Working Paper

Mission Accomplished? A Post-Assessment of EU ETS Impact on Power Sector Emissions

Mohammadehsan Eslahi[1], Anna Creti[2], Maria-Eugenia Sanin[3]

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Contact: M. Eslahi m.eslahi@ieseg.fr

1 IESEG School of Management, Univ. Lille, CNRS, UMR 9221 - LEM - Lille Economie Management, F-59000 Lille, France

2 Universit´e Paris-Dauphine - PSL, Place du Mar´echal de Lattre de Tassigny, 75016 Paris, France

3 Universit´e Paris-Saclay, Univ Evry, EPEE, 91025, Evry-Courcouronnes, France

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Mission Accomplished? A Post-Assessment of EU ETS Impact on Power Sector Emissions

Mohammadehsan Eslahi[a,*], Anna Creti[b], Maria-Eugenia Sanin[c]

[a] *IESEG School of Management, Univ. Lille, CNRS, UMR 9221 - LEM - Lille Economie Management, F-59000 Lille, France*
[b] *Université Paris-Dauphine - PSL, Place du Maréchal de Lattre de Tassigny, 75016 Paris, France*
[c] *Université Paris-Saclay, Univ Evry, EPEE, 91025, Evry-Courcouronnes, France*

Abstract

One of the most challenging aspects of (environmental) policy impact evaluation studies is the construction of credible counterfactuals for causal inference. In this paper, we leverage a method that does not require the creation of benchmarks or the identification of external comparable control units to evaluate the effectiveness of the first three phases of the European Union Emissions Trading System (EU ETS) (2005-2019) in reducing power sector fossil fuel CO_2 emissions across 24 EU ETS Member States. Considering the beginning of each trading period (phase) as a policy intervention, the paper adopts a Bayesian structural time series (BSTS) modeling framework alongside a set of contemporaneous predictors related to power sector emissions to build counterfactual estimates of emissions for each post-intervention period and analyze the policy implementation effect by comparing actual emissions with counterfactual estimates. The results indicate a statistically significant emissions reduction in the second and third phases. The dominance of the power sector within the ETS since its inception emphasizes the importance of our findings in advancing emissions reduction objectives.

Keywords: The EU ETS, Fossil Fuel CO_2 Emissions, Climate Variables, Predictive Modeling, Spatio-temporal Analysis, Counterfactual Inference

1. Introduction

Carbon dioxide (CO_2) emissions resulting from fossil fuel combustion constitute approximately 80% of all human-driven greenhouse gas (GHG) emissions in the European Union, as reported by the statistical office of the European Union.

*Corresponding author
Email address: m.eslahi@ieseg.fr (Maria-Eugenia Sanin)

[1] These emissions originate from the burning of non-renewable energy sources like coal, natural gas, and petroleum products, primarily used for electricity and heat generation, transportation, and industrial manufacturing. While the emission intensity of electricity generation varies considerably among European Union Member States due to differences in national electricity mixes, power generation continues to be the predominant source of CO_2 emissions (Ang, 2007; Apergis & Payne, 2009; Iwata et al., 2012; Shafiei & Salim, 2014; European Environment Agency, 2020).

Economists have long held that carbon pricing through cap-and-trade systems is one of the most cost-effective ways to decarbonize the economy (Meckling et al., 2017). As the pioneering and second biggest carbon market across the globe (preceded by China's Emissions Trading Scheme, introduced in 2021), the European Union Emissions Trading System (abbreviated as the EU ETS) is the keystone of the European Union's policy to fight climate change, and its central tool for reducing CO_2 and other greenhouse gas emissions under the 1997 Kyoto Protocol's commitment periods (European Comission, 2021). The EU ETS covers emissions from electricity and heat generation, along with the most energy-intensive industrial sectors, collectively representing up to 70% of emissions in each member state (Ellerman & Buchner, 2008). Since its inception, the scheme has split into a number of trading periods or phases, each characterized by specific features and legislation. The first (pilot) trading period started in January 2005 and ended in December 2007. The second phase extended across a period of five years from the beginning of 2008 to the end of 2012. The third phase started in January of 2013 and continued until the end of December 2020. At the time of writing this paper, the system was in its fourth phase, which started in January 2021 and was planned to continue until the end of December 2030.

A growing body of literature has examined the effectiveness of different phases of the EU ETS in reducing CO_2 emissions at sector, firm, country, and EU levels, but with no decisive results (see Laing et al., 2013). While some works have evaluated the effectiveness of the EU ETS over time periods covering more than one phase, extensive large-scale empirical assessments of the effectiveness of all the first three phases remain scarce. Given that the power sector stands as the predominant source of EU emissions, a comprehensive understanding of the specific effectiveness of the EU ETS in reducing emissions within this sector is crucial. This insight is of great importance not only for assessing the overall success of this trading system but also for informing and shaping future climate policies. The primary objective of this study is to address a major gap in the understanding of the impact of the EU ETS implementation on CO_2 emissions in the power sector. Specifically, the research aims to evaluate the effectiveness of the first three phases of the EU ETS in reducing monthly power sector fossil fuel CO_2 emissions across the ETS zone. Leveraging a cutting-edge counterfactual-based causal modeling technique, we establish an

[1]https://ec.europa.eu/eurostat

innovative methodological framework to facilitate a comparison between actual monthly power sector fossil fuel CO_2 emissions from 2005 to 2020 under the EU ETS with a counterfactual scenario where the scheme did not exist. By using a comprehensive set of unaffected-by-policy variables and indices as predictors, we isolate the true impact of the EU ETS, offering a fresh perspective on its effectiveness in curbing emissions in the power sector.

There are several important areas where this research makes an original contribution to the existing literature on the EU ETS.

Firstly, it provides a notable methodological contribution to evaluating the environmental effectiveness of the EU ETS, by leveraging an advanced and credible counterfactual modeling framework that eliminates the need for external control units and enabling causal inference without relying on comparisons with external benchmarks. This approach is particularly useful for analyzing the effectiveness of emissions reduction policies in the power sector, where, unlike other sectors, finding appropriate control units or establishing benchmarks for comparison is extremely challenging (if not impossible), due to its unique characteristics and complexities. The study's specific focus on the power sector sets it apart from some recent works that explore other sectors within the EU ETS (see for example Colmer et al., 2023). The power sector's dominance since the scheme's inception, its critical role in EU ETS emissions, and its vulnerability to climate variations make it a particularly important area of investigation.

Secondly, the study evaluates the temporal evolution of the EU ETS emissions reduction impact in the power sector, not only over the course of each phase (at an intra-annual time scale) but also cumulatively, from a transitional standpoint from the first phase to the third phase. This objective is of utmost importance, as any effectiveness analysis of the EU ETS should not only focus on assessing the overall effectiveness of the scheme in individual phases but also on whether its main objective (emissions reduction) has been increasingly improved across phases.

Thirdly, from a methodological standpoint, the introduction of novel indices for capturing the effect of (weather-related) renewable electricity generation on EU ETS emissions in the power sector, as well as the potential overlap of climate and energy policies and measures across the EU ETS zone based on the latest available data, is a major contribution. These indices can be easily adapted for use in a wide range of analyses concerning renewable energy and policy impacts within the extensive literature on climate change and energy economics. The inclusion of these indices has enabled us to isolate the effects of overlapping mechanisms and measures and controlling for additional effects to the maximum extent possible.

Finally, to the best of the authors' knowledge, no previous study has examined the effectiveness of the EU ETS in reducing CO_2 emissions from fossil fuels in the power sector throughout all completed trading periods (2005-2020). This EU-level sectoral analysis serves as a valuable addition to existing studies, which have primarily focused on specific sub-periods within the first three phases of the EU ETS.

The structure of this paper is organized as follows: Section 2 offers an overview of existing research on the effectiveness evaluation of the EU ETS, establishing the groundwork for the methodology employed in constructing counterfactual emissions within the proposed framework. The research setting, data, and methodology of the empirical analysis are detailed in Section 3, with the presentation of results in Section 4. The paper concludes by discussing limitations and suggesting avenues for future research in Sections 5 and 6.

2. Background and Literature Review

When it comes to the effectiveness assessment of carbon markets, carbon price is regularly the touchstone of choice where low prices are, explicitly or implicitly, associated with ineffectiveness (Bayer & Aklin, 2020). Carbon price provides an economic signal to emitters of CO_2 and enables them to decide whether to lower their emissions, or continue emitting and paying for their emissions. This emphasis on carbon price as a pivotal metric has led to a plethora of studies focusing on the structural determinants of carbon prices– ranging from weather conditions and electricity demand to energy prices and fuel switching, recognizing the vital role these determinants play in shaping market dynamics and influencing decisions related to emission reduction (see among others (Eslahi & Mazza, 2023)).

While understanding the drivers behind emissions allowance prices is crucial for interpreting market responsiveness and gauging the implicit effectiveness of the scheme, directly evaluating the outcomes of emission reduction measures provides a more tangible measure of the environmental impact. This direct assessment serves to validate (or challenge) the effectiveness of the market mechanism, and provides insights into the real-world implications of emissions trading. Indeed, studies have demonstrated that carbon abatement remains justifiable even in the presence of low market prices, highlighting the potential efficacy of the EU ETS in reducing emissions under such conditions (Bayer & Aklin, 2020). In this context, the primary measure for evaluating the performance of any emissions trading scheme, including the EU ETS, should be the actual extent of emissions reduction (Ellerman et al., 2016). Consequently, the effectiveness assessment of the EU ETS should not solely rely on market prices but should instead center on an evaluation of whether the policy has resulted in a reduction in emissions (Bayer & Aklin, 2020). Methodologically, this assessment poses challenges, as it necessitates comparing actual emissions under the EU ETS with counterfactual emissions that would have occurred if the EU ETS had not been implemented (see Bayer & Aklin, 2020; Grubb et al., 2012; Ellerman et al., 2010; Helm & Sprinz, 2000). Given the unobservable nature of counterfactual emissions, their estimation becomes imperative for a comprehensive evaluation of the EU ETS's impact on emissions reduction.

Causal inference based on counterfactuals is well-established in impact evaluation studies in economics (see among others Ellerman & Buchner, 2008; Declercq et al., 2011; Anderson & Di Maria, 2011). One of the most challenging aspects of any counterfactual analysis lies in the selection of appropriate comparison groups unaffected by the corresponding policy intervention. Broadly, counterfactual approaches to causal inference fall into three categories: experimental (e.g., randomized controlled trials), non-experimental (e.g., logically-constructed counterfactuals), and quasi-experimental (e.g., difference in differences, (propensity score-based) matching, instrumental variables estimation, regression discontinuity, and statistically-created counterfactuals) research designs. Previous studies have examined the effectiveness of the EU ETS in reducing carbon emissions in various sectors across different temporal and spatial scopes, utilizing a range of non-experimental and quasi-experimental approaches. For a detailed summary of these studies, please refer to Table A.4 in Appendix A.

On the one hand, non-experimental studies in this context, specifically those relying on baselines or logically-constructed counterfactuals, mainly suffer from potential bias in and imperfect comparability of data across Europe (Ellerman & Buchner, 2008). On the other hand, classical quasi-experimental methods such as (propensity score-based) matching and difference in differences are either reliant upon strong assumptions, such as the conditional independence assumption, or limited in terms of explaining the time evolution of the intervention effect (Brodersen et al., 2015). From these premises, it could be argued that within the specific context of evaluating the effectiveness of the EU ETS, counterfactual designs created through statistical methods hold an advantage over other quasi-experimental approaches. An effective statistical technique for creating counterfactuals is to amalgamate a collection of potential predictor series into a synthetic control (Brodersen et al., 2015; Abadie et al., 2010; Abadie & Gardeazabal, 2003).

Perhaps the most relevant research of this type within the framework of the effectiveness evaluation of the EU ETS is the study by Bayer & Aklin (2020), which considers the start of the first and second trading periods (2005 and 2008) as points of policy intervention and utilizes emissions series from non-ETS sectors (those not covered by the EU ETS) across the European Union as synthetic control group units to estimate counterfactual emissions. Naturally, using non-ETS sectors (or firms) as a comparison or control group relies on the fundamental assumption that such sectors (or firms) are not subject to any parallel carbon constraint regulations that may have been implemented simultaneously with the EU ETS (see Jaraite-Kažukauske & Di Maria, 2016). However, this assumption may not hold true for all non-participant sectors (or firms) at the European level. For instance, the French Environment and Energy Management Agency (ADEME)[2] reports that in conjunction with the EU ETS as a union policy, France has concurrently implemented domestic mechanisms to reduce emissions from sectors not covered by the emissions trading system. More importantly, since 2008, most sectors not included in the EU ETS have been targeted by the Effort Sharing regulation set by the European Union,[3], with the aim of achieving a 30% emissions reduction target in the affected

[2] `https://bilans-ges.ademe.fr/`

[3] `https://ec.europa.eu/clima/policies/effort_en`

sectors by 2030. On another note, as the EU ETS already includes the biggest emitters, finding suitable non-ETS counterparts in terms of absolute emissions across Europe is unlikely (Jaraite-Kažukauske & Di Maria, 2016). Therefore, at least in theory, non-ETS sectors (or firms) may not be the most appropriate control units in a European-scale study.

Since its inception, the inclusion of the power sector in the EU ETS has been integral to its design and implementation. Unlike other sectors, the power sector's participation in emissions trading cannot be benchmarked against historical data or compared directly with analogous industries outside the EU ETS framework. The unique nature of power generation installations, coupled with their significant representation within the EU ETS (Ahamada & Kirat, 2015), further complicates efforts to establish comparable control units for conducting comprehensive assessments of emission reductions. Given the challenges associated with finding suitable counterparts outside the EU ETS, traditional methods reliant on identifying comparable units for comparison may prove impractical. Therefore, alternative methodologies that do not rely on finding direct counterparts (like the one employed in the present study) become imperative for accurately evaluating the impact and effectiveness of the EU ETS in the power sector.

To address the challenge of identifying appropriate control units for establishing counterfactual power sector fossil fuel CO_2 emissions, we adopt an approach that, rather than relying on external units (such as non-ETS sectors) as control groups, relies on a set of variables and novel indices that remain unaffected by the EU ETS and that can be used as predictors of such emissions. These chosen contemporaneous predictors serve as a basis for estimating counterfactual emissions during each phase of the EU ETS, providing a more internally consistent and robust framework for analysis. Considering the beginning of each phase as a policy intervention, a Bayesian counterfactual time series model is trained during the pre-intervention period to establish the relationship between the target series (power sector fossil fuel CO_2 emissions) and a range of contemporaneous predictors at both the country and European levels. Subsequently, the model is applied to the post-intervention period to predict the outcome. These predictions provide the counterfactual estimates of power sector fossil fuel CO_2 emissions. In contrast to methods proposed by Abadie et al. (2010) and Abadie & Gardeazabal (2003), the approach adopted here avoids imposing restrictions, such as convexity conditions, on how potential predictor series should be combined. Instead, it exclusively leverages predictors based on their ability to predict the outcome of interest during the pre-intervention period. The predictive modeling framework employed in this study should be distinguished from a forecasting scheme. Unlike forecasting, which uses historical data to predict a variable's future values within a specific time horizon, the proposed framework focuses on learning how emissions can be explained as a function of contemporaneous predictors to make counterfactual predictions. It then capitalizes on disparities between actual and counterfactual emissions, which are interpreted as the casual impact of the EU ETS on fossil fuel CO_2 emissions.

While the EU ETS is a unified carbon market aimed at reducing emissions at the European level, the response to its implementation varies across Member States, leading to diverse emissions profiles and behaviors. To thoroughly evaluate the effectiveness and impact of the EU ETS, a comprehensive European-scale study must hence consider the specificities and heterogeneity among the contributing countries. The distinctions in power sector fossil fuel CO_2 emissions across the EU ETS Member States in each phase of the EU ETS can be attributed to several factors, including economic structure, energy mix, historical emissions, weather conditions and renewable electricity generation potential, energy efficiency measures, national policies and regulations, and interconnection and energy trade. For the purpose of this analysis, we employ a set of variables and indices as predictors of power sector fossil fuel CO_2 emissions to capture pivotal factors from those enumerated above. This includes two aggregate indicators for electricity demand (as a direct driver of power generation, influencing fuel use and emissions) and air temperature (to consider spatial variability of weather conditions across the EU ETS zone). Additionally, three indices for global energy prices (crude oil, natural gas, and coal) are utilized to capture the economic viability of different generation sources, influencing the fuel mix and CO_2 emissions. Lastly, two renewable electricity indices (embracing solar and wind power generation and potential across the EU ETS zone) and an overlapping policy and measure index (capturing the potential concurrent impact of parallel national climate and energy policies and measures on power sector emissions) are included in the analysis. The focus here is not to encompass the entire set of potentially pertinent explanatory factors for predicting power fossil fuel CO_2 emissions. Indeed, the analysis in this paper is narrowed down to a set of predictors of fossil fuel CO_2 emissions that remain unaffected directly by the implementation of the EU ETS, and whose nature of relationship with the target variable remains consistent before and after the commencement of each trading period. Lastly, and most importantly, the choice of potential predictors is guided by the availability of data at the temporal and spatial resolution required for this study.

When considering its impact on CO_2 emissions, air temperature is often associated with its connection to energy demand, particularly in electricity consumption. Low (high) temperatures increase the need for heating (cooling), thereby increasing both electric and non-electric (fossil fuel) energy consumption[4]. This, in turn, contributes to heightened CO_2 emissions (see, among others, Mansanet-Bataller et al., 2007; Alberola et al., 2008; Benz & Trück, 2009; Hintermann, 2010; Yao, 2021). Increasing temperatures can also influence the electricity supply side by either raising water temperatures, negatively affecting the cooling efficiency of thermal (nuclear and fossil fuel) power plants, or diminishing the efficiency of solar photovoltaic panels–both scenarios result in

[4]The impact of high temperatures on the use of fossil fuels for purposes other than electricity generation is less clear since air conditioning systems used for satisfying cooling demand are predominantly powered by electricity (Melillo et al., 2014).

increased emissions levels (Ebinger & Vergara, 2011). Although air temperature affects energy needs, the direct driver of emissions is the demand for electricity, which necessitates power generation often reliant on fossil fuels. Therefore, including an indicator for electricity demand alongside air temperature becomes crucial for counterfactual estimation of power sector fossil fuel CO_2 emissions.

Given the expected reduction in carbon emissions with an increased share of renewable energy sources (Dogan & Seker, 2016; Bento & Moutinho, 2016), it is crucial to highlight the role of renewable energy generation as a complementary climate change mitigation tool to the EU ETS. As a result, this analysis incorporates the level of renewable energy generation and potential (measured by capacity factor) in each Member State to construct aggregate renewable electricity indices. These indices are used as contemporaneous predictors for counterfactual estimation of power sector fossil fuel CO_2 emissions, aiming to capture the potential impact of renewables on total emissions across the EU ETS zone. Ultimately, while the EU ETS establishes the overarching framework, Member States retain the flexibility to implement additional policies and regulations tailored to their specific circumstances, influencing power generation sector emissions. In a comprehensive study evaluating the effectiveness of the EU ETS on power sector emissions, it is thus essential to account for the potential overlapping impact of these policies and measures, justifying the inclusion of an overlapping policy index.

3. Materials and Methods

3.1. Research Setting and Data

This research examines the environmental effectiveness of the EU ETS in reducing power sector emissions within a geographical zone covering 24 countries that were participants in the EU ETS during all three initial phases.[5] The study area is hereinafter referred to as the EU ETS zone. We use monthly data on power sector fossil fuel CO_2 emissions within this zone, along with a number of contemporaneous predictors associated with these emissions to estimate counterfactual scenarios following the launch of each EU ETS phase. Further details on the counterfactual estimation of power sector emissions and the nature of contemporaneous predictors are provided in Section 3.2.2. The datasets used to compile the final sample for analysis can be listed as follows: country-level monthly time series of power sector fossil fuel CO_2 emissions; country-level monthly weather and energy indicators, namely air temperature, electricity demand, wind power generation and capacity factor, solar power generation and capacity factor. The power generation and capacity factor indicators contribute

[5] These countries consist of 23 EU Member States (Austria, Belgium, Czechia, Cyprus, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, and Sweden) plus the United Kingdom.

to the construction of European-scale renewable electricity indices; monthly energy price indices for oil, natural gas, and coal, capturing global fluctuations in prices of key fossil fuel energy commodities; and national climate and energy policies and measures, used to construct an overlapping policy and measure index that reflects the comprehensive parallel regulatory framework for climate and energy across the EU ETS zone. The final aggregate dataset retained for empirical analysis, derived from an intermediate country-month dataset with 6048 observations, consists of 252 observations with monthly timestamps that span from January 2000 to December 2020, covering five full years before the launch of the first EU ETS phase through the end of the third phase.

3.1.1. Power Sector Fossil Fuel CO_2 Emissions

Monthly time series of power sector fossil fuel CO_2 emissions, expressed in kiloton (kt), for the 24 EU ETS Member States under study over the 2000-2020 period are retrieved from the Emissions Database for Global Atmospheric Research (EDGAR v7.0)[6] (Crippa et al., 2022). The EDGAR offers independent estimates of global anthropogenic emissions and emission trends based on publicly available statistics, categorized by main source.[7] For the purpose of this study and to align with its objectives, the original dataset is subsetted to focus only on fossil fuel CO_2 emissions in each country under the 2006 IPCC[8] Guidelines for National Greenhouse Gas Inventories code 1.A.1.a (Main Activity: Electricity and Heat Production). Monthly emissions values for each month in the study period are aggregated to derive a total for the entire EU ETS zone. These monthly-summed values serve as the target time series for the analysis. Summing the time series across countries to obtain an aggregate indicator is consistent with the additive nature of emissions.

3.1.2. Weather and Energy Indicators

Country-level data on air temperature (K), electricity demand (MW), and renewable (wind and solar photovoltaic[9]) power generation indicators (MW and capacity factor ratio) are obtained from the Copernicus Climate Change Service (C3S) operational energy dataset (ECMWF, 2020), provided by the European Centre for Medium-Range Weather Forecasts (ECMWF).[10] Air temperature and electricity demand indicators are employed as stand-alone contemporaneous predictors in the counterfactual estimation of power sector emissions. Meanwhile, renewable electricity measures (power and capacity factor ratio) are used

[6] `https://edgar.jrc.ec.europa.eu/dataset_ghg70`

[7] `https://data.europa.eu/doi/10.2904/JRC_DATASET_EDGAR`

[8] Intergovernmental Panel on Climate Change

[9] Data on hydropower generation from run-of-river units and units with reservoirs is available for only 9 EU ETS Member States included in this analysis–countries with substantial installed hydropower capacity (Austria, Germany, Spain, Finland, France, Italy, Portugal, Sweden and Slovakia). For consistency in constructing renewable electricity indices, the analysis is hence confined to wind and solar photovoltaic power generation.

[10] `https://cds.climate.copernicus.eu/`

to construct composite indicators, which are subsequently employed as contemporaneous predictors (Section 3.2.2).

3.1.3. Energy Price Indices

Monthly global price indices (reference year 2016) for crude oil (petroleum), natural gas, and coal over the period 2000-2020 are sourced from the International Monetary Fund (IMF) Primary Commodity Prices database (International Monetary Fund, 2023) and are employed as contemporaneous predictor series in the analysis.

3.1.4. National Climate and Energy Policies and Measures

Data on policies and measures (PaMs) at the national level (outside the EU ETS) that were implemented or adopted before 2020 and affect emissions covered by the EU ETS are obtained from the European Environment Agency (EEA) Database on Integrated National Climate and Energy Policies and Measures in Europe (Dauwe et al., 2023).[11] The database encompasses policies and measures (PaMs) aimed at achieving climate change mitigation and energy targets, such as reducing greenhouse gas (GHG) emissions, producing additional renewable energy, or reducing overall energy consumption in different sectors. For the purpose of this study, only those PaMs targeting CO_2 emissions in the energy supply sector in each country are subsetted, resulting in a total of 95 policies (including economic, fiscal, regulatory, information, planning, education, research, and voluntary ones) across 23 countries. The national policies in this dataset are summarized into a European-scale overlapping policy and measure index for each month. This index is subsequently used as a contemporaneous predictor series in the analysis (Section 3.2.2).

3.2. Methodology

The methodology employed in this study is centered around three primary themes: defining the structure of the predictive model for estimating counterfactual power sector fossil fuel CO_2 emissions, determining the contemporaneous predictors used by the model for counterfactual estimation of such emissions, and, ultimately, establishing how causal inferences are derived from the model's results. All aspects of data analysis, modeling, and visualization in this study were carried out using the R programming language (R Core Team, 2020).

3.2.1. Counterfactual Estimation of Power Sector Emissions

To estimate the causal effect of the launch of each EU ETS phase (considered as a policy intervention) on power sector emissions across the EU ETS zone, we employ CausalImpact (Brodersen et al., 2015)–a Bayesian structural time series (BSTS) model. The BSTS framework allows assessment of the causal impact of an intervention or treatment on a particular outcome variable, while accounting for underlying time series dynamics and other confounding factors.

[11] `https://pam.apps.eea.europa.eu/`

This approach is based on a state-space model, assumes that the observed time series data is generated by a combination of unobserved components, including the underlying trend, seasonality and a linear regression on the contemporaneous predictors. The space includes the parameters defining how these components interact.

The BSTS model is initially constructed for a pre-intervention period. Subsequently, the post-intervention period is specified, representing the timeframe during which the causal effect is anticipated. The model is then utilized to predict a counterfactual scenario, i.e., what would have occurred in the absence of the intervention. The difference between the predicted and observed values during the post-intervention period provides the estimated causal impact. To assess the credibility of the estimated impact, posterior intervals are derived through sampling in a purely Bayesian setting, and the tail probability of a non-zero causal impact is computed. In simple mathematical terms, the following structural time series model is created for the pre-intervention period:

$$\begin{aligned} y_t &= Z_t \alpha_t + \varepsilon_t \\ \alpha_{t+1} &= T_t \alpha_t + R_t \eta_t \end{aligned} \tag{1}$$

The first line in Equation 1 links the observed value of the time series y_t in the pre-intervention period to a latent state vector α_t. Z_t is a matrix of coefficients that relates the latent state to the observed values and ε_t is a random error term. The second line governs the evolution of the state vector α_t through time. T_t is a transition matrix that describes how the latent state evolves over time, R_t is a matrix of coefficients that relates the latent state to the random error term η_t. For full technical details on the definition of the model, components of state and posterior inference, see Brodersen et al. (2015).

The most important state component for the application considered in this study is a regression component (with static coefficients to avoid overspecification) that allows for construction of counterfactual predictions by creating a synthetic control based on a combination of predictor series that were not influenced by the intervention, i.e. the launch of each EU ETS phase. The construction of a credible synthetic control necessitates leveraging three key sources of information: the historical behavior of the target series (power sector fossil fuel CO_2 emissions) before the policy intervention (all the months in the data preceding the launch of each EU ETS phase), the behavior of other contemporaneous series capable of predicting the target series during the pre-intervention period, and the available prior knowledge about the model parameters (Brodersen et al., 2015). The contemporaneous control series are chosen based on their behavior during the pre-intervention period, but their relevance for predicting the counterfactual lies in their post-intervention behavior (i.e. in all the months in the data following the launch of each EU ETS phase). This aligns with the fundamental assumption that the chosen control series are unaffected by the policy intervention themselves and hence continue to exhibit a stable relationship with the target series even after the policy intervention. Choosing an appropriate set of series to serve as contemporaneous controls thus represents the most challenging aspect of the methodological approach employed in this study.

In the context of the present analysis, the BSTS framework offers four distinct advantages over classical statistical and econometric models. First, it can handle multiple covariates, which can help to control for confounding factors, such as renewable electricity generation potential and overlapping policies and measures that might influence the impact of the intervention–the launch of each EU ETS phase. Secondly, in contrast to classical models that primarily focus on estimating the overall average effect, the utilized approach can demonstrate the temporal evolution of the policy intervention's effect–the launch of each EU ETS phase–throughout the duration of the phase. Thirdly, the model effectively handles non-stationarity through accommodating multiple sources of variation in the time series such as local trends and seasonality. Ultimately, by incorporating uncertainty into the modeling process, the model provides not only point estimates of counterfactual emissions but also probabilistic assessments of the causal impact. Using parameter priors and the provided data, the model computes the posterior distribution of the response variable (emissions) anticipated in the absence of the policy intervention (the launch of each EU ETS phase). subsequently, it compares the observed actual emissions to this distribution and quantifies the tail-area probability, representing the likelihood, under the calculated posterior, that the emissions deviate at least as significantly from the expected value as observed.

For each phase of the EU ETS, all available data preceding the launch of that phase is utilized to estimate counterfactual emissions throughout the phase's duration. This approach enables the drawing of causal inferences regarding the effectiveness of each phase separately and independently from the previous phase(s)–in the case of the second and third phases. The presumption here is that the BSTS model inherently incorporates the impacts of preceding phase(s) on power sector fossil fuel CO_2 emissions, if any. An underlying assumption of this phase assessment approach is that no omitted relevant factors are correlated with both the launch month of each EU ETS phase and variations in fossil fuel CO_2 emissions.

3.2.2. Contemporaneous Predictors of of Power Sector Emissions

The BSTS model relies on a set of contemporaneous predictors to estimate power sector fossil fuel CO_2 emissions during post-intervention periods. These predictors include average electricity demand and air temperature across the EU ETS zone for each month, along with monthly global energy price indices for crude oil, natural gas, and coal. Additionally, the model incorporates two composite indicators as predictors. The first is a European-scale renewable electricity index for each renewable energy type (wind and solar photovoltaic), which combines the renewable electricity potential across the EU ETS zone (as measured by capacity factor ratios) with the proportion of renewable power production in each country on a monthly basis. The second is an overlapping policy and measure index that consolidates the national climate and energy policies and measures (PaMs) within the EU ETS zone for a given month. This index is designed to capture the potential overlapping impact of these PaMs on power sector EU ETS emissions through a unified European-scale indicator. The construction details of these two indices will be elaborated in the subsequent sections.

Renewable Electricity Indices

For each month t, the renewable electricity index (REI) for wind and solar photovoltaic (PV) power generation across the EU ETS zone are computed as follows:

$$\mathrm{REI}_t^{(j)} = \sum_i \left(\frac{\text{Renewable Electricity}_{i,t}^{(j)}}{\sum_i \text{Renewable Electricity}_{i,t}^{(j)}} \times \text{Capacity Factor}_{i,t}^{(j)} \right) \tag{2}$$

Here, $j \in \{\mathrm{W}, \mathrm{PV}\}$ and the summation index i runs across all countries under study in the EU ETS Zone. The capacity factor is a measure of how efficiently power systems operate, expressed as the ratio of actual power generated to maximum potential power generation (installed capacity). By considering the renewable power generation of each country in relation to the total renewable power generation in the EU ETS zone, the proposed composite indicator offers a relative measure of each country's contribution to overall renewable power generation–a significant predictor of emissions in the power sector. It is noteworthy that countries with similar levels of renewable power generation might have different capacity factors due to variations in weather conditions or renewable technology. Including the capacity factor in the calculation adds a dynamic aspect to the index, accounting for variations in the efficiency of renewable power generation in each country.

Overlapping Policy and Measure Index

For each month t, the overlapping policy and measure index (OPMI) is computed as follows:

$$\mathrm{OPMI}_t = \sum_i \left(\frac{\text{No. of Policies and Measures}_{i,t}}{\sum_i \text{No. of Policies and Measures}_{i,t}} \times \text{No. of Policies and Measures}_{i,t} \right) \tag{3}$$

Here, the summation index i runs across all countries under study in the EU ETS Zone. This composite indicator represents a weighted average that takes into account the heterogeneity in the number of policies and measures across the overall climate and energy policy landscape of the EU ETS zone, as well as the actual number of policies and measures implemented or adopted by each country at each time point. The index assigns more weight to countries contributing a higher share of the total policies each month. It serves as a method of acknowledging both the quantity and the relative contribution of each country's policies to the overall set of implemented or adopted measures, the outcomes of which may potentially overlap with emissions reduction resulting from the EU ETS over the first three phases.

3.2.3. Causal Inference from Counterfactual Power Sector Emissions

After establishing the counterfactual estimation, the causal effect of each EU ETS phase on power sector emissions is assessed by comparing observed data to counterfactual predictions–indicating what would have occurred in the absence of this emissions reduction mechanism. Let y_t and y_t' denote the total power sector emissions across the EU ETS zone at time t with and without the implementation of the trading scheme, respectively. y_t and y_t' may not be observed simultaneously. Instead, what is observable at time t is

$$y_t = \delta_t y_t + (1 - \delta_t) y_t' \tag{4}$$

where $\delta_t = 1$ if t denotes a point in time (month) after the policy intervention (the launch of each EU ETS phase, denoted by T_0), and $\delta_t = 0$ if t is a time point (month) before the policy intervention and

$$y_t' = \begin{cases} y_t & t = 1, ..., T_0 - 1 \\ \hat{y}_t & t = T_0, ..., T \end{cases}$$

Here, $\hat{y}_t$ represents the estimated counterfactual total power sector emissions across the EU ETS zone at time t, derived from the BSTS model, with T_0 denoting the policy intervention point–the month when each EU ETS phase was launched. In practice, the comparison between $\hat{y}_t$ and y_t is achieved by drawing samples ($n = 10000$ in the present analysis) from the posterior predictive distribution of the counterfactual series. For each draw τ, the pointwise impact ϕ (defined as the difference between the observed and counterfactual values) at each time point (month) t is calculated as

$$\phi_t^{(\tau)} = y_t - \hat{y}_t^{(\tau)} \quad \forall t = T_0, ..., T \tag{5}$$

To quantify the cumulative effect of the EU ETS over time, we also compute the cumulative sum of the pointwise impacts:

$$\sum_{i=T_0}^{t} \phi_i^{(\tau)} \quad \forall t = T_0, ..., T \tag{6}$$

This cumulative sum is particularly useful in the context of this study since the observed data represent power sector emissions across the EU ETS zone–a flow quantity measured over a specific interval (month).

4. Results

As can be seen from Table 1, during the post-intervention period of Phase I (January 2005 to December 2007), power sector fossil fuel CO_2 emissions averaged approximately 120.02 $\times 10^3$ kt. The credible intervals reported in the table represent a range of values within which there is a 99% probability that the true parameter lies. Posterior tail-area probability refers to the Bayesian probability of observing the estimated causal effect or a more extreme effect under the assumption that there is no causal effect. It represents the probability of obtaining the observed effect or a stronger effect purely by chance. If the posterior tail-area probability is small, the effect of the intervention can be considered significant. In the absence of the first phase of the EU ETS, the expected average emissions would have been 116.34 $\times 10^3$ kt, with a 99% interval ranging from 111.13 $\times 10^3$ kt to 123.41 $\times 10^3$ kt. Subtracting this prediction from the observed emissions reveals a (non-significant, see below) causal effect of 3.67 $\times 10^3$ kt, with a 99% interval from -3.39 $\times 10^3$ kt to 8.89 $\times 10^3$ kt. Cumulatively, the emissions totaled 4.32 $\times 10^6$ kt during the post-intervention period. Without the first phase of the EU ETS, the expected sum would have been 4.19 $\times 10^6$ kt, with a 99% interval ranging from 4.00 $\times 10^6$ kt to 4.44 $\times 10^6$ kt.

Phase I (2005-2007)	**Average**	**Cumulative**
Actual Emissions	120018	4320665
Predicted Emissions (SD)	116344 (1980)	4188376 (71295)
99% Credible Interval	[111130, 123408]	[4000665, 4442683]
Absolute Effect (SD)	3675 (1980)	132290 (71295)
99% Credible Interval	[-3389, 8889]	[-122017, 320000]
Relative Effect (SD)	3.2% (1.7%)	
99% Credible Interval	[-2.7%, 8%]	
Posterior Tail-Area Probability	**0.04**	

Table 1: The EU ETS impact on power sector fossil fuel CO_2 emissions in Phase I (2005-2007), summarizing actual and predicted emissions, absolute (pointwise) and relative effects, and Bayesian 99% credible intervals. Emissions are expressed in units of kt.

In relative terms, there was a +3% increase in power sector fossil fuel CO_2 emissions during the first phase, with the 99% interval for this percentage ranging from -3% to +8%. The probability of obtaining this causal effect by chance is approximately 0.04, suggesting that while the launch of the first EU ETS phase appears to have had a positive effect on emissions, this effect may be spurious and not statistically significant when considering the entire post-intervention period (2005-2007).

Figure 1 shows the monthly time series of actual (observed) and counterfactual (predicted) emissions both before and during the first phase of the EU ETS, along with absolute and cumulative effects. The observed significant positive absolute (pointwise) effect in January 2007, the only time point where the lower limit of the impact time series exceeded zero, could potentially be attributed to random fluctuations unrelated to the EU ETS.[12] The pointwise and cumulative effect panels in this figure suggest that there is no overall under- or overestimation of emission values by the BSTS model during the pre-intervention period.

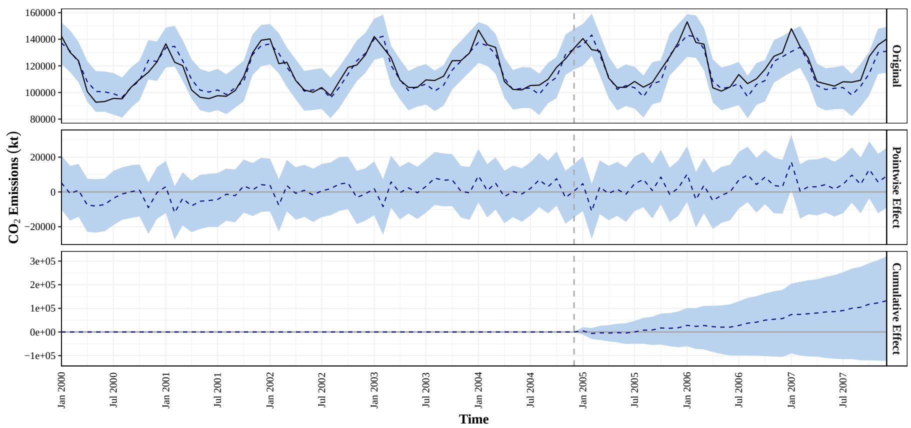

Figure 1: Monthly trajectories of actual (observed) and counterfactual (predicted) emissions (top panel); pointwise absolute difference between actual (observed) and counterfactual (predicted) emissions, accompanied by 99% credible intervals derived from 10000 Markov chain Monte Carlo (MCMC) samples (middle panel); cumulative absolute difference between actual (observed) and counterfactual (predicted) emissions, accompanied by 99% credible intervals derived from 10000 Markov chain Monte Carlo (MCMC) samples (middle panel) (bottom panel) for the first phase of the EU ETS (2000-2007).

It is evident from Table 2 that, during the post-intervention period of Phase II (January 2008 to December 2012), power sector fossil fuel CO_2 emissions averaged approximately 107.67 $\times 10^3$ kt. In the absence of this policy intervention, the expected average value would have been 122.92 $\times 10^3$ kt, with a 99% interval ranging from 116.62 $\times 10^3$ kt to 132.23 $\times 10^3$ kt. Subtracting this prediction from the observed emissions yields an estimate of the (statistically significant, as discussed below) causal effect the policy intervention had on the target series, resulting in a reduction of -15.26 $\times 10^3$ kt of emissions. The 99% interval for this effect ranges from -24.56 $\times 10^3$ kt to -8.96 $\times 10^3$ kt. Summing up the individual monthly values of the target series in the post-intervention period, power sector fossil fuel CO_2 emissions had an overall value of 6.46 $\times 10^6$ kt. In contrast, in the absence of the second phase of the EU ETS, the expected sum would have been 7.38 $\times 10^6$ kt, with a 99% interval ranging from 7.00 $\times 10^6$ kt to 7.93 $\times 10^6$ kt.

Beyond these absolute effects, emissions values demonstrated a relative decrease of -12%, with a 99% interval for this percentage ranging from -19%

[12]From a technical standpoint, this may also be attributed to the shorter intervention period for the first phase compared to the other two phases (36 months in the first phase, as opposed to 60 and 96 months for the second and third phases, respectively). This short intervention period could cause the model to struggle in distinguishing the signal from the noise.

Phase II (2008-2012)	**Average**	**Cumulative**
Actual Emissions	107667	6459999
Predicted Emissions (SD)	122925 (3158)	7375473 (189490)
99% Credible Interval	[116624, 132229]	[6997429, 7933736]
Absolute Effect (SD)	-15258 (3158)	-915474 (189490)
99% Credible Interval	[-24562, -8957]	[-1473737, -537429]
Relative Effect (SD)	**-12% (2.2%)**	
99% Credible Interval	**[-19%, -7.7%]**	
Posterior Tail-Area Probability	**0.00**	

Table 2: The EU ETS impact on power sector fossil fuel CO_2 emissions in Phase II (2007-2012), summarizing actual and predicted emissions, absolute (pointwise) and relative effects, and Bayesian 99% credible intervals. Emissions are expressed in units of kt.

to -8%. This indicates that the negative effect observed during the intervention period is statistically significant for Phase II. The probability of obtaining this effect by chance is extremely small (Bayesian one-sided tail-area probability $= 1e-4$), confirming the statistical significance of the causal effect.

Figure 2 shows the monthly time series of actual (observed) and counterfactual (predicted) emissions both before and during the second phase of the EU ETS, along with absolute and cumulative effects. It can be seen that, throughout the second phase, the lower limit of the impact time series never exceeded zero. This indicates the absence of any statistically significant positive absolute (pointwise) effect, or an increase in emissions, observed across the EU ETS zone in individual months throughout the second phase. The cumulative effect chart reveals a consistently decreasing pattern after the launch of the second phase, indicating a systematic reduction in power sector fossil fuel CO_2 emissions over time as a consequence of this implemented policy intervention.

Table 3 provides an overview of the EU ETS impact on power sector fossil fuel CO_2 emissions in the third phase (January 2013 to December 2020). During the post-intervention period of Phase III, emissions averaged approximately 85.31×10^3 kt. In the absence of the policy intervention, the anticipated average emissions would have been 105.58×10^3 kt. The 99% interval for this counterfactual prediction spans from 98.61×10^3 kt to 112.13×10^3 kt. By subtracting this prediction from the observed emissions, we obtain an estimate of the causal effect of the intervention on the target series. This (statistically significant, as detailed below) effect, amounts to -20.27×10^3 kt, with a 99% interval ranging from -26.82×10^3 kt to -13.30×10^3 kt. The cumulative value of power sector fossil fuel CO_2 emissions was found to be 8.19×10^6 kt. Had the third phase of the EU ETS not taken place, the predicted sum would have been 10.14×10^6 kt. The 99% prediction interval for this counterfactual scenario ranges from 9.47

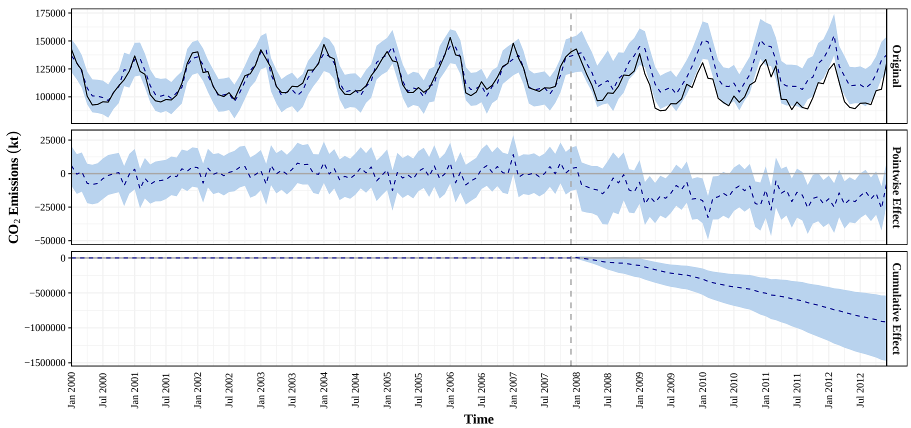

Figure 2: Monthly trajectories of actual (observed) and counterfactual (predicted) emissions (top panel); pointwise absolute difference between actual (observed) and counterfactual (predicted) emissions, accompanied by 99% credible intervals derived from 10000 Markov chain Monte Carlo (MCMC) samples (middle panel); cumulative absolute difference between actual (observed) and counterfactual (predicted) emissions, accompanied by 99% credible intervals derived from 10000 Markov chain Monte Carlo (MCMC) samples (middle panel) (bottom panel) for the second phase of the EU ETS (2000-2012).

$\times 10^6$ kt to 10.76 $\times 10^6$ kt.

In relative terms, emissions exhibited a decline of -19%, with a 99% confidence interval spanning from -24% to -13%.This indicates that the negative effect observed during the intervention period is statistically significant for Phase III. The probability of obtaining this effect by chance is extremely small (Bayesian one-sided tail-area probability $= 1e - 4$), indicating that if the policy intervention had no effect on emissions, there would be a chance of almost 0% to see a negative effect at least as large as the one observed.

In relative terms, emissions exhibited a decline of -19%, with a 99% confidence interval ranging from -24% to -13%. This indicates that the negative effect observed during the intervention period is statistically significant for Phase III. The probability of obtaining this effect by chance is extremely small (Bayesian one-sided tail-area probability $= 1 \times 10^{-4}$), suggesting that if the policy intervention had no effect on emissions, there would be almost a 0% chance of observing a negative effect as substantial as the one obtained.

Figure 3 illustrates the monthly time series of actual (observed) and counterfactual (predicted) emissions before and during the third phase of the EU ETS, accompanied by absolute and cumulative effects. Much like the second phase, the lower limit of the absolute (pointwise) impact time series consistently remains below zero throughout the third phase, signifying the absence of any statistically significant increase in emissions observed across the EU ETS zone in individual months throughout the second phase. The cumulative effect curve displays a continual decrease after the launch of the third phase, with a more pronounced decline compared to the second phase. For all three phases, dur-

Phase III (2013-2020)	**Average**	**Cumulative**
Actual Emissions	85306	8189397
Predicted Emissions (SD)	1.1e+05 (2571)	1.0e+07 (246769)
99% Credible Interval	[98610, 1.1e+05]	[9466577, 1.1e+07]
Absolute Effect (SD)	-20275 (2571)	-1946359 (246769)
99% Credible Interval	[-26819, -13304]	[-2574647, -1277180]
Relative Effect (SD)	**-19% (2%)**	
99% Credible Interval	**[-24%, -13%]**	
Posterior Tail-Area Probability	**0.00**	

Table 3: The EU ETS impact on power sector fossil fuel CO_2 emissions in Phase III (2013-2020), summarizing actual and predicted emissions, absolute (pointwise) and relative effects, and Bayesian 99% credible intervals. Emissions are expressed in units of kt.

ing the pre-intervention period, the model-derived estimates align closely with the actual (observed) emissions, and the BSTS model successfully captures the seasonal patterns.

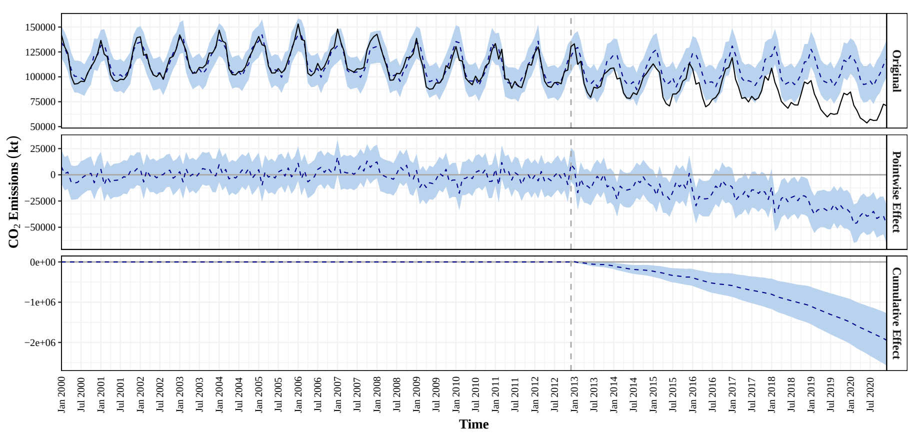

Figure 3: Monthly trajectories of actual (observed) and counterfactual (predicted) emissions (top panel); pointwise absolute difference between actual (observed) and counterfactual (predicted) emissions, accompanied by 99% credible intervals derived from 10000 Markov chain Monte Carlo (MCMC) samples (middle panel); cumulative absolute difference between actual (observed) and counterfactual (predicted) emissions, accompanied by 99% credible intervals derived from 10000 Markov chain Monte Carlo (MCMC) samples (middle panel) (bottom panel) for the third phase of the EU ETS (2000-2020).

5. Discussion

With reference to the relative ineffectiveness of the first (pilot) phase of the EU ETS in reducing power sector fossil fuel CO_2 emissions from 2005 to 2007, the results of this study are consistent with what has been found in previous studies (see for example Bayer & Aklin, 2020; Ellerman, 2015). As highlighted by Ellerman (2015), such relative ineffectiveness may be attributed to the oversupply of emissions allowances in the first phase. As expected, the analysis has shown that the third phase, which encompassed more sectors, was more effective than the second phase in reducing power sector fossil fuel CO_2 emissions.

Like most studies, the findings of this paper must be considered within the context of certain limitations, many (if not all) of which are commonly shared with existing literature. However, thanks to the methodology we have employed, we have addressed one of the most critical limitations in existing literature, namely, the challenge of building credible counterfactuals for power sector emissions without the need to find comparable units.

The first limitation is that it may not be entirely realistic to attribute all (absolute and cumulative) reductions in CO_2 emissions from fossil fuels in the power sector between 2005 and 2020 solely to the EU ETS. Other policy packages at regional, national and EU levels, long-term tendency towards increased energy efficiency (Ellerman et al., 2016), shareholder and stakeholder pressure, and heightened environmental awareness may also have contributed to emissions reduction across Europe during the period under study. As emphasized by Martin et al. (2016), isolating the impacts of emissions trading systems on emissions reduction from those of other factors is an extremely challenging, if not impossible, practice. In the current analysis, an effort to control for the potential influence of overlapping policies and measures (PaMs) on EU ETS CO_2 emissions in the power sector is made by incorporating an overlapping policy and measure index. This index is derived from the count of relevant national climate and energy PaMs implemented or adopted before 2020, specifically targeting the energy supply sector. However, this index primarily relies on the quantity of PaMs across the EU ETS zone and unavoidably overlooks the quality of these PaMs in terms of their potential impact on emissions reduction. Ideally, the construction of such an index should involve the quantification of CO_2 emissions reduction attributable to each PaM under examination. Due to the unavailability of data on these reductions, reliance on the quantity of policies remains the most feasible approach.

To assess the robustness of the constructed overlapping policy and measure index, we employed the OECD Climate Actions and Policies Measurement Framework (CAPMF) database (Nachtigall et al., 2022) as an alternative source for constructing comparable indices to serve as contemporaneous predictors of power sector fossil fuel CO_2 emissions. This allowed us to evaluate the consistency of our findings across different data sources for climate and energy PaMs. The CAPMF database provides annual data on two key measures for the vast majority of countries analyzed in this study. These measures include information on both the quantity of implemented market- and non-market-based actions and policies (both sectoral and aggregate) and the stringency of these actions and policies. To ensure balanced data availability and facilitate comparison, we focused only on the number of actions and policies in the new dataset, similar to our original index construction. By employing the same methodology described in Section 3.2.2, we constructed two alternative overlapping policy and measure indices from the CAPMF database: one for market-based policies and the other for non-market-based policies in the electricity sector across the EU ETS zone.[13] These alternative indices were then incorporated into the BSTS model as contemporaneous predictors of power sector fossil fuel CO_2 emissions.

The results obtained using the newly constructed dual indices (market-based and non-market based) aligned with those obtained using the single overlapping policy and measure index in the first and third phases of the EU ETS. Notably, a statistically non-significant relative increase of +6.2% in emissions was observed during the post-intervention period of the first phase, while a statistically significant +15% decrease in emissions was obseved during the post-intervention period of the third phase. The analysis of the second phase, however, presented challenges when using the dual indices. The model's prediction intervals widened significantly from January 2010, hindering the validity of statistical inferences. This issue stemmed from a technical limitation of the BSTS model and the nature of the non-market based index, which exhibited a sharp transition from dummy values (0 or 1) in the entire pre-intervention period (January 2000 to December 2007) to a different set of values in the post-intervention period. This abrupt shift disrupted the model's ability to effectively leverage patterns and relationships established during the pre-intervention period for accurate counterfactual predictions in the post-intervention period. Consequently, the wider prediction intervals reflected increased uncertainty due to the model's difficulty in adapting to the new pattern of one of the contemporaneous predictors. In the first and third phases, the distribution of values for the non-market-based index did not present challenges for the model's learning process. In the first phase, dummy values covered the entire duration of both pre-intervention and post-intervention periods. In the third phase, the shift in values occurred during the pre-intervention period, ensuring its incorporation into the model's learning process. In light of this robustness analysis, the single overlapping policy and measure index constructed using the EEA Database on Integrated National Climate and Energy Policies and Measures emerges as a reliable choice for a contemporaneous predictor, as it demonstrates stability across all three phases and avoids challenges in causal inference. Therefore, it remains the preferred index for our analysis.

This study focused solely on the power sector's CO_2 emissions within the EU ETS, neglecting emissions from other covered sectors. This presents a limitation in the overall picture of the EU ETS's impact. However, it is important to note that the power sector is a dominant source of emissions within the EU ETS.

[13] Due to data availability limitations in this new dataset, the market-based and non-market-based indices covered 23 and 21 countries, respectively.

By focusing on this crucial sector, the study provides valuable insights into the potential effectiveness of the program. Further research on other sectors is certainly warranted for a more comprehensive understanding, but the focus on the power sector offers a strong foundation for future investigations.

Other limitations?

6. Conclusion

As the cornerstone of the European Union's policy to address climate change and reduce CO_2 emissions, the EU ETS has attracted great attention of scholars since its launch in January 2005. Despite widespread research attention to this trading scheme, comprehensive empirical evidence on achievement of its main target (i.e. emissions reduction) over the course of the first three phases remains scarce. In an effort to partially fill this gap, this paper offered a counterfactual-based causal inference approach to the effectiveness evaluation of the the EU ETS with regard to reducing power sector fossil fuel CO_2 emissions over the 2005-2019 period.

By employing a Bayesian structural time series (BSTS) model and data on several contemporaneous predictors, this study was able to verify whether each of the three phases of the EU ETS could reduce monthly power sector fossil fuel CO_2 emissions across 24 EU ETS Member States. The analysis found support for a statistically significant reduction in emissions during the second and, notably, the third phases of the EU ETS. Conversely, the first phase showed a statistically non-significant increase in emissions. From an evolutionary perspective, it is evident that the effectiveness of the scheme has progressively improved from the first to the third phases. This evolution highlights a notable shift towards greater efficacy in emission reduction over time.

At the end, it should be emphasized that the primary purpose of this explorative study was to examine whether the European Union's main carbon pricing instrument could attain its principal objective of cutting fossil fuel CO_2 emissions in the power sector, and to propose a novel methodological framework for causal inference based on counterfactuals within the context of the EU ETS environmental effectiveness assessment. Providing the full story behind the findings of this research necessitates an in-depth analysis based on extensive country-level data–an exercise that goes beyond the scope of this paper and is left to future research.

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Appendix A. Summary of Previous Studies on EU ETS Effectiveness

Table A.4: Summary of the literature on the effectiveness of the EU ETS in reducing carbon emissions. Contents of this table were partially adapted from Rafaty et al. (2020) and Green (2021).

Reference	Study Period	Geographical Scope	Method	Comparison/Control Group	Outcome of Interest	Finding(s)
Anderson & Di Maria (2011)	2005-2007	25 EU Member States	Dynamic panel data modeling	Baseline emissions estimated based on industrial economic activity levels, energy prices and weather effects (heating degree days, cooling degree days and precipitation)	Industrial CO_2 emissions	2.8% net CO_2 emissions reduction over the study period
Bayer & Aklin (2020)	2008-2016	25 EU Member States	Generalized synthetic control	Non-ETS sectors	Sector-level CO_2 emissions	3.8% CO_2 emissions reduction compared to the total emissions over the study period
Bel & Joseph (2015)	2005-2012	25 EU Member States	Dynamic panel data modeling	-	National installation-level GHG emissions from electricity and industry sectors	11.47% and 13.84% of total GHG reduction over the study period
Dechezleprêtre et al. (2018)	2005-2012	France, the Netherlands, Norway and the United Kingdom	difference in differences	-	Installation-level carbon emissions	6% carbon emissions reduction from 2005 to 2007 and 15% reduction from 2008 to 2012
Egenhofer et al. (2011)	2005-2009	25 EU Member States	Comparison of emissions reduction with business-as-usual (BAU) emissions	BAU emissions projected from the 2000-2004 period (proposed by Ellerman et al., 2010)	Sector-level CO_2 emissions	1% average annual intensity improvement from 2005 to 2007 and 3.35% intensity improvement from 2008 to 2009
Ellerman & Buchner (2008)	2005-2006	25 EU Member States	Comparison with baseline emissions	Baseline emissions estimated based on indicators of economic activity	Installation-level CO_2 emissions	3% CO_2 emissions reduction over the study period
Ellerman et al. (2016)	2004-2014	25 EU Member States	Comparison with long-term perspective on ETS sector emissions	-	Sector-level CO_2 emissions	2.1% average annual CO_2 emissions reduction in ETS sectors from 2004 to 2014
Gloaguen & Alberola (2013)	2005-2012	21 EU Member States	Dynamic panel data modeling	BAU emissions based on manufacturing activity, development of renewable energies, energy efficiency, carbon price, and energy ratio	Country-level CO_2 emissions of all ETS sectors	7.3% CO_2 emissions reduction over the study period
Jaraite-Kažukauske & Di Maria (2016)	2003-2010	Lithuania	Matching	Non-ETS firms	Firm-level CO_2 emissions	No significant CO_2 emissions reduction
Ellerman & McGuinness (2008)	2005-2006	The United Kingdom	Panel data modeling	Counterfactual emissions based on individual units' planned generation and availability	Plant-level CO_2 emissions from combined cycle gas turbine and coal power plants	Between 13 million and 21 million tons of CO_2 emissions reduction in 2005 and from 14 to 21 million tons of reduction in 2006 as a result of fuel-switching
Petrick & Wagner (2014)	2005-2010	Germany	Difference in differences	Non-ETS firms	Plant-level CO_2 emissions from manufacturing firms	No significant emissions reduction from 2005 to 2007, 20% emissions reduction between 2007 and 2010
Wagner et al. (2014)	2005-2010	France	Propensity score-based difference in differences	Non-ETS firms	Plant-level CO_2 emissions from manufacturing firms	An average of 15-20% emissions reduction from 2007 to 2010; no significant reduction from 2005 to 2007
Klemetsen et al. (2016)	2001-2013	Norway	Propensity score-based difference in differences	Non-ETS firms	Plant-level CO_2, N_2O and PFCs (measured in CO_2 equivalents) emissions	A weak tendency of emissions reduction from 2008 to 2012
Abrell et al. (2011)	2005-2008	21 EU Member States	Dynamic panel modeling with propensity score matching	Non-ETS firms	Firm-level CO_2 emissions growth rate	3% emissions reduction in 2007-2008 relative to 2005-2006
Gretszel et al. (2020)	2005-2018	22 EU Member States	Generalized method of moments (GMM)	Benchmark variant	Installation-level CO_2 emissions	Significant emissions reduction especially in low-polluting economies
Colmer et al. (2023)	2005-2012	France	Matched Difference-In-Differences	2004 and Linear Trend Benchmarks	Manufacturing firm-level CO_2 emissions	14-16% emissions reduction with no contractions in economic activity