The Impact of the EU Emissions Trading System on CO_2 Emissions: A Matrix Completion Analysis

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Abstract. Despite the negative externalities on the environment and human health, today's economies still produce excessive CO_2 emissions. As a result, governments are trying to shift production and consumption to more sustainable models that reduce the impact of CO_2 emissions. The European Union, in particular, has implemented an innovative policy to reduce CO_2 emissions by creating a market for emission rights, the Emissions Trading System (ETS). The objective of this paper is to perform a counterfactual analysis to measure the impact of the ETS on the reduction of CO_2 emissions. For this purpose, a Statistical Machine Learning (SML) technique called Matrix Completion (MC) is used. We apply MC to the prediction of missing counterfactual entries of a CO_2 emissions matrix whose elements (indexed row-wise by country and column-wise by year) represent emissions without ETS for country-year pairs. The results obtained, confirmed by robust diagnostic tests, show a significant effect of the ETS on the reduction of CO_2 emissions: the majority of EU countries included in our analysis reduced their total CO_2 emissions by about 20% during the ETS treatment period 2005–2016, compared to the total CO_2 emissions that would have been achieved in the absence of the ETS policy.

Keywords: Matrix completion; Counterfactual analysis; Causal inference; Green economy; Pollution.

1 Introduction

Global warming is mainly a consequence of human activities and the use of fuels in an economic system. Limiting carbon dioxide (CO_2) emissions can be an effective way to reduce the effects of global warming (e.g., by slowing the rise in temperature). In fact, increases in such production lead, for example, to greater drought areas (and thus food shortages) and sea level rise (and thus a reduction in available dry land). Global warming is a hot topic because, among other things, it causes natural disasters such as hurricanes, floods, and droughts over large areas. They all cause persistent damage to agriculture and more generally to the whole economic system (Tol, 2009; Van Aalst, 2006). Currently, there is an extensive economic literature that examines various aspects related to CO_2 emissions (Machado et al., 2021; Sun et al., 2022; Zhang et al., 2023). For example, scholars have examined CO_2 emissions of selected countries in relation to economic outcomes such as Gross Domestic Product (GDP) growth (Romero-Ávila, 2008), innovation (Chen and Lee, 2020), manufacturing output (Yang et al., 2021), trade and foreign direct investments (Ren et al., 2014).

Emerging economies are commonly regarded as the world's biggest polluters. Conversely, developed countries are generally considered cleaner. This perception is also theoretically supported by the concept of the Kuznets curve (Kuznets, 1955). Originally, the Kuznets curve was introduced to explain the existence of an inverted "U" relationship between income inequality and GDP within countries. A few decades later, the idea behind this particular relationship was taken up by environmental economics (Grossman and Krueger, 1995). According to the environmental Kuznets curve, there is an inverted "U" relationship between GDP and CO_2 emissions. There are several scientific studies that empirically confirm the idea behind the environmental Kuznets theory, which is applied to the study of emerging economies such as China in the context of the green economy (Dong et al., 2018). The presence of the environmental Kuznets curve has also been found in other studies, such as those by Doytch et al. (2023), Hove and Tursoy (2019), Sarkodie and Strezov (2018) and Sugiawan and Managi (2016). However, it is worth noting that some other studies have found no evidence for the existence of the environmental Kuznets curve or have found that its existence is ambiguous and depends on the model specification (Al-Mulali et al., 2015; Luzzati and Orsini, 2009; Luzzati et al., 2018). One possible explanation for the occurrence of the Kuznets curve lies in the fact that during the first phase of industrialization, countries dramatically increase their industrial production (without caring about pollution and environmental issues), and after the general welfare of the population becomes higher, environmental issues are perceived as relevant. Therefore, companies are more efficient, and policy makers (supported by public opinion) also introduce environmentally friendly legislation. In recent years, some possible measures to mitigate climate change have been proposed by governments, international organizations, and associations. But not all countries are taking significant action. One notable example of a policy to reduce CO_2 emissions is the Emissions Trading System (ETS), which was introduced by the European Union (EU) in 2005 and has come into effect in various stages. The ETS sets an annual cap on CO_2 emissions for companies in certain industries. The basic idea behind this policy is that CO_2 emissions are the main cause of current global warming and that reducing CO_2 emissions can lead to stopping or slowing climate change. A significant portion of new CO_2 emissions is caused by human impacts on the environment during manufacturing, transportation, and energy production (from fossil sources) that use large quantities of hydrocarbons. Since the amount of (EU) green certificates is set by the authorities and a fine per ton is imposed if emissions are exceeded, the EU can effectively curb CO_2 emissions. This policy has come into force in different steps (the first was in 2005, the second in 2008, and the third in 2013). The EU ETS policy is consistent with the 2016 Paris Agreement, which calls for a 55% reduction in CO_2 emissions by 2030, using 1990 levels as the basis for calculation (Martin et al., 2016). On the other hand, non-EU countries have implemented their CO_2 reduction policies later and softer.

Although the effects of the EU ETS policy have already been studied (see the literature review in Section 1.1), an examination of the literature reveals the following gaps: (i) few studies analyzed the impact of the EU ETS policy at the European level, while the rest of the analyses focused on specific EU countries; (ii) the results of the analyses conducted in different papers were often contradictory; (iii) few studies used a rigorous counterfactual analysis; (iv) typically, only the first phase of the EU ETS policy was analyzed, not its long-term impact.

In this work, we have addressed the above gaps by using a state-of-the-art machine learning method (namely, Matrix Completion or MC), which Athey et al. (2021) have recently shown to be a more effective method for evaluating policies than other, more traditional methods used for panel data analysis. Our study, therefore, highlights the need to use more reliable and general methods to estimate the impact of policies, such as EU ETS, on pollution reduction. This issue is particularly important given the current prominence of climate change and, more generally, environmental issues and the lessons we can draw from the EU experience for policymakers in developing countries.

1.1 State of the art on the analysis of the EU ETS policy

The topic of the implementation of markets for emission rights, and in particular the implementation of the one designed by the EU (ETS), has already been studied in the literature from different points of view (Teixidó et al., 2019). One of them is the empirical analysis of the effective reduction of total CO_2 emissions in the countries of the old continent. However, there is no consensus in the current literature on the impact of the ETS policy (Verde, 2020). One very relevant paper is certainly Calel (2020), which combines a nearest-neighbor matching approach, between treated large plants and untreated small plants, with Difference-in-Differences (DiD) and Difference-in-Means (DiM) estimators. However, in that work, whose analysis was focused on the UK from 2000 to 2012, no significant effect of UK ETS on CO_2 emissions reductions was found. In Jaraitė and Maria (2016), the impact of EU ETS on Lithuanian companies was studied by analyzing data from 2003 to 2010[1]. In their analysis, the authors combined nearest neighbor matching with DiD and then applied kernel matching as a robustness check. They concluded that the ETS did not significantly reduce CO_2 emissions in Lithuania (in some treated years, only minor effects were achieved as the old plants of the large polluters were released). A similar methodological approach was used for the Norwegian case by Klemetsen et al. (2020)[2]. In that work, the authors used a fixed-effects DiD approach and selected a control group through nearest-neighbor matching, specifically assuming exact industry-level matching between treated and untreated firms. However, the results obtained were inconclusive. Another stream of literature has shown that EU ETS had a positive impact on reducing CO_2 emissions of selected European countries. For example, Petrick and Wagner (2014) found a relevant reduction in CO_2 production in Germany due to an increase in the energy efficiency of plants. Their econometric methodology used propensity score matching to weigh treated and non-treated firms. Similarly, Wagner et al. (2014) observed a significant reduction in CO_2 production in France. In our opinion, these approaches may hide a problem in obtaining a fair evaluation of the policy, since the treated plants were quite large, while the ones in the control group were small. As a result, there may be economies of scale in CO_2 emissions that were not captured by the models. In other words, if the control group has different characteristics (i.e., in particular, a different order of magnitude in size) than the treated group, approaches based on (classical) matching cannot produce an adequate control group because the control group obtained cannot be entirely similar to the treated group. A very recent article by Dechezleprêtre et al. (2023) found a reduction of about 10% in CO_2 emissions between 2005 and 2012 in four countries studied (i.e., France, the Netherlands, Norway, and the United Kingdom). However, in their one-to-one matching approach, it was necessary to exclude a number of companies for which it was not possible to find a good match (e.g., large electricity production companies). This might have biased the results of their analysis due to the possible exclusion of some of the most important examples of potential CO_2 emissions reductions. Finally, a significant methodological improvement in studying the performance of EU ETS in reducing pollution was made by Bayer and Aklin (2020), where researchers applied a Synthetic Control Method (SCM) at the industry level and concluded that the presence of the EU ETS policy significantly reduced CO_2 production in the EU by 3.8% between 2008 and 2016, compared to its absence. However, the SCM may fail under various circumstances, especially if the period of pre-treatment observations is not long enough (Abadie, 2021). The SCM was also used in (Anderson et al., 2023), where the scholars concentrated their analysis on estimating the effects on emissions for Australia if Australia had adopted the EU ETS scheme, finding a statistically significant reduction in the CO_2 emissions per capita.

1.2 Contribution of the work

Considering the limitations of the methods discussed in the previous subsection, in our analysis we have chosen to use another recently developed method coming from the Statistical Machine Learning literature (SML), namely Matrix Completion (MC), in order to verify whether the results found in Bayer and Aklin (2020) are confirmed or not with this novel approach. Moreover, our use of MC allows us to fill the four gaps in the literature highlighted at the end of Section 1, namely: (i) the opportunity of focusing the analysis on a larger set of countries; (ii) the necessity of using reliable estimation methods; (iii) the requirement of performing a rigorous counterfactual analysis; (iv) the need of analyzing the various phases of the EU ETS policy.

The main idea of MC is to minimize a suitable tradeoff between the approximation error on a set of observed entries of a matrix (training set) and a proxy for the rank of the reconstructed matrix, e.g., its

[1] Lithuania joined the EU in 2004, so 2004 was considered the pre-treatment period for all observed firms.
[2] Although Norway is not an EU member, it adopted the EU ETS policy in 2008.

nuclear norm. Matrix completion is a state-of-the-art quantitative method particularly suited for counterfactual analyses, as recently demonstrated by Athey et al. (2021), where it was successfully compared with other methods such as DiD and the SCM. Other successful examples of the use of MC include the works by Metulini et al. (2022), in which MC was applied in the context of international trade for the reconstruction of World Input-Output Database (WIOD) subtables (Timmer et al., 2015), and by Gnecco et al. (2022) and Gnecco et al. (2023), in which MC was used for the analysis of economic complexity.

Accordingly, our main research question is to investigate whether EU countries – through the EU ETS policy – have reduced CO_2 production significantly more than the rest of the world, which is equivalent to assessing the effectiveness of the EU ETS policy in reducing CO_2 emissions. Our goal is not limited to assessing whether or not reductions have occurred but also includes quantifying (through a robust SML approach) the reduction in CO_2 emissions due to the presence of the EU ETS policy. Specifically, we perform a counterfactual analysis based on MC to estimate the (unobserved) CO_2 emissions of EU countries in the years of treatment in the absence of the EU ETS policy.

In this work, we aim to contribute to the academic debate by examining the impact of the EU ETS policy on reducing CO_2 emissions. This work can be viewed as a development of Huang et al. (2021) and of our earlier conference article Biancalani et al. (2023a) on the application of MC to the prediction of CO_2 emissions, each based on two different data sets[3]. In contrast to these papers (in which only the predictive accuracy of MC was evaluated), here we perform a counterfactual analysis, based on MC. Moreover, this analysis is based on a different choice of the matrix to which MC is applied, as well as an appropriate choice of matrix elements provided as inputs to MC. We also use a different MC method that is more appropriate for estimating causal effects. To our knowledge, no other previous work analyzed the effects of the EU ETS policy using MC. Finally, in our analysis, we apply MC to a country-and industry-level database covering several years in the recent past.

With the aforementioned goal in mind, in the present paper we propose to perform a counterfactual analysis by referring to the approach used by Athey et al. (2021) (MCFE, hereafter), based on a nuclear norm MC optimization problem, which is an extension of the optimization problem introduced by Mazumder et al. (2010) (MC, hereafter) and solved numerically by applying the soft-impute algorithm developed in the latter work. The MCFE method is specifically designed for panel data analysis (where the rows and columns of the matrix may refer to individuals and time points, for example). It introduces a two-way (individual and time) fixed effects component to the MC optimization problem to increase the performance of matrix completion (or matrix reconstruction). The performance of MCFE compared to MC was recently evaluated in our conference paper Metulini et al. (2023) using a simulation study for CO_2 emission data. Therein, we found that the inclusion of individual and time fixed effects in the MC optimization problem, as well as an appropriate pre-processing of the original data achieved by applying an l_1 row-normalization, increases the predictive performance of the MC method. In particular, the latter normalization filters out the possible side effect of differences in CO_2 emission levels between countries. Therefore, also in the present work, we apply l_1 normalization by row (i.e., by country) as an appropriate preprocessing of the matrix. In summary, as described in the next sections, our analysis finds that the EU ETS policy reduced CO_2 emissions by about 20% in the European countries studied during the 2005–2016 period, ranging from no impact for Denmark to a reduction of almost 30% for Greece.

[3] The analysis made in Biancalani et al. (2023a) was further extended recently in Biancalani et al. (2023b), showing that the predictive accuracy of MC, applied to a matrix of CO_2 emissions, can be improved by combining it with a baseline estimate (e.g., an estimate of fixed effects). In that work, an ensemble machine-learning approach was followed, in which first the baseline estimate was generated, then MC was applied to the residual. The MC approach by Athey et al. (2021), used in the present work, is based on a similar idea, in which fixed-effects estimation and MC are performed simultaneously.

1.3 Structure of the work

The work is organized as follows: Section 2 describes the available data set; Section 3 presents the methodology used; Section 4 shows the results obtained by applying this methodology to the pre-processed CO_2 emission matrix; Section 5 concludes the work and sheds light on possible future developments.

2 Description of the data set

In this paper, we use data on total CO_2 emissions (including those generated by households) by country. In our analysis of the causal effects of the EU ETS policy (covering the period 2000–2016), we can consider EU countries as "treated" and selected high-income non-EU countries as "untreated", since for the latter the potential treatment (before 2016) is limited compared to that of the EU countries (Bayer and Aklin, 2020). The database used (Corsatea et al., 2019) can be accessed for free at `https://joint-research-centre.ec.europa.eu/document/download/b572c87b-a2fb-4ab6-af38-ff0451273e9e_en?filenameco2em56.zip`[4]. It covers the period between 2000 and 2016 and 42 countries (29 European and 13 non-European). In addition, the amount is given in thousand tons of CO_2 for 56 industries and is also related to households. Since the ETS is mandatory for EU countries, we consider the following 13 countries as "treated" for our study: Austria (AUT), Belgium (BEL), Germany (DEU), Denmark (DNK), Spain (ESP), Finland (FIN), France (FRA), United Kingdom (GBR)[5], Greece (GRC), Ireland (IRL), Italy (ITA), Portugal (PRT), and Sweden (SWE). All these countries were members of the EU between 2000 and 2016. We do not consider small countries such as Cyprus, Luxembourg, and Malta, as they may be subject to small shocks (as the cessation of production of a single plant could have a large impact on their respective total CO_2 emissions). As a control group (non-treated countries, without ETS), we consider countries that were not members of the EU between 2000 and 2016 and that were not associated with or had special agreements with the EU during this period (i.e., Iceland, Liechtenstein, Norway, and Switzerland are excluded)[6]. Our control group for this work consists of large non-EU high-income countries in the available database that are almost in the same phase of the Kuznets curve as selected EU countries. Specifically, we include the following five countries in the control group: Australia (AUS), Canada (CAN), Japan (JPN), South Korea (KOR), and the United States of America (USA). Although some non-EU countries have taken specific measures to reduce CO_2 emissions, the impact of these measures has been relatively negligible compared to the EU ETS policy until 2016 (Narassimhan et al., 2018).

In our analysis, we aggregate the values of CO_2 emissions originally available at the country-industry-year level in the database (Corsatea et al., 2019) to the country-year level by adding the values of all sectors and household (i.e., end-user) emissions (Missbach et al., 2023). In this way, the resulting 18×17 CO_2 emission matrix represents the (total) amount of emissions for each country and year. The goals of this approach are twofold. First, we reduce the computational burden of repeatedly applying MC by using a smaller matrix as input. Second, we simplify the analysis by focusing on the aggregate level for each country. Comparing countries, industries, and years (i.e., using three dimensions in the analysis) would make the approach to completing the matrix much more complex, possibly calling for its extension to the tensor case (Song et al., 2019). It could also be that the policy indirectly affected non-treated but related industries in the treated EU countries. Therefore, to reduce the risk of possible policy transmission, we preferred to consider countries and/or years that were not affected by EU policies as inputs to our matrix completion approach.

[4] This hyperlink was accessed in March 2023. The original 2019 version of the database, available at `https://joint-research-centre.ec.europa.eu/system/files/2019-09/co2em56.zip`, also included data on the Netherlands (NLD), which has been removed in the updated version of the database.

[5] Brexit came into effect in 2021, so the UK was a member of the EU during the study period.

[6] Iceland, Liechtenstein, and Norway introduced EU ETS in 2008 (i.e., during Phase 2), while Switzerland has several bilateral agreements with EU countries.

3 Methodology

In this paper, we opt for an innovative methodological approach in the field of policy evaluation. Clearly, it is not possible to conduct a randomized control trial because we have data on sovereign countries, and in the specific case, our data are unlikely to focus on (pilot) policies at the national and local levels (Aron-Dine et al., 2013; Ludwig et al., 2013). For this reason, the ideal situation of a randomized sample in which treated subjects have ex-ante the same characteristics as untreated subjects cannot be achieved. Therefore, we should use techniques that can provide good counterfactual data for the elements of the treated group. When randomized controls are not available (which is the case in most policy impact analyses), various techniques, such as Instrumental Variables (IVs), are often used in the literature to evaluate interventions. A relevant example of the use of IVs in the context of ecological economics comes from Martelli et al. (2018), who studied the effects of voluntary adoption of green programs on mayoral elections, using as IV the existence of a Covenant Territorial Coordinator. They found that participation in non-mandatory green programs at the local level was not a barrier to re-election. Another typical IV application was considered in Binder and Neumayer (2005), where the authors examined the impact of environmental Non-Governmental Organisations (NGOs) on air quality. In this case, IVs are represented by the number of international NGOs per capita and membership density of international NGOs. Unfortunately, in our case, it is not possible to find at least one valid IV among the available variables. Another technique is Regression Discontinuity Design (RDD), which can be applied when there is at least one specific threshold that separates treated and untreated units. For example, Soliman (2022) examined water conservation in California using three discontinuity points in the timeline: June 2015, February 2016, and November 2016 (i.e., the dates of key legislative events). In Doremus (2019), the author used a spatial regression discontinuity design to examine whether the Forest Stewardship Council (FSC) has changed (or not) the standard of living of indigenous people in Congo. For our purposes, this methodology does not appear to be applicable because there is no sharp temporal or spatial threshold between treated and untreated countries. The use of DiD may provide a good alternative approach (Koch and Themann, 2022), but its application requires the so-called parallel trend assumption, which is often difficult to be met. Adjustments to the control group such as propensity score matching (Heckman et al., 1997) and Mahalanobis distance matching and entropy (or Hainmueller) balancing (Hainmueller, 2012) are not conclusive given the large heterogeneity and small number of countries in our sample. These problems (especially the comparison between a small number of states or regions) can be solved with the Synthetic Control Method (SCM). Pellegrini et al. (2021) applied the SCM to analyze the impact of oil production in Basilicata (a small region in southern Italy) on socioeconomic indicators. Given the peculiarity of our specific problem and data structure, in our analysis we prefer a Matrix Completion (MC) approach for the following reasons: (i) the numerical results reported in Athey et al. (2021) show that their proposed Matrix Completion (MC) method for policy evaluation generally outperforms other alternative methods, such as the SCM and elastic net estimators; (ii) the MC approach can also be interpreted as a generalization of earlier approaches such as the SCM. Indeed, these approaches share the same objective function (the Fröbenius norm of the difference between a latent matrix and the observed matrix), but have different constraints (which are less stringent in the case of the proposed MC method).

For the application considered in this paper, the use of MC is justified by the fact that the counterfactual CO_2 emission levels for the treated countries (namely the EU countries) are not known in the years of treatment when the ETS policy was in force. Therefore, based on the method introduced by Athey et al. (2021), we use MC to generate estimates of such counterfactual values and compare them to the actual CO_2 emission values, with the ultimate goal of estimating the effect of the treatment on CO_2 emission values through the ETS policy. The main idea is to consider the treated values (i.e., the CO_2 emission values of EU countries in the years of treatment) as missing values and the other entries of the CO_2 emission matrix as given data. Specifically, in this paper, we apply the following formulation to the matrix completion fixed effects (MCFE) optimization problem proposed by Athey et al. (2021):

$$\underset{\hat{\mathbf{M}}\in\mathbb{R}^{m\times n},\hat{\mathbf{L}}\in\mathbb{R}^{m\times n},\hat{\mathbf{\Gamma}}\in\mathbb{R}^{m\times 1},\hat{\mathbf{\Delta}}\in\mathbb{R}^{n\times 1}}{\text{minimize}} \left(\frac{1}{|\Omega^{\text{tr}}|}\sum_{(i,j)\in\Omega^{\text{tr}}}\left(M_{i,j}-\hat{M}_{i,j}\right)^2+\lambda\|\hat{\mathbf{L}}\|_*\right),$$
$$\text{subject to } \hat{\mathbf{M}}=\hat{\mathbf{L}}+\hat{\mathbf{\Gamma}}\mathbf{1}_n^\top+\mathbf{1}_m\hat{\mathbf{\Delta}}^\top, \tag{1}$$

where

- Ω^{tr} is a subset of pairs of indices (i,j) corresponding to the positions of known entries of a matrix $\mathbf{M}\in\mathbb{R}^{m\times n}$ (using a machine learning expression, Ω^{tr} can be called a training set of pairs of indices);
- $\mathbf{1}_n$ and $\mathbf{1}_m$ are column vectors consisting of n entries and m entries, respectively, all equal to 1;
- $\hat{\mathbf{M}}$ is the completed matrix decomposed as

$$\hat{\mathbf{M}}=\hat{\mathbf{L}}+\hat{\mathbf{\Gamma}}\mathbf{1}_n^\top+\mathbf{1}_m\hat{\mathbf{\Delta}}^\top \tag{2}$$

  (where $\hat{\mathbf{L}}$, $\hat{\mathbf{\Gamma}}$ and $\hat{\mathbf{\Delta}}$ must be chosen to solve the above optimization problem);
- $\lambda\geq 0$ is a regularization constant;
- $\|\hat{\mathbf{L}}\|_*$ is the nuclear norm of the matrix $\hat{\mathbf{L}}$, i.e., the summation of all its singular values.

The two terms $\hat{\mathbf{\Gamma}}\mathbf{1}_n^\top$ and $\mathbf{1}_m\hat{\mathbf{\Delta}}^\top$ model, respectively, estimates of row-fixed effects (e.g., of unit-fixed effects) and of column-fixed effects (e.g., of time-fixed effects) in the reconstruction $\hat{\mathbf{M}}$ of $\mathbf{M}$ according to equation (2). The regularization constant λ controls the tradeoff between adequately fitting the known entries of the matrix $\mathbf{M}$ and achieving a small nuclear norm of the first term $\hat{\mathbf{L}}$ of its reconstruction. Here, the nuclear norm plays a similar role as the well-known l_1-norm regularization term used in the well-known and widely used Least Absolute Shrinkage and Selection Operator (LASSO) regularization method (Hastie et al., 2015). It is worth noting that, in contrast to earlier formulations of the MC optimization problem – see, e.g., Mazumder et al. (2010) – the nuclear norm $\|\hat{\mathbf{L}}\|_*$ is used in the optimization problem (1) instead of the nuclear norm $\|\hat{\mathbf{M}}\|_*$. In other words, the estimated fixed effects $\hat{\mathbf{\Gamma}}\mathbf{1}_n^\top$ and $\mathbf{1}_m\hat{\mathbf{\Delta}}^\top$ are not regularized. In the present context, this is an important point because otherwise, by using the alternative regularization term $\lambda\|\hat{\mathbf{M}}\|_*$ instead of $\lambda\|\hat{\mathbf{L}}\|_*$ (i.e., by regularizing the entire reconstructed matrix $\hat{\mathbf{M}}$), one could obtain biased estimates that might underestimate the true values (Wang et al., 2022). In other words, any estimated element $\hat{M}_{i,j}$ could be a systematic underestimate of the corresponding element $M_{i,j}$ for the optimal choice of λ, making it difficult to obtain reliable counterfactual values. As described in the literature, this is a common problem when using regularization methods, since the LASSO regularization method may be affected by underestimation problems (An et al., 2020; Feng et al., 2012).

In this paper, the optimization problem (1) is solved numerically by applying the soft-impute algorithm developed by Mazumder et al. (2010) and adapted to the case of the optimization problem (1) by Athey et al. (2021). It is worth noting that the MCFE estimator used in this work was demonstrated in Athey et al. (2021) — using two applications to smoker data and stock market data – to outperform several alternative methods such as DiD, SCM, vertical regression with elastic net regularization, and horizontal regression with elastic net regularization (Athey et al., 2021).

The soft-impute algorithm for calculating the MCFE estimator goes as follows. Let the projection operator $\mathbf{P}_{\Omega^{\text{tr}}}:\mathbb{R}^{m\times n}\to\mathbb{R}^{m\times n}$ be defined as $[\mathbf{P}_{\Omega^{\text{tr}}}(\mathbf{M})]_{i,j}:=M_{i,j}$ if $(i,j)\in\Omega^{\text{tr}}$, 0 otherwise. Similarly, let the projection operator $\mathbf{P}_{\Omega^{\text{tr}}}^{\perp}:\mathbb{R}^{m\times n}\to\mathbb{R}^{m\times n}$ be defined as $[\mathbf{P}_{\Omega^{\text{tr}}}^{\perp}(\mathbf{M})]_{i,j}:=M_{i,j}$ if $(i,j)\notin\Omega^{\text{tr}}$, 0 otherwise. For a matrix $\mathbf{M}\in\mathbb{R}^{m\times n}$ with rank r, let its Singular Value Decomposition (SVD) be

$$S_r(\mathbf{M})=\mathbf{U}\mathbf{D}_r\mathbf{V}^T, \tag{3}$$

where $\mathbf{D}_r \in \mathbb{R}^{r\times r}$ is a diagonal matrix, which collects the r singular values $d_1,\ldots,d_r$ of $\mathbf{M}$. Then, the soft-thresholded version of the SVD of $\mathbf{M}$ reads as

$$S_\lambda(\mathbf{M}) := \mathbf{U}\mathbf{D}_\lambda\mathbf{V}^T \,, \tag{4}$$

where

$$\mathbf{D}_\lambda := \mathrm{diag}[(d_1-\lambda)_+,\ldots,(d_r-\lambda)_+] \tag{5}$$

and the subscript "+" stands for the non-negative part of a real number. According to the soft-impute algorithm, we first initialize $\hat{\mathbf{L}}$ as $\hat{\mathbf{L}}^{\mathrm{old}} = \mathbf{P}_{\Omega^{\mathrm{tr}}}(\mathbf{M}) \in \mathbb{R}^{m\times n}$ and create a decreasing grid $\lambda_1 > \cdots > \lambda_K$. Let $\varepsilon > 0$ denote a selected tolerance.

Then, for each $k = 1,\ldots,K$, set $\lambda = \lambda_k$ and

1) Iterate until convergence the following:
   (a) Given the current $\hat{\mathbf{L}} = \hat{\mathbf{L}}^{\mathrm{old}}$, get $\hat{\mathbf{\Gamma}}$ and $\hat{\mathbf{\Delta}}$ by imposing the first-order optimality conditions in the optimization problem (1);
   (b) Compute $\hat{\mathbf{L}}^{\mathrm{new}} \leftarrow \mathbf{S}_{\frac{\lambda|\Omega^{\mathrm{tr}}|}{2}}\left(\mathbf{P}_{\Omega^{\mathrm{tr}}}(\mathbf{M} - \hat{\mathbf{\Gamma}}\mathbf{1}_n^\top - \mathbf{1}_m\hat{\mathbf{\Delta}}^\top) + \mathbf{P}^{\perp}_{\Omega^{\mathrm{tr}}}(\hat{\mathbf{L}}^{\mathrm{old}})\right)$;
   (c) If $\frac{\|\hat{\mathbf{L}}^{\mathrm{new}} - \hat{\mathbf{L}}^{\mathrm{old}}\|_F^2}{\|\hat{\mathbf{L}}^{\mathrm{old}}\|_F^2} \leq \varepsilon$, go to Step 2);
   (d) Set $\hat{\mathbf{L}}^{\mathrm{old}} \leftarrow \hat{\mathbf{L}}^{\mathrm{new}}$;
2) Set $\hat{\mathbf{L}}_\lambda \leftarrow \hat{\mathbf{L}}^{\mathrm{new}}$ and $\hat{\mathbf{M}}_\lambda \leftarrow \hat{\mathbf{L}}_\lambda + \hat{\mathbf{\Gamma}}\mathbf{1}_n^\top + \mathbf{1}_m\hat{\mathbf{\Delta}}^\top$.

Since it has been shown that MCFE performs better when the elements of the matrix to which it is applied have similar magnitudes (e.g., when they are row-normalized, as in Metulini et al. (2023)), in our application the original matrix of annual CO_2 emissions is pre-processed by dividing each row (country) by the l_1-norm of that row restricted to the training set[7], and multiplied by the fraction of observed entries in that row. Then MCFE is actually applied to the resulting matrix $\mathbf{M}$.

In our application, where $\mathbf{M}$ is derived from the 18×17 true CO_2 emission matrix, with rows referring to countries and columns to years, the tolerance parameter ε is chosen as $\varepsilon = 10^{-30}$. If convergence is not achieved, the soft-impute algorithm is stopped after $N^{\mathrm{it}} = 10^4$ repetitions to reduce computation time.

In the present application, as shown in Figure 1:

- the training set Ω^{tr} corresponds to the union of the positions of all entries for the years 2000–2004 (pre-treatment period) and 75% (randomly selected) of the positions of entries belonging to non-EU countries in the years 2005–2016 (treatment period covered in the database);
- the validation set Ω^{val} corresponds to the other 25% of the items of the entries belonging to non-EU countries in 2005–2016 that are not part of the training set;
- the test set Ω^{test} corresponds to the items belonging to EU countries in the treatment period covered in the database (2005–2016).

It is noteworthy that while ground truth without treatment is available for the validation set Ω^{val} (which refers to untreated non-EU countries), this is not true for the test set Ω^{test} (which refers to treated EU countries). To generate confidence intervals and represent the best/worst scenarios for the estimates for each treated country, MC is applied 80 times[8], each time randomly selecting the training and validation sets as described above.

In each application of MCFE, the regularization constant λ is selected via an approach similar to that proposed by Athey et al. (2021). In particular, the optimization problem (1) is solved for multiple choices λ_k for λ. To explore different scales, these values are exponentially distributed as $\lambda_k = 2^{k/2-25}$, for $k =$

[7] This restriction is applied to avoid any use of the validation and test sets in the pre-processing phase.
[8] This number was chosen as a tradeoff between reducing machine processing time and a satisfactory number of generations.

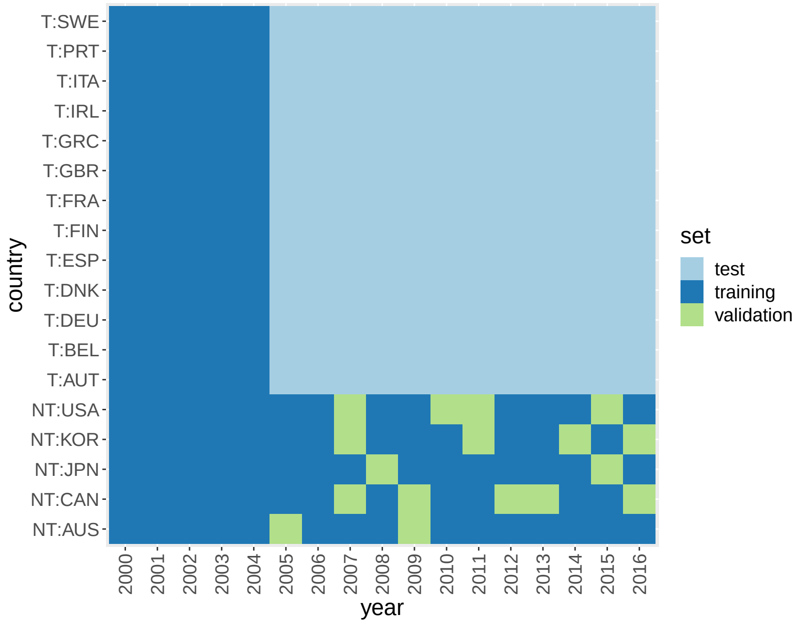

Fig. 1. Partition of the considered matrix into training, validation and test sets. Countries are indicated on the y axis, while years are indicated on the x axis. T stands for "Treated" and NT stands for "Non Treated". The training set Ω^{tr} corresponds to the union of the positions of all entries for the years 2000–2004 and 75% (randomly selected) of the positions of entries belonging to industrialized non-EU countries in the years 2005–2016. The validation set Ω^{val} corresponds to the other 25% of the positions of the entries belonging to industrialized non-EU countries in 2005–2016 that are not part of the training set. The test set Ω^{test} corresponds to the positions of the items belonging to the 13 considered EU countries in 2005–2016.

$1, \ldots, 100$. For each λ_k, the Root Mean Square Error (RMSE) of the matrix reconstruction on the validation set is calculated as follows:

$$RMSE_{\lambda_k}^{\mathrm{val}} := \sqrt{\frac{1}{|\Omega^{\mathrm{val}}|} \sum_{(i,j)\in\Omega^{\mathrm{val}}} \left(M_{i,j} - \hat{M}_{\lambda_k,i,j}\right)^2} \tag{6}$$

then the choice λ_k° that minimizes the $RMSE_{\lambda_k}^{\mathrm{val}}$ for $k = 1, \ldots, 100$ is found. For each λ_k, the RMSE of the matrix reconstruction on the training set ($RMSE_{\lambda_k}^{\mathrm{tr}}$) is defined in a similar way, as

$$RMSE_{\lambda_k}^{\mathrm{tr}} := \sqrt{\frac{1}{|\Omega^{\mathrm{tr}}|} \sum_{(i,j)\in\Omega^{\mathrm{tr}}} \left(M_{i,j} - \hat{M}_{\lambda_k,i,j}\right)^2}\,. \tag{7}$$

In particular, the focus is on the values of $RMSE_{\lambda_k}^{\mathrm{val}}$ and $RMSE_{\lambda_k}^{\mathrm{tr}}$ calculated for $\lambda = \lambda_k^{\circ}$. Since there is no ground truth for the counterfactual values in the test set (i.e., the values without treatment), the RMSE for the test set is not calculated in this application of MCFE.

4 Results

The MCFE methodology described in Section 3 was applied starting from the 18×17 country-year level CO_2 emissions matrix where sectors are aggregated (see Section 2), and then pre-processed according to the methodology described in Section 3.

To further motivate the adoption of the MCFE method described in Section 3 (which also includes individual and time fixed effects), we performed some statistical tests for the presence of significant individual and time effects in our data. More specifically, we conducted an F-test for the null hypothesis of the absence of such effects in the context of a within regression model for panel data (Baltagi, 2008). We found a significant departure from the null hypothesis of absence of individual effects (F=2.0104, p-value=0.0111). Time-fixed effects, conditional to allowing for individual fixed effects were found to be significantly different from the ones of the null hypothesis (F=2.8333, p-value=0.0004). Thus, the inclusion of both effects seems necessary. In addition, it should be noted that, as also mentioned by Athey et al. (2021), the inclusion of the individual and temporal components also aims to improve the quality of the imputation by penalizing only the residual component of the completed matrix in the optimization problem (1) (i.e., the one obtained by filtering out the individual and temporal components). Thus, it would make sense to include them even if the F-test does not reject the null hypothesis. As mentioned in Section 3, not including such components would lead to underestimates. It is worth noting that a necessary condition for obtaining credible counterfactual results is that the MC (FE) method achieves satisfactory performance in reconstructing the original matrix without any treatment. In the specific analysis, underestimation of the predicted values would not be recommended, as it could lead to incorrect conclusions about the impact of the ETS policy on different EU countries. In other words, in this context, it is crucial to avoid systematically underestimating the predicted values. It is worth mentioning that the performance of nuclear norm-based MC methods was assessed through a simulation study by Metulini et al. (2023) by applying such methods to the CO_2 emission matrix limited to the period 2000–2005. We found that the MCFE method proposed by Athey et al. (2021) outperformed the MC method developed by Mazumder et al. (2010) in terms of goodness of fit (Mean Absolute Percentage Error – MAPE – was used in that study). In particular, the MAPE of the MCFE was very low even with a rather large number of unobserved entries in the matrix.

The following results refer to the comparison of the estimated counterfactual values (without treatment) with the actual values (with treatment). To summarize the results of the analysis, we report our main findings in Figure 2. The estimated CO_2 emission values of the treated countries were obtained by applying MCFE. In other words, we used MCFE to estimate CO_2 emissions in the years of treatment for EU countries (i.e., treated countries) as if they had not received the treatment. We repeated the estimation process 80 times, each time randomly splitting the untreated portion of the matrix into training and validation sets, as described in Section 3. Then, Figure 2 shows, for the elements of the test set related to the treated countries, the actual values of CO_2 emissions (i.e., those obtained in the case of treatment) against the appropriate statistics of the corresponding estimated values obtained by MCFE in the case of no treatment. Points are used for the medians (black), 10^{th} percentiles (red), and 90^{th} percentiles (blue) of the distributions of estimated values (obtained in the no-treatment case) in the 80 repetitions (one distribution for each treated country). The actual values (corresponding to the case of treatment) are shown through dark green points[9]. It is worth noting that the actual and estimated values presented in the figure have been row-normalized, since the application of the MCFE method was done after performing the l_1-norm row-normalization. At first glance, we can see that the estimated values are higher than the actual values for almost all treated countries in our analysis (except for the case of Denmark and, – to a lesser extent, – Spain and Ireland for some consecutive years after the start of treatment). In other words, according to our results, the ETS policy has generally reduced CO_2 emissions of treated countries in the years after the end of the first treatment phase (i.e., from 2008 onwards), as intended by the policy itself. It is worth noting that to obtain such a result, it was necessary to use the MCFE method by Athey et al. (2021) instead of the MC method (without fixed effects estimation) by Mazumder et al. (2010), as explained in Section 3.

A parametric t-student test for the difference between means in independent populations (paired data t-test) was also performed to test whether the difference between actual values and estimated values was statistically significant under the hypothesis of no treatment. The test was performed for both the raw data and their natural logarithmic transformation (to more easily satisfy the normality assumption). To perform this statistical test, we considered two samples (S_1, with the actual values and S_2, with the imputed values) with the same sample size of $n_1 = n_2 = 156$, where 156 is the product of the number of countries

[9] The numerical values corresponding to the years of treatment for the plots shown in Figure 2 are given in Table A.1 in the Appendix.

treated (13) and the number of years of treatment (12). For all 80 simulations performed (with both raw and log normalized data), we rejected the null hypothesis of equal means. This simple evidence combined with Figure 2 might suggest that the introduction of the EU ETS had a significant effect on reducing CO_2 emissions. At the same time, without a further check, we cannot rule out that this preliminary result is the consequence of using a positively biased estimator, i.e., the method used might tend to yield higher values than the actual values. To verify that this was not the case, we compared, as a diagnostic test, the true values and the values estimated with the MCFE method for both the training and validation sets in the case of the untreated countries (this comparison was not possible for the test set because the counterfactual values were not available as ground truth). If the MCFE method we used were robust (i.e., if there were no significant overestimates or underestimates), then the true and estimated values for these countries would be essentially indistinguishable (especially in the case of the training set). This would be particularly important in the case of the validation set because it would rule out the overfitting of the training set. Figure 3 and Figure 4 – referring respectively to the training set (restricted to the untreated countries after the start of treatment for treated countries) and the validation set (which, by construction, refers only to the untreated countries), – show that the differences between the true values and the values estimated by the MCFE were, as expected, quite negligible.

To further verify that our main results, related to the significant reduction of CO_2 emissions by the treatment, were not affected by a systematic overestimation, we decided to perform a counter-proof as a robustness test. To this end, we repeated the counterfactual analysis by reversing the roles of treated and untreated countries. In other words, this time we considered the EU countries as untreated and the non-EU countries as treated. So, for this second analysis, the (modified) test set was for the non-EU countries over the period 2005–2016.

As can be seen in Figure 5, the treatment effects (artificial this time) remained very strong and, in particular, we can rule out the problem of systematic overestimation of the method used, since the predicted values on the new test set looked much lower than the observed values.

As an additional robustness check, we repeated the analysis on Figure 2 by excluding household emissions in the calculation of total emissions (i.e., for this analysis only the emissions due to industrial activities were considered). The obtained results, presented in Figure 6, qualitatively confirmed those already reported in Figure 2 for the case in which household emissions were included.

To return to the original analysis, as can be seen in Figure 2, when comparing the actual values of treated countries in the years of treatment with the medians of the corresponding counterfactual estimates[10] (in the case of no treatment) obtained by the MCFE simulations, we can conclude that the EU ETS policy was effective in reducing CO_2 emissions. This is in line with other literature such as Petrick and Wagner (2014) and Bayer and Aklin (2020). As shown in Table A.2 in the Appendix, during the whole treatment period covered in the database (2005–2016), the majority of the EU countries included in our analysis achieved a ratio between the sum of the observed values and the sum of the medians of the estimated values (expressed as a percentage) of about 80%. The smallest value (71.27%) was obtained in the case of Greece (i.e., Greece's CO_2 emissions were reduced to almost 3/10 of the sum of the medians of the estimated counterfactual values associated with no treatment throughout the analysis period). The largest value (100.45%) was found in the case of Denmark (this means that the amount of CO_2 emissions of Denmark did not decrease during the whole treatment period covered in the database, i.e. 2005–2016, due to the EU ETS policy). In general, however, we can conclude that the EU ETS policy did not have an irrelevant impact on total CO_2 emissions in the EU. According to the results of our analysis, the reduction was even larger than that estimated in Bayer and Aklin (2020). In that paper, the authors estimated a reduction in CO_2 emissions (with respect to the case of the absence of the EU ETS policy) of about 3.8% using the SCM across the European Union for the period 2008–2016. According to the results of our analysis (based on the medians of the estimates),

[10] For simplicity, we consider here and below the medians of the estimated values instead of the estimated values themselves, since these are random variables.

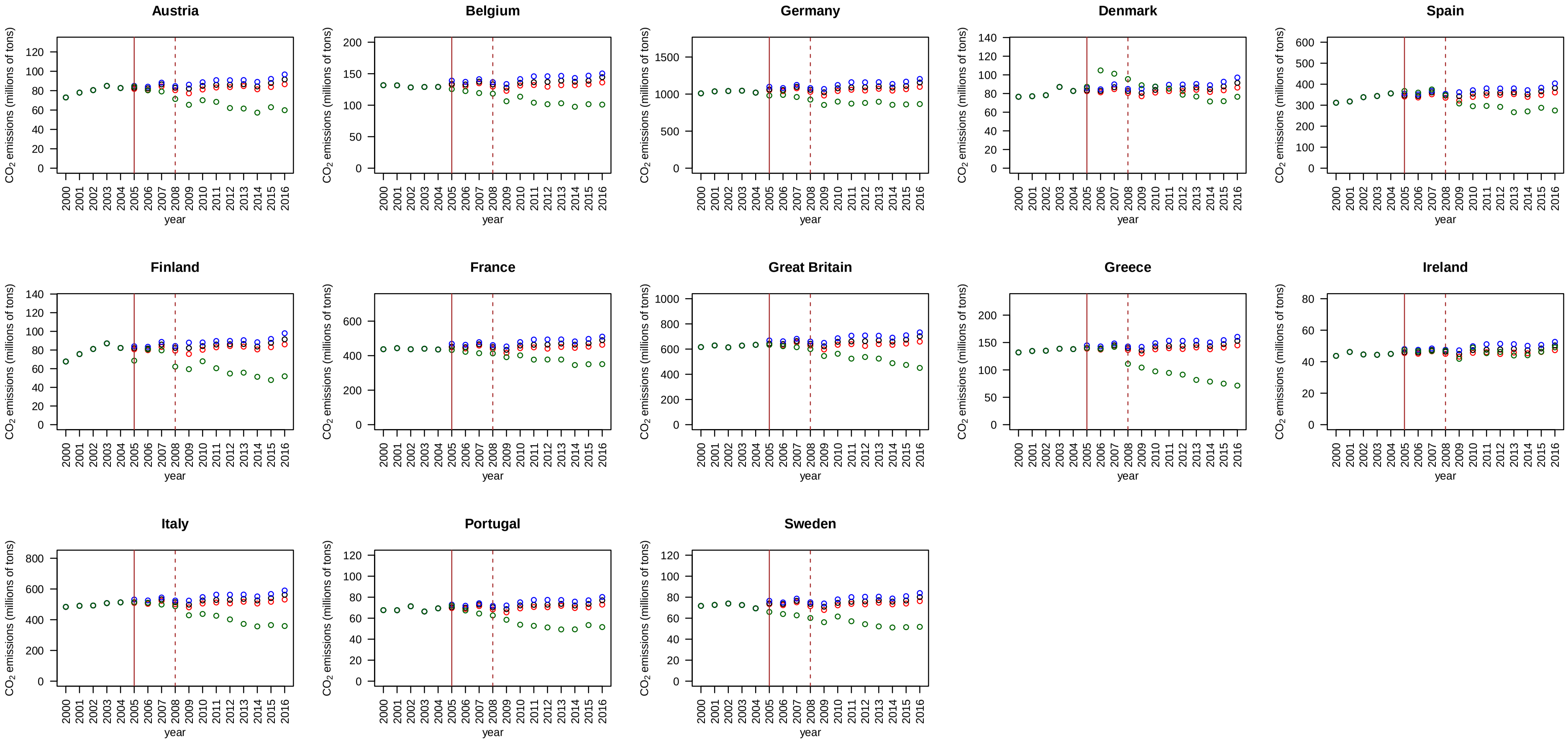

Fig. 2. Total CO_2 emissions of treated countries. Actual values (dark green points) compared to values calculated by MCFE for the no-treatment hypothesis (test set). Medians (black points), 10^{th} percentiles (red points), and 90^{th} percentiles (blue points) considering the 80 MCFE random simulations. The solid vertical red line divides the period into pre-treatment and treatment periods. The dashed vertical red line represents the start of the second phase of ETS.

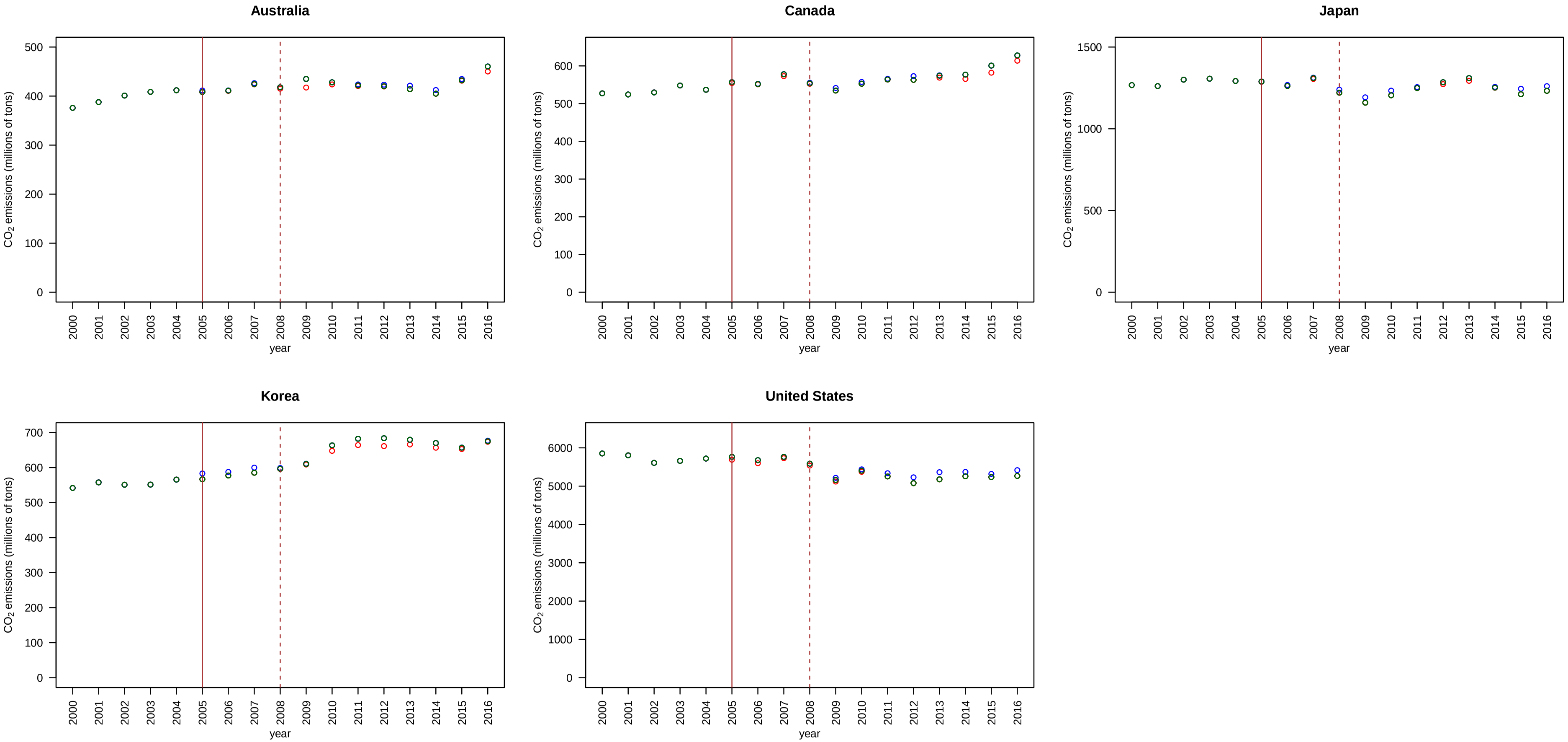

Fig. 3. Total CO_2 emissions of untreated countries. Actual values (dark green points) compared to values calculated by MCFE for the no-treatment hypothesis (training set only, after the start of treatment of treated countries). Medians (black points), 10^{th} percentiles (red points), and 90^{th} percentiles (blue points) considering the 80 MCFE random simulations. The solid vertical red line divides the period into pre-treatment and treatment periods. The dashed vertical red line represents the start of the second phase of ETS.

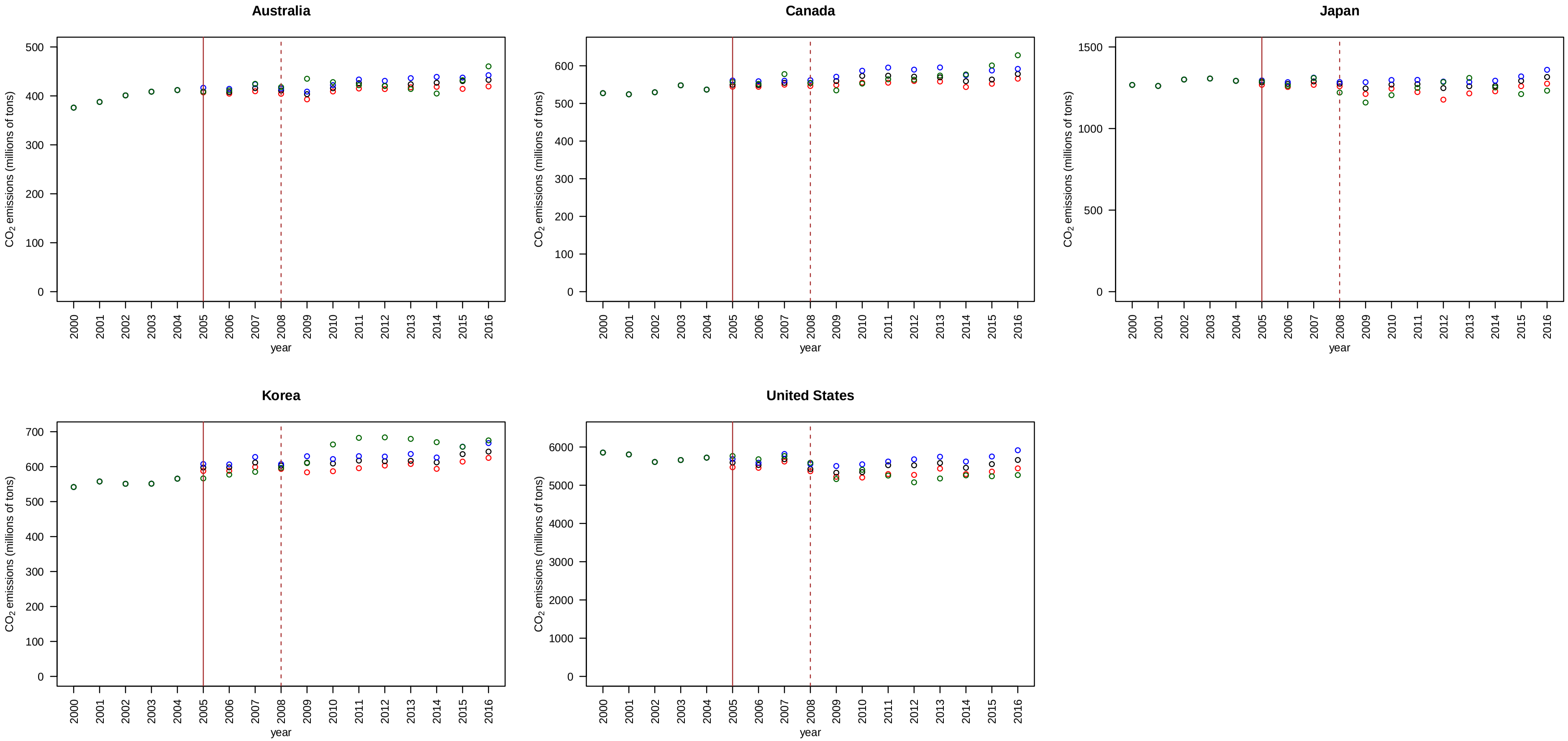

Fig. 4. Total CO_2 emissions of untreated countries. Actual values (dark green points) compared to values calculated by MCFE for the no-treatment hypothesis (validation set only). Medians (black points), 10^{th} percentiles (red points), and 90^{th} percentiles (blue points) considering the 80 MCFE random simulations. The solid vertical red line divides the period into pre-treatment and treatment periods. The dashed vertical red line represents the start of the second phase of ETS.

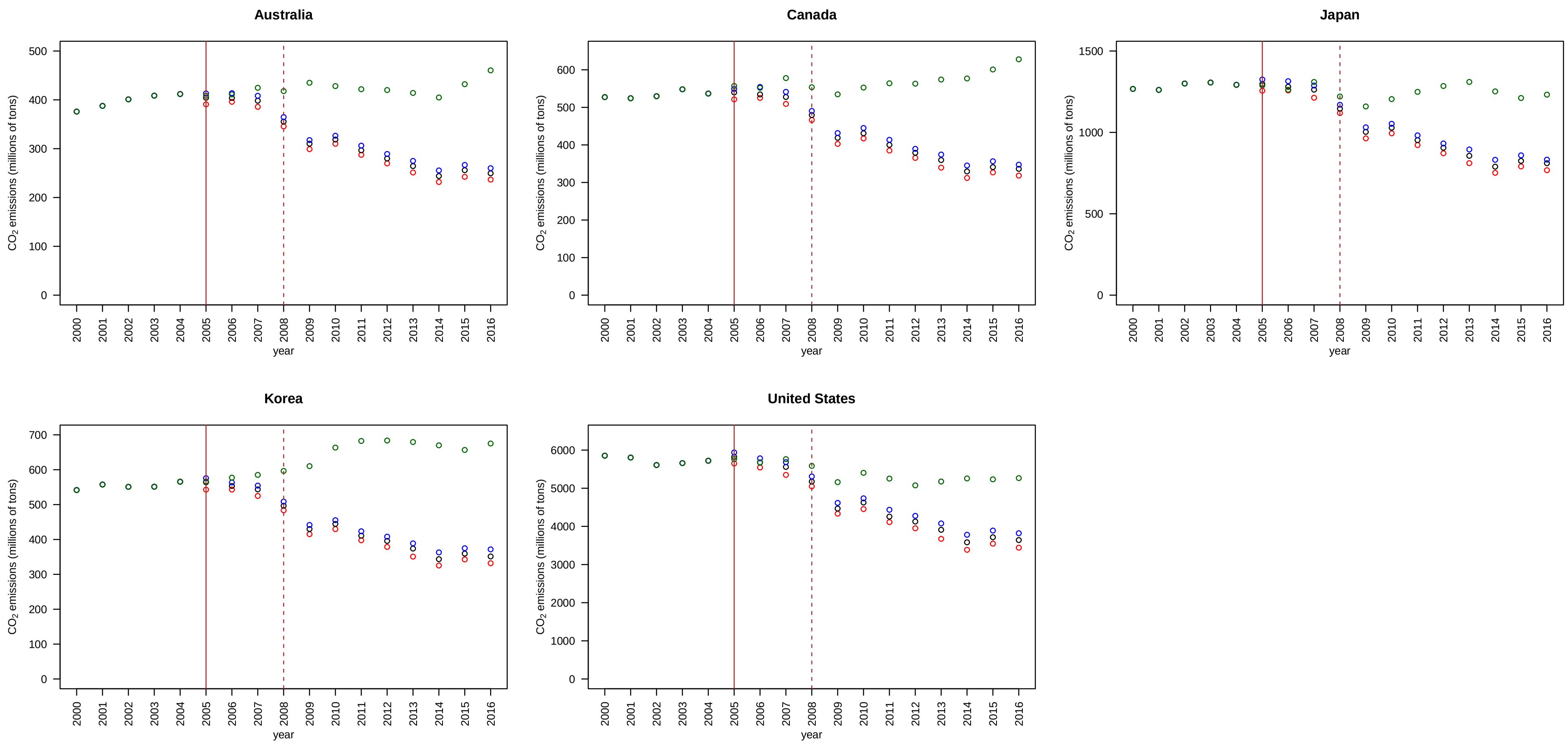

Fig. 5. Inversion of treated and untreated countries in MCFE analysis. Total CO_2 emissions of untreated countries. Actual values (dark green points) versus values calculated by MCFE in the treatment hypothesis (modified test set). Medians (black points), 10^{th} percentiles (red points), and 90^{th} percentiles (blue points) considering the 80 MCFE random simulations. The solid vertical red line divides the period into pre-treatment and treatment periods. The dashed vertical red line represents the start of the second phase of ETS.

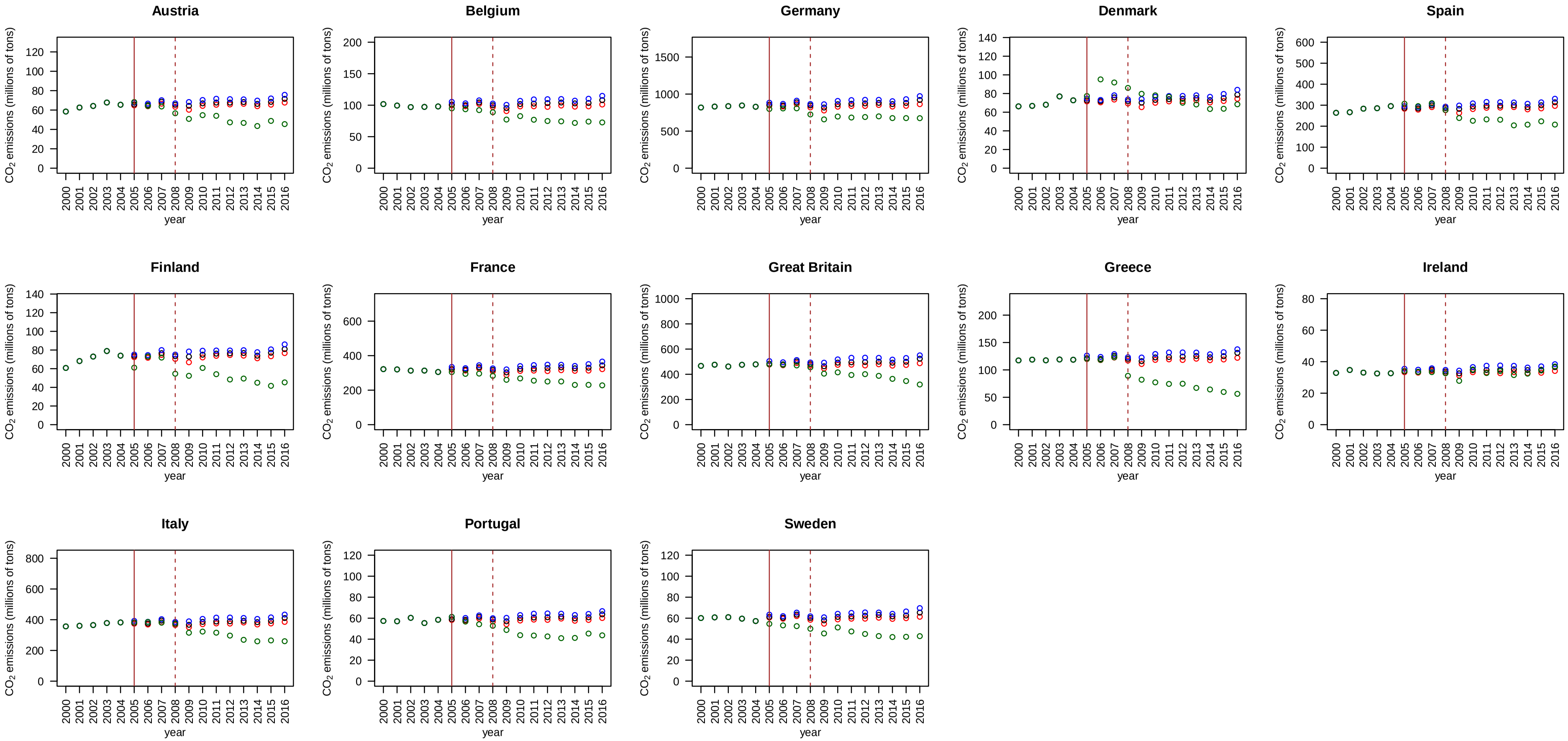

Fig. 6. Total CO_2 emissions (excluding household emissions) of treated countries. Actual values (dark green points) compared to values calculated by MCFE for the no-treatment hypothesis (test set). Medians (black points), 10^{th} percentiles (red points), and 90^{th} percentiles (blue points) considering the 80 MCFE random simulations. The solid vertical red line divides the period into pre-treatment and treatment periods. The dashed vertical red line represents the start of the second phase of ETS.

the reduction in CO_2 emissions for all EU countries included in our analysis[11] was approximately 21.0% in the same period 2008–2016 which was considered in Bayer and Aklin (2020); 17.0% in the entire 2005–2016 treatment period (these results were obtained from the data included in Figure 7). Our results are consistent with the large increase in CO_2 emissions compared to the pre-treatment period, as shown in Figure 4. Although both our analysis and that presented in Bayer and Aklin (2020) show positive effects of the EU ETS policy, some differences are observed in the magnitude of the effects achieved. This result could be explained not only by the different selection of EU countries considered in the two analyses and by the different methods used (MC and SCM), but also by the fact that Bayer and Aklin (2020), neglecting possible transmission effects, derived all their control and treated units within the same group of EU countries (i.e., their control and treated units were, respectively, economic sectors of EU countries directly affected by EU ETS policy and other economic sectors of the same EU countries not directly affected by EU ETS policy). Instead, our analysis is done at a more aggregate level (i.e., EU countries are treated as a whole, while the control units are other countries outside the EU).

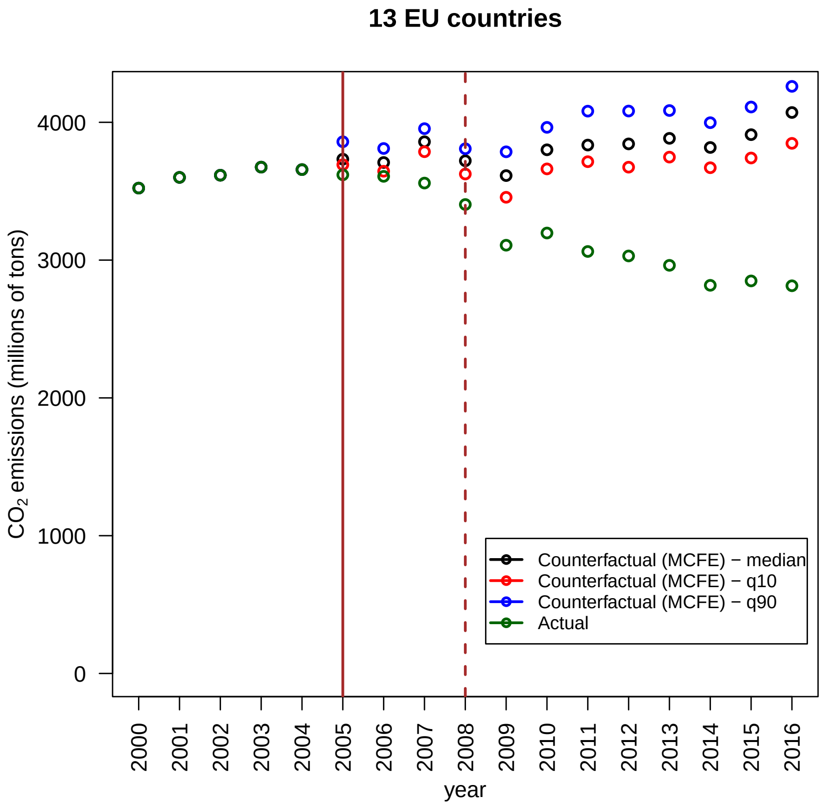

Fig. 7. Total CO_2 emissions of the entire group of treated EU countries. Actual values (dark green points) compared to values calculated by MCFE for the hypothesis without EU ETS treatment (test set). Sum of medians across treated countries (black points), sum of 10^{th} percentiles across treated countries (red points), and sum of 90^{th} percentiles across treated countries (blue points) considering the 80 MCFE random simulations. The solid vertical red line divides the period into the pre-treatment and treatment periods. The dashed vertical red line represents the start of the second phase of ETS.

It is worth noting that our results change somewhat if we consider CO_2 emissions reductions only in the first phase of the EU ETS policy (2005–2007), as indicated in Table A.3 in the Appendix. In this case, the

[11] This reduction was calculated by comparing the sum of CO_2 emissions for each period for all EU countries included in the analysis with the sum of the medians of the estimated counterfactual CO_2 emissions for the same period for all EU countries.

reduction in CO_2 emissions from the EU ETS policy was much smaller. In particular, looking at the median estimates, the reduction in CO_2 emissions across the entire group of EU countries included in the analysis was about 4.6% in 2005–2007. Moreover, in three countries (Denmark, Spain, and Ireland) the sums of the medians of the estimated counterfactuals were even higher than the corresponding sums of the observed values. In the first phase of the policy, the penalty for CO_2 emissions exceeding the quota was indeed small. This fact could be a possible explanation for the lower reduction in the first years of the policy. It is also worth noting that the projections for the 2005–2007 period were less prone to possible sources of error than the projections for the remaining 2008–2016 period, since the period before the policy was implemented was quite short (five years).

Nowadays, the well-being of a country is not directly related to GDP, because the environmental damage caused by an economic system should be considered as a negative component in the well-being function (Fleurbaey, 2009; Giannetti et al., 2015). Indeed, other indicators have been proposed in the literature, such as the Index of Sustainable Economic Welfare (ISEW), the Genuine Progress Indicator (GPI), and various versions of green GDP (Boyd, 2007; England, 1998; Talberth and Bohara, 2006; Xu et al., 2010). It is beyond the scope of this paper to propose another sustainable ecological economic index. However, the results of our analysis allow us to express in monetary terms the reduction in ecological damage resulting from the adoption of the EU ETS policy. For example, suppose that a ton of CO_2 emitted has a negative value of 185 USD (in real terms for 2020), as recently reported in Rennert et al. (2022). If we take as an example the case of Germany – which is considered the first producer in the Eurozone – our results show that CO_2 emissions in 2016 were about 865 million tons, while the median of the estimated counterfactual in case of no treatment was 1,156 million tons. This means that the EU ETS policy saved about 290 million tons in one year in Germany alone. Converting these values to monetary values and also converting them to per capita values[12], this means 652 USD per capita (real-term value for 2020). We found analogous results (as shown in Table A.4 in the Appendix) for all other EU countries we included in our analysis: for the year 2016 we obtained about 400 – 700 USD per capita for most of them. Also for 2007, we found about 100 – 300 USD per capita for most of the treated countries. Moreover, the amount of reduced environmental damage per capita has been shown to generally increase over time. In fact, by 2009, this amount was even below 600 USD (except for Finland with 699 USD). The case of Denmark (and to a lesser extent the cases of Spain and Ireland) is quite peculiar, as in some years higher values for CO_2 emissions were found than without the policy of EU ETS, but in subsequent years lower values were obtained. In the case of Denmark, the threshold year for this change was 2011.

5 Conclusions and future research directions

CO_2 emissions represent a growing problem closely related to pollution and climate change. Economic systems produce large amounts of CO_2 through the use of fossil energy. Therefore, governments are trying to shift production to new systems in order to reduce emissions (Sgarciu et al., 2023). In this context, the EU has introduced a market for emission rights, called the Emissions Trading Scheme (ETS), which was launched in 2005 and further expanded in subsequent years, as the second phase began in 2008. The impact of EU ETS on reducing CO_2 emissions is still debated in the literature. In this paper, we present a new approach to quantify the impact of EU ETS policy on CO_2 emissions reductions. A counterfactual analysis to evaluate the policy allows us to quantify the reduction in CO_2 emissions from the ETS.

The novelty of our work is that we developed a state-of-the-art Statistical Machine Learning (SML) method based on Matrix Completion (MC) for counterfactual analysis. The importance of using MC for this task becomes clear when one considers that conventional policy evaluation methods such as matching techniques – e.g., Propensity Score Matching (PSM), Mahalanobis and Hainmueller balancing – and the

[12] Population data were taken from the World Bank's free database available at `https://data.worldbank.org/`.

Synthetic Control Method (SCM) are not always suitable for performing true policy evaluation, since in some applications it may be nearly impossible to identify an appropriate control group for these methods. Applying this novel method to the CO_2 emissions matrix at the country level allowed us to quantitatively assess the impact of EU ETS on reducing emissions.

Using robust statistical tests and diagnostic controls, the effect of EU ETS was found to be statistically significant, in line with some recent contributions. Based on our analysis, the CO_2 reduction from the EU policy appears to be higher than that found in the previous literature. We believe that the previous literature tends to underestimate the CO_2 reduction because it focused on the first phase of the policy and selected countries using less sophisticated methods to establish a valid counterfactual. We believe that overcoming such drawbacks through the adoption of MC is a significant result in terms of policy evaluation. Moreover, we quantified the effects of the ETS policy in monetary terms in a reduction of the environmental damage approximately equal to 500 USD per capita in 2016 (i.e., the last observed year available for our analysis). This finding is relevant since policies like the EU ETS are sometimes accused of representing obstacles to production and growth. Although it is out of the scope of this article to estimate if the EU ETS policy provoked adverse effects on "classical" economic growth, we can claim that its reduction of environmental impact was not negligible.

For future research, we consider developing a more sophisticated model that examines (in monetary terms) whether or not the decrease in output due to the price of CO_2 emissions outweighs the reduced environmental damage (this would require an appropriate definition of green GDP). In addition, the analysis could be extended to a less aggregate level (with larger matrices) after accelerating/parallelizing the application of MC, as was done recently in Gnecco et al. (2023) for another application of this method. This is important for application to the three-dimensional data set of countries, industries, and years. Finally, more sophisticated methods could be applied to obtain an estimate of the indirect impact of the EU ETS policy (e.g., related to carbon leakage to other non-EU countries) to better estimate the overall impact of the EU ETS policy.

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Authors' contributions

The authors equally contributed to the work.

Conflicts of interest

The authors have no conflicts of interest.

Data availability

The database used (Corsatea et al., 2019) can be accessed for free at `https://joint-research-centre.ec.europa.eu/document/download/b572c87b-a2fb-4ab6-af38-ff0451273e9e_en?filename=co2em56.zip`. Population data were taken from the World Bank's free database available at `https://data.worldbank.org/`.

Appendix

Table A.1 reports numerical values corresponding to the years of the treatment for the plots of Figure 2.

Austria												
Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Actual	84294	80342	79163	71406	65431	70132	68446	62079	61555	57325	62941	59850
10^{th} percentile	81771	80760	84327	80457	77238	81209	83245	83638	84729	81408	83752	86626
Median	82950	82430	86446	82962	82106	84933	86031	86150	86673	84390	87873	91573
90^{th} percentile	84955	84112	88277	84678	86183	88699	90866	90791	90957	89075	92120	96753

Belgium												
Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Actual	125516	122431	119281	118295	106258	113520	104000	101579	103016	97561	101607	100965
10^{th} percentile	132209	130169	134830	129499	122788	131170	131981	129333	131787	131548	133168	136067
Median	133799	132865	137355	133094	127848	135552	136477	136985	138967	137245	138840	144497
90^{th} percentile	139057	137067	141320	136641	133622	141473	145877	145975	146585	143200	146924	150438

Germany												
Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Actual	980189	988849	960745	925825	853758	898560	871378	880920	896745	855312	861048	865548
10^{th} percentile	1052903	1039316	1078119	1030010	980542	1041355	1057904	1047753	1070843	1046505	1065863	1097260
Median	1062893	1055631	1097425	1057471	1024008	1078237	1089374	1091912	1104670	1088214	1109511	1155793
90^{th} percentile	1098836	1081585	1123815	1080742	1069014	1122784	1160335	1159111	1160863	1136491	1167600	1204459

Denmark												
Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Actual	87189	104792	101229	95522	88924	87493	85286	78753	76789	71498	71812	76535
10^{th} percentile	82470	81283	84682	80592	77077	81009	82554	82509	83966	81613	83463	86355
Median	83368	82794	86767	82730	80615	83922	85253	85464	86565	84711	87608	91444
90^{th} percentile	85782	84521	89862	84935	85121	87330	89362	89635	90259	88945	92636	97168

Spain												
Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Actual	367776	359910	374958	348386	308150	295045	296509	292142	266558	270386	287768	274796
10^{th} percentile	341089	336693	351719	335396	322318	339285	346915	348895	352493	339394	348185	360611
Median	346255	343895	361000	346380	342687	354919	359372	359719	361570	352122	365882	381945
90^{th} percentile	355004	351409	368182	353881	361714	371290	380148	379547	380022	371518	383136	403841

Finland												
Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Actual	68615	80650	79619	62187	59478	67961	60504	54809	55753	51307	47855	51885
10^{th} percentile	80735	79836	83288	79253	75778	80276	82887	84229	83613	80622	83052	86043
Median	82100	81617	85887	82269	82135	84184	85902	86197	86427	83767	87691	91456
90^{th} percentile	84043	83489	88688	84309	87963	88127	89660	89786	90561	88362	91877	97987

France												
Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Actual	432515	422251	414279	413064	391160	401726	376896	377612	377373	345587	350293	350911
10^{th} percentile	448030	441529	458317	439899	416204	443437	447986	440415	450322	444996	452265	462894
Median	452367	449243	465910	449828	433752	458782	463114	463886	469944	463569	471762	489745
90^{th} percentile	468970	462968	478111	461209	453210	478702	493309	493869	494053	482564	497045	510220

Great Britain												
Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Actual	633973	623064	615083	600149	545276	563004	524184	537303	524550	488332	474426	450554
10^{th} percentile	637048	628770	652700	628177	596740	634151	638990	625042	639510	633524	643725	659136
Median	643758	640692	663764	642194	622070	657917	660826	663110	669142	659473	675033	701829
90^{th} percentile	668694	662190	681554	659768	649693	686135	706409	708074	706272	690771	709408	732686

Greece												
Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Actual	139792	138028	142127	111113	104341	97343	94532	91418	81723	78656	74962	71373
10^{th} percentile	138717	137096	142500	136387	130052	137578	139551	138154	140967	137689	140701	144743
Median	140139	139189	145016	139778	135439	142839	143853	144089	145676	143219	146983	153068
90^{th} percentile	144751	142880	148329	142793	142053	148751	153297	153056	153381	150099	154408	160369

Ireland												
Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Actual	47425	46833	46807	46981	41811	48998	45417	46178	43933	44079	46313	49104
10^{th} percentile	45472	45042	46601	44970	43196	45603	46034	44870	45785	45350	46169	47293
Median	46073	45904	47445	46320	44919	47349	47628	47777	48074	47306	48377	50369
90^{th} percentile	48026	47555	48411	47535	47218	49834	51109	51357	51156	50107	50672	52610

Italy												
Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Actual	513883	509526	498800	487925	428896	437579	425745	402053	372699	356597	365070	359005
10^{th} percentile	508944	503301	522977	500613	480701	505344	512051	506068	516991	505221	516598	531236
Median	514295	510638	532615	513935	498478	525329	528921	529327	535286	525581	540595	562449
90^{th} percentile	531453	525437	544705	524873	524214	547310	563326	562905	563827	551753	567396	590320

Portugal												
Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Actual	71982	67336	64419	62595	58475	53819	52720	51190	49283	49364	53440	51532
10^{th} percentile	69604	68839	71516	68307	65515	69317	70640	70412	71786	69640	70311	72929
Median	70458	70025	73005	70396	68604	72144	72694	72868	73636	72089	73554	77024
90^{th} percentile	72958	71833	74237	71741	72083	75134	77391	77440	77329	75761	77018	80190

Sweden												
Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Actual	65943	63968	62716	60166	56164	61592	57081	54286	52187	51176	51454	51765
10^{th} percentile	73398	72368	75135	71437	67807	72214	73565	73166	74705	73166	73920	76220
Median	74120	73586	76523	73587	70928	74577	75646	75955	77152	75789	76852	80129
90^{th} percentile	76567	74999	78640	75131	74021	77907	80094	80411	80500	78773	80977	83940

Table A.1. Comparison between actual values (in thousands of tons) and estimated counterfactual values (in thousands of tons) for the treated countries in the years of treatment.

Table A.2 reports, for the treated countries: the sum of actual values (in thousands of tons) over the whole period of treatment covered in the database; the sum of the medians of the estimated counterfactual values (in thousands of tons) over the same period; their ratio (expressed as a percentage).

	Sum of Actual (period: 2005–2016)	**Sum of Estimated (period: 2005–2016)**	**Sum of Actual/Sum of Estimated (expressed as a percentage)**
Austria	822964	1024517	80.33
Belgium	1314029	1633524	80.44
Germany	10838877	13015139	83.28
Denmark	1025822	1021241	100.45
Spain	3742384	4275746	87.53
Finland	740623	1019632	72.64
France	4653667	5531902	84.12
Great Britain	6579898	7899808	83.29
Greece	1225408	1719288	71.27
Ireland	553879	567541	97.59
Italy	5157778	6317449	81.64
Portugal	686155	866497	79.89
Sweden	688498	904844	76.09

Table A.2. For the treated countries: sum of actual values (in thousands of tons) over the whole period of treatment covered in the database (Sum of Actual), sum of the medians of the estimated counterfactual values (in thousands of tons, median is used) over the same period (Sum of Estimated), and the ratio Sum of Actual/Sum of Estimated, expressed as a percentage.

Similarly, Table A.3 reports, for the treated countries: the sum of actual values (in thousands of tons) over the first period of treatment; the sum of the medians of the estimated counterfactual values (in thousands of tons) over the same period; their ratio (expressed as a percentage).

	Sum of Actual (period: 2005–2007)	**Sum of Estimated (period: 2005–2007)**	**Sum of Actual/Sum of Estimated (expressed as a percentage)**
Austria	243799	251826	96.81
Belgium	367228	404019	90.89
Germany	2929783	3215949	91.10
Denmark	293210	252929	115.93
Spain	1102644	1051150	104.90
Finland	228884	249604	91.70
France	1269045	1367520	92.80
Great Britain	1872120	1948214	96.09
Greece	419947	424344	98.96
Ireland	141065	139422	101.18
Italy	1522209	1557548	97.73
Portugal	203737	213488	95.43
Sweden	192627	224229	85.91

Table A.3. For the treated countries: sum of actual values (in thousands of tons) over the first period of treatment (Sum of Actual), sum of estimated counterfactual values (in thousands of tons, median is used) over the same period (Sum of Estimated), and the ratio Sum of Actual/Sum of Estimated, expressed as a percentage.

Table A.4 expresses the reduced damage in monetary terms per capita (in USD 2020) for the treated EU countries during the whole treatment period covered in the database.

	Reduced damage in monetary terms per capita (expressed in USD 2020)											
Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Austria	-30	47	162	257	370	327	388	528	548	586	534	672
Belgium	146	183	315	256	370	374	544	590	596	655	611	711
Germany	186	150	307	297	385	406	502	485	477	532	563	652
Denmark	-130	-748	-490	-431	-278	-119	-1	222	322	433	514	482
Spain	-91	-67	-57	-8	138	238	249	267	377	325	311	426
Finland	476	34	219	699	785	560	872	1073	1043	1100	1345	1332
France	58	78	149	106	122	162	244	243	259	329	338	385
Great Britain	30	54	147	126	228	280	400	365	417	490	570	709
Greece	6	19	48	479	518	757	822	882	1079	1097	1231	1403
Ireland	-60	-40	27	-27	127	-67	89	64	166	128	81	49
Italy	1	4	107	82	218	274	321	395	499	514	535	621
Portugal	-27	47	151	137	177	321	350	381	431	404	359	457
Sweden	168	196	279	269	294	256	363	421	481	470	479	529

Table A.4. Reduced damage in monetary terms per capita (expressed in USD 2020) for the treated EU countries in the treatment period covered in the database.

Bibliography

Abadie, A. (2021). Using synthetic controls: Feasibility, data requirements, and methodological aspects. *Journal of Economic Literature 59*(2), 391–425.

Al-Mulali, U., B. Saboori, and I. Ozturk (2015). Investigating the environmental Kuznets curve hypothesis in vietnam. *Energy Policy 76*, 123–131.

An, B., Z. Zhao, S. Wang, S. Chen, and X. Chen (2020). Sparsity-assisted bearing fault diagnosis using multiscale period group lasso. *ISA Transactions 98*, 338–348.

Anderson, H. M., J. Gao, G. Turnip, F. Vahid, and W. Wei (2023). Estimating the effect of an EU-ETS type scheme in Australia using a synthetic treatment approach. *Energy Economics 125*, 106798.

Aron-Dine, A., L. Einav, and A. Finkelstein (2013). The RAND health insurance experiment, three decades later. *Journal of Economic Perspectives 27*(1), 197–222.

Athey, S., M. Bayati, N. Doudchenko, G. Imbens, and K. Khosravi (2021). Matrix completion methods for causal panel data models. *Journal of the American Statistical Association 116*(536), 1716–1730.

Baltagi, B. H. (2008). *Econometric Analysis of Panel Data* (4 ed.). Springer.

Bayer, P. and M. Aklin (2020). The European Union emissions trading system reduced CO_2 emissions despite low prices. *Proceedings of the National Academy of Sciences 117*(16), 8804–8812.

Biancalani, F., G. Gnecco, R. Metulini, and M. Riccaboni (2023a). Matrix completion for the prediction of yearly country and industry-level CO_2 emissions. In *Machine Learning, Optimization, and Data Science, 8th International Workshop, LOD 2022, Certosa di Pontignano, Italy, September 19–22, 2022, Revised Selected Papers, Part I*, pp. 14–19.

Biancalani, F., G. Gnecco, R. Metulini, and M. Riccaboni (2023b). Prediction of annual CO_2 emissions at the country and sector levels, based on a matrix completion optimization problem. *Optimization Letters*. forthcoming.

Binder, S. and E. Neumayer (2005). Environmental pressure group strength and air pollution: An empirical analysis. *Ecological Economics 55*(4), 527–538.

Boyd, J. (2007). Nonmarket benefits of nature: What should be counted in green GDP? *Ecological Economics 61*(4), 716–723.

Calel, R. (2020). Adopt or innovate: Understanding technological responses to cap-and-trade. *American Economic Journal: Economic Policy 12*(3), 170–201.

Chen, Y. and C.-C. Lee (2020). Does technological innovation reduce CO_2 emissions? Cross-country evidence. *Journal of Cleaner Production 263*, 121550.

Corsatea, T. D., S. Lindner, I. Arto, M. V. Román, J. M. Rueda-Cantuche, A. Velázquez Afonso, A. F. Amores, and F. Neuwahl (2019). World input-output database environmental accounts. Update 2000–2016. JRC Technical Report.

Dechezleprêtre, A., D. Nachtigall, and F. Venmans (2023). The joint impact of the European Union emissions trading system on carbon emissions and economic performance. *Journal of Environmental Economics and Management 118*, 102758.

Dong, K., R. Sun, H. Jiang, and X. Zeng (2018). CO_2 emissions, economic growth, and the environmental Kuznets curve in China: What roles can nuclear energy and renewable energy play? *Journal of Cleaner Production 196*, 51–63.

Doremus, J. (2019). Unintended impacts from forest certification: Evidence from indigenous Aka households in Congo. *Ecological Economics 166*, 106378.

Doytch, N., M. Elheddad, and S. Hammoudeh (2023). The financial Kuznets curve of energy consumption: Global evidence. *Energy Policy 177*, 113498.

England, R. W. (1998). Measurement of social well-being: Alternatives to gross domestic product. *Ecological Economics 25*(1), 89–103.

Feng, Z. Z., X. Yang, S. Subedi, and P. D. McNicholas (2012). The LASSO and sparse least squares regression methods for SNP selection in predicting quantitative traits. *IEEE/ACM Transactions on Computational Biology and Bioinformatics 9*(2), 629–636.

Fleurbaey, M. (2009). Beyond GDP: The quest for a measure of social welfare. *Journal of Economic Literature 47*(4), 1029–75.

Giannetti, B., F. Agostinho, C. Almeida, and D. Huisingh (2015). A review of limitations of GDP and alternative indices to monitor human wellbeing and to manage eco-system functionality. *Journal of Cleaner Production 87*, 11–25.

Gnecco, G., F. Nutarelli, and M. Riccaboni (2022). A machine learning approach to economic complexity based on matrix completion. *Scientific Reports 12*(1), 9639.

Gnecco, G., F. Nutarelli, and M. Riccaboni (2023). Matrix completion of world trade: An analysis of interpretability through Shapley values. *The World Economy*. Forthcoming.

Grossman, G. M. and A. B. Krueger (1995). Economic growth and the environment. *The Quarterly Journal of Economics 110*(2), 353–377.

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis 20*(1), 25–46.

Hastie, T., R. Tibshirani, and M. Wainwright (2015). *Statistical Learning with Sparsity*, Volume 143 of *Monographs on Statistics and Applied Probability.* CRC Press.

Heckman, J. J., H. Ichimura, and P. E. Todd (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies 64*(4), 605–654.

Hove, S. and T. Tursoy (2019). An investigation of the environmental Kuznets curve in emerging economies. *Journal of Cleaner Production 236*, 117628.

Huang, W., D. Wei, C. Wang, and C. Lin (2021). Matrix completion-based prediction analysis in carbon emissions. *International Journal of Embedded Systems 14*, 143–148.

Jaraitė, J. and C. D. Maria (2016). Did the EU ETS make a difference? An empirical assessment using Lithuanian firm-level data. *The Energy Journal 37*(1), 1–23.

Klemetsen, M., K. E. Rosendahl, and A. L. Jakobsen (2020). The impacts of the EU ETS on Norwegian plants' environmental and economic performance. *Climate Change Economics 11*(01), 2050006.

Koch, N. and M. Themann (2022). Catching up and falling behind: Cross-country evidence on the impact of the eu ets on firm productivity. *Resource and Energy Economics 69*, 101315.

Kuznets, S. (1955). Economic growth and income inequality. *The American Economic Review 45*(1), 1–28.

Ludwig, J., G. J. Duncan, L. A. Gennetian, L. F. Katz, R. C. Kessler, J. R. Kling, and L. Sanbonmatsu (2013). Long-term neighborhood effects on low-income families: Evidence from moving to opportunity. *American Economic Review 103*(3), 226–31.

Luzzati, T. and M. Orsini (2009). Investigating the energy-environmental Kuznets curve. *Energy 34*(3), 291–300. WESC 2006 Advances in Energy Studies.

Luzzati, T., M. Orsini, and G. Gucciardi (2018). A multiscale reassessment of the environmental Kuznets curve for energy and CO_2 emissions. *Energy Policy 122*, 612–621.

Machado, F. L. V., V. Halmenschlager, P. R. Abdallah, G. da Silva Teixeira, and U. R. Sumaila (2021). The relation between fishing subsidies and CO_2 emissions in the fisheries sector. *Ecological Economics 185*, 107057.

Martelli, S., G. Janssens-Maenhout, P. Paruolo, T. Bréchet, E. Strobl, D. Guizzardi, A. K. Cerutti, and A. Iancu (2018). Do voters support local commitments for climate change mitigation in italy? *Ecological Economics 144*, 27–35.

Martin, R., M. Muûls, and U. J. Wagner (2016). The impact of the European Union emissions trading scheme on regulated firms: What is the evidence after ten years? *Review of Environmental Economics and Policy 10*(1), 129–148.

Mazumder, R., T. Hastie, and R. Tibshirani (2010). Spectral regularization algorithms for learning large incomplete matrices. *The Journal of Machine Learning Research 11*, 2287–2322.

Metulini, R., F. Biancalani, G. Gnecco, and M. Riccaboni (2023). Assessing the performance of nuclear norm-based matrix completion methods on CO_2 emissions data. In *Book of the Short Papers - SIS 2023 - Statistical Learning, Sustainability and Impact Evaluation (Eds. F. M. Chelli, M. Ciommi, S. Ingrassia, F. Mariani, M. C. Recchioni)*, pp. 724–729. Pearson.

Metulini, R., G. Gnecco, F. Biancalani, and M. Riccaboni (2022). Hierarchical clustering and matrix completion for the reconstruction of world input–output tables. *AStA Advances in Statistical Analysis*, 1–46. online first.

Missbach, L., J. C. Steckel, and H. Ward (2023). Assessing distributional effects of carbon pricing in Israel. *Energy Policy 180*, 113672.

Narassimhan, E., K. S. Gallagher, S. Koester, and J. R. Alejo (2018). Carbon pricing in practice: A review of existing emissions trading systems. *Climate Policy 18*(8), 967–991.

Pellegrini, L., L. Tasciotti, and A. Spartaco (2021). A regional resource curse? A synthetic-control approach to oil extraction in Basilicata, Italy. *Ecological Economics 185*, 107041.

Petrick, S. and U. J. Wagner (2014). The impact of carbon trading on industry: Evidence from German manufacturing firms. Kiel Working Paper No. 1912.

Ren, S., B. Yuan, X. Ma, and X. Chen (2014). International trade, FDI (foreign direct investment) and embodied CO_2 emissions: A case study of China's industrial sectors. *China Economic Review 28*, 123–134.

Rennert, K., F. Errickson, B. C. Prest, L. Rennels, R. G. Newell, W. Pizer, C. Kingdon, J. Wingenroth, R. Cooke, B. Parthum, D. Smith, K. Cromar, D. Diaz, F. C. Moore, U. K. Mueller, R. J. Plevin, A. E. Raftery, H. Sevcikova, H. Sheets, J. H. Stock, T. Tan, M. W. T. E. Wong, and D. Anthoff (2022). Comprehensive evidence implies a higher social cost of CO_2. *Nature 610*(7933), 687–692.

Romero-Ávila, D. (2008). Convergence in carbon dioxide emissions among industrialised countries revisited. *Energy Economics 30*(5), 2265–2282.

Sarkodie, S. A. and V. Strezov (2018). Empirical study of the environmental Kuznets curve and environmental sustainability curve hypothesis for Australia, China, Ghana and USA. *Journal of Cleaner Production 201*, 98–110.

Sgarciu, S., D. Scholz, and F. Müsgens (2023). How CO_2 prices accelerate decarbonisation – the case of coal-fired generation in Germany. *Energy Policy 173*, 113375.

Soliman, A. (2022). Prescriptive drought policy and water supplier compliance. *Ecological Economics 197*, 107429.

Song, Q., H. Ge, J. Caverlee, and X. Hu (2019). Tensor completion algorithms in big data analytics. *ACM Transactions on Knowledge Discovery from Data (TKDD) 13*(1), 1–48.

Sugiawan, Y. and S. Managi (2016). The environmental Kuznets curve in Indonesia: Exploring the potential of renewable energy. *Energy Policy 98*, 187–198.

Sun, X., Y. Dong, Y. Wang, and J. Ren (2022). Sources of greenhouse gas emission reductions in OECD countries: Composition or technique effects. *Ecological Economics 193*, 107288.

Talberth, J. and A. K. Bohara (2006). Economic openness and green GDP. *Ecological Economics 58*(4), 743–758.

Teixidó, J., S. F. Verde, and F. Nicolli (2019). The impact of the EU emissions trading system on low-carbon technological change: The empirical evidence. *Ecological Economics 164*, 106347.

Timmer, M. P., E. Dietzenbacher, B. Los, R. Stehrer, and G. J. De Vries (2015). An illustrated user guide to the world input–output database: The case of global automotive production. *Review of International Economics 23*(3), 575–605.

Tol, R. S. J. (2009). The economic effects of climate change. *Journal of Economic Perspectives 23*(2), 29–51.

Van Aalst, M. K. (2006). The impacts of climate change on the risk of natural disasters. *Disasters 30*(1), 5–18.

Verde, S. F. (2020). The impact of the EU emissions trading system on competitiveness and carbon leakage: The econometric evidence. *Journal of Economic Surveys 34*(2), 320–343.

Wagner, U. J., M. Muûls, R. Martin, and J. Colmer (2014). The causal effect of the European Union emissions trading scheme: Evidence from French manufacturing plants. In *Proceedings of the IZA Workshop: Labor Market Effects of Environmental Policies.* 33 pages.

Wang, L., S. Ma, and Q. Han (2022). Enhanced sparse low-rank representation via nonconvex regularization for rotating machinery early fault feature extraction. *IEEE/ASME Transactions on Mechatronics 27*(5), 3570–3578.

Xu, L., B. Yu, and W. Yue (2010). A method of green GDP accounting based on eco-service and a case study of Wuyishan, China. *Procedia Environmental Sciences 2*, 1865–1872. International Conference on Ecological Informatics and Ecosystem Conservation (ISEIS 2010).

Yang, M., E.-Z. Wang, and Y. Hou (2021). The relationship between manufacturing growth and CO_2 emissions: Does renewable energy consumption matter? *Energy 232*, 121032.

Zhang, Y., F. Wang, and B. Zhang (2023). The impacts of household structure transitions on household carbon emissions in China. *Ecological Economics 206*, 107734.