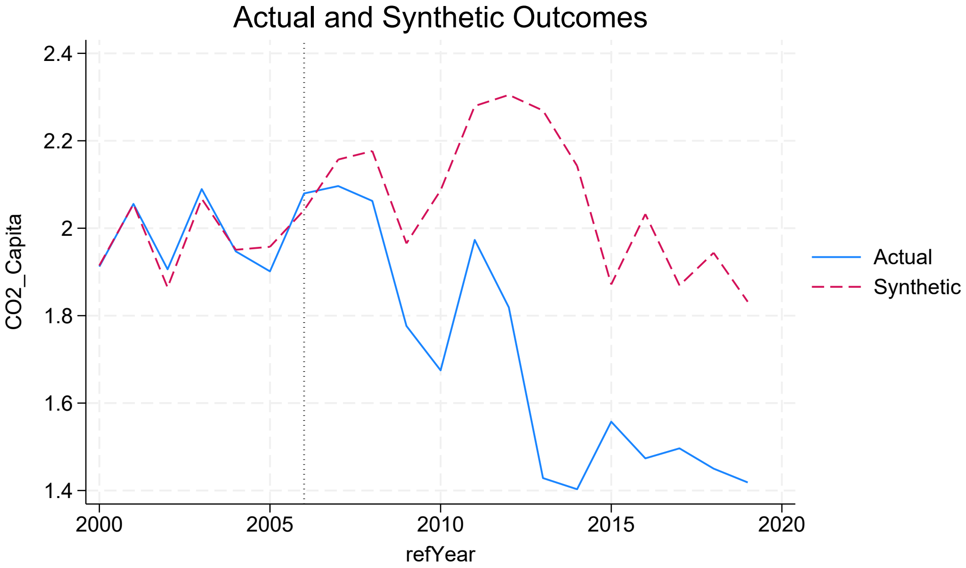

Figure 9.4: Stage 3: SCM Robustness Test: SCM Actual and Predicted Counterfactual CO_2 Emissions from Domestic Romanian Electricity Production per capita

9.1 AI Disclosure

We have used ChatGPT (both standalone and as part of Copilot), Gemini, and Claude to assist with coding in Stata and R. As the packages that we used were very specialized, the AI tools often did not grasp every nuance that had to be considered, and their proposed solutions were not as reliable as our own code. However, they were very good at discovering errors such as syntax errors. Thus, AI has mostly served to troubleshoot the code. A typical prompt example was “Where is the error in the following code given this error message?” or "Explain this error message". Moreover, they are good at adapting code with small changes. This could be, for example, “Take this code that renames the variable and now replace in the same way all variables’ names [input list 1] with each of the variables’ names of this list [input list 2]”. As we are still fully able to understand the code, there was little risk in using AI, but it saved us considerable time.

AI has also supported us in fine-tuning formulations when drafting the text through prompts such as “Give a synonym for X”, “Provide a more elegant formulation for sentence Y”, or “Propose a fitting connector between these sentences A and B”. As the examples show, AI was more important in optimizing the drafting process rather than replacing it. Therefore, we did not see a significant risk for AI hallucinations. Nevertheless, we, of course, reread every output before using it.