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Do strict environmental policies in European countries reduce CO_2 emissions?

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Abstract. This article uses fixed-effects and random-effects panel data models to examine the effectiveness of environmental policies, and additional determinants on carbon dioxide (CO_2) emissions in 21 selected European OECD countries from 1990 to 2020. Specifically, the analysis investigates the impact of individual subgroups constituting the total Environmental Policy Stringency (EPS) index, namely market-based instruments, non-market-based instruments and technological support. Furthermore, the impact of these instruments is examined considering two types of CO_2 measurements: production-based (PBA) and consumption-based (CBA). The obtained results demonstrate that the impact of each subgroup varies and the strength of their influence depends on the method of CO_2 measurement. Finally, the study examines whether the 2008 changes to the Emissions Trading System (ETS) influenced the effectiveness of the instruments within the EPS. The results indicate that these changes significantly improved policy effectiveness when CO_2 is measured using the PBA. In contrast, the post-2008 changes had a minimal effect on reducing CO_2 emissions measured using the CBA, which may be related to the phenomenon of outsourcing.

Keywords: EPS, carbon dioxide, environmental policies, emissions
JEL: Q54, Q56, Q50

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1. Introduction

Society in the 21st century is facing one of its most serious challenges - global warming. Greenhouse gases, with carbon dioxide (CO_2) at the forefront, are the main contributors to this phenomenon. This chemical is emitted into the atmosphere mainly as a result of human activities, such as the burning of fossil fuels and massive deforestation. Scientists emphasize that greenhouse gases, especially CO_2, have been identified as the most significant factor influencing climate change (Lv & Xu, 2019). However, it is worth noting that CO_2 emissions are not only caused by human activities, but also by natural processes such as volcanic eruptions.

Countries, especially the more developed ones, are trying to slow down the warming process by reducing carbon emissions. To this end, legislative bodies are formulating various policy programmes to mitigate the negative impact of economic entities on the natural environment.

The European Union (EU) plays a major role in environmental protection across Europe. Currently, the climate policy of this organisation encompasses 142 directives. The first significant document is Directive 2003/87/EC, concerning the greenhouse gas emissions trading scheme. The objective of this policy is to reduce the production of atmospheric pollutants by 62% compared to the levels in 2005. However, according to European Council & Council of the European Union (n.d. a, n.d. b), by 2023 emissions had decreased by 41%. The system aims to ensure that entities producing pollutants contribute financially to the green transformation within the EU. A cap is set for the total amount of greenhouse gases that can be produced by facilities covered by the programme, including factories and power plants.

However, the year 2008 is more important from the perspective of research on the effectiveness of the Emissions Trading System (ETS) (ETS Phase II), when the EU significantly expanded the scope of the system, thus initiating its practical implementation. Another important EU project aimed at environmental protection is ‘Fit for 55’. Introduced in 2021, this package of climate regulations aims to reduce greenhouse gas emissions by 55% by 2030. It includes a reformed EU ETS that will encompass emissions from maritime transport and increase the stringency of the policy by gradually phasing out free allowances.

The Environmental Policy Stringency (EPS) index, developed by Botta and Koźluk (2014), was created for comparative research on environmental policies. It consists of three subgroups of environmental policy instruments: market-based, non-market-based and technology support. In the countries of the EU, the most important instrument is the ETS, which sets a cap on CO_2 emissions. Entities participating in this market can buy and sell allowances depending on their CO_2 emission levels. It is worth noting that a higher price in the ETS is associated with a more stringent policy aimed at reducing greenhouse gas emissions.

The literature distinguishes between two main approaches to measuring CO_2 emissions. The first is production-based accounting (PBA), which focuses on accounting only for gases produced within the territory of a given country or geographic area. The primary criticism of this measurement method is the phenomenon of outsourcing, whereby activities with a significant environmental impact are relocated to countries with less stringent climate regulations. In response to this criticism, a second approach was developed: consumption-based accounting (CBA). CBA takes into account CO_2 emissions based on both domestic activities and imports. This is particularly relevant when a country imports a significant amount of goods whose production processes emit large quantities of greenhouse gases. As noted by Papież et al. (2021), EU countries tend to show a greater reduction in emissions when measured by PBA than by CBA. This trend may be related to the issue of outsourcing.

Studies on the impact of EPS instruments on CO_2 emission has been conducted in BRICS countries (Wang et al., 2022), in both BRICS and G7 countries (Sezgin et al., 2021), in China, the USA, India, Russia and Japan (Yirong, 2022), and in Czechia, Greece, Hungary, Korea, South Africa, and Turkey (Wolde-Rufael & Mulat-Weldemeskel, 2021). The most extensive study (covering the largest number of OECD countries) was conducted by Albulescu et al. (2022) and Frohm et al. (2023). The impact of EPS in the most polluted Asian countries was examined by Liu et al. (2023).

In previous studies, variables such as GDP *per capita* (Ahmed & Ahmed, 2018; Albulescu et al., 2022; Frohm et al., 2023; Liu et al., 2023; Wang et al., 2022; Wolde-Rufael & Mulat-Weldemeskel, 2021; Yirong, 2022), the Human Development Index (HDI) (Sezgin et al., 2021), the share of renewable energy sources (RES) (Albulescu et al., 2022; Khan & Imran, 2023; Liu et al., 2023; Morales-Lage et al., 2016; Wang et al., 2022; Wolde-Rufael & Mulat-Weldemeskel, 2021), industrial value added (Wang et al., 2022), the inflow of foreign direct investment (FDI) (Albulescu et al., 2022; Aller et al., 2021), the impact of environmental and energy taxes (Wolde-Rufael & Mulat-Weldemeskel, 2021), and globalisation (Sabir & Gorus, 2019) have been used to model CO_2 emissions.

In most studies, the authors considered only production-based (i.e. PBA) CO_2 emissions (Ahmed & Ahmed, 2018; Albulescu et al., 2022; Frohm et al., 2023; Liu et al., 2023; Wang et al., 2022). However, the use of the consumption-based (i.e. CBA) CO_2 emissions by Wolde-Rufael and Mulat-

Weldemeskel (2021) and the measurement of CO_2 as the sum of production and consumption activities by Sezgin et al. (2021) are worth highlighting.

In all the mentioned studies, the EPS index was treated as a whole, customarily not considering its subgroups separately. In the current literature, the separate impact of the instrument subgroups was examined by Guo et al. (2021). Furthermore, due to the analysis focusing mainly on countries outside the non-EU or non-European countries, none of the above works takes into account the impact of EU policies, including the ETS.

The objective of this study is to examine the impact of strict environmental policies on the production of CO_2 *per capita* in 21 selected European countries that are members of the Organisation for Economic Co-operation and Development (OECD) from 1995 to 2020. The study is limited to selected European OECD countries due to the availability and quality of EPS index data.

Panel data estimation methods, such as the fixed effects estimator and random effects estimator, were used in the study to determine their relationships. The main hypothesis posited in the study is:

- environmental policy instruments included in the EPS index significantly impact the reduction of CO_2 emissions *per capita*.

The following hypotheses are also considered in detail in this paper:

- the choice of the CO_2 measurement method, whether based on the place of CO_2 production (PBA) or consumption (CBA), influences the effectiveness of environmental policies in reducing CO_2 emissions *per capita*;
- the introduction of changes to the EU ETS in 2008 affects the effectiveness of environmental policies in reducing CO_2 emissions *per capita* in the European OECD countries;

- the different subgroups of the EPS index, i.e. market-based, non-market-based and technology support vary in terms of their impact on CO_2 production.

This paper presents three novelties. The first novelty of this article is to examine whether the introduction of the ETS system in 2008 has a significant impact on the effectiveness of environmental policies in reducing CO_2 emissions. Most of the countries selected for analysis are members of the EU, and it can therefore be hypothesised that the currently most important ETS has influenced the level of CO_2 production.

The second novelty is the fact that two groups of models are considered: one using the PBA method as the dependent variable and the other using the CBA method. In the aforementioned studies, most researchers rely on either one of these two approaches (usually PBA). There is a lack of research in the current literature on the impact of the EPS index on $CO0_2$ production measured using both approaches, which would allow for an assessment of whether CO_2 reduction in Europe results from internal European actions to limit CO_2 and is a consequence of stringent policies, or merely from the relocation of production to countries with less stringent environmental regulations.

The third novelty of the work involves the examination of whether the different subgroups of the EPS indicator, i.e. market-based, non-market-based and technology support differ in their impact on CO_2 production. The existing literature lacks such studies, as most authors consider the simultaneous impact of all subgroups in their models based on calculating an arithmetic mean. This approach does not allow for a deeper understanding of how each subgroup individually affects the reduction of CO_2 emissions.

This paper is organised as follows. Section 2 reviews the relevant literature concerning the analysis of CO_2 emissions in European OECD countries. Section 3 is devoted to presenting the area under study, the used methodology is sketched in Section 4, while Section 5 presents the main outcome of this work. Finally, Section 6 shows the conclusions and policy implications.

2. Literature review

The most extensive study on the impact of the EPS index on CO_2 emission reductions was conducted by Albulescu et al. (2022). In their work, they used data from 30 countries, either OECD members or developing countries, concerning the overall EPS index, GDP *per capita*, the inflow of FDI, the share of RES and CO_2 production. The relationship between the EPS index, additional determinants and CO_2 production was examined using panel data models based on quantile regression with fixed effects. Their results show that the greatest impact on reducing CO_2 emissions through increased environmental stringency occurs in countries with low levels of emissions. Furthermore, the impact of the EPS index is greater in EU countries due to the 20-20-20 targets for greenhouse gas emissions.

The second most extensive study in terms of the number of countries is the analysis conducted by Frohm et al. (2023). They include data on the total EPS index, GDP *per capita* and the share of fossil fuels in energy consumption from 30 selected OECD countries. Panel data models were used for the analysis. They find that the impact of policies is significant but varies across economic sectors. This variation may result from the differing intensity of fossil fuel usage in the particular sectors of the economy. In order to achieve net-zero emissions by 2050, it is necessary for the current policies to be rapidly tightened.

In Asian countries, the role of EPS instruments in reducing CO_2 emissions has been analysed by Liu et al. (2023). Using the autoregressive distributed lag stationarity (ARDL) and nonlinear autoregressive distributed lag (NARDL) models, they conclude that the positive impact of environmental policies is greatest in the most polluted countries. Due to stringent regulations, enterprises are compelled to implement changes in production technologies toward more environmentally friendly solutions. This, in turn, encourages companies to seek innovations in zero-emission technologies.

Ahmed and Ahmed (2018) analyse the impact of environmental policy stringency instruments in China based on PBA emissions and the overall EPS index and GDP *per capita* in US dollars using the corrected grey model with convolution (CGMC). They find that the EPS index positively impacts CO_2 production, but its strength is weaker compared to the negative impact of GDP *per capita*.

A broader analysis of the impact of the EPS index and the HDI on CO_2 production was conducted by Sezgin et al. (2021). The study utilised data from the BRICS and G7 countries. They measure CO_2 production as the sum of production and consumption activities. Using cointegration tests and Granger causality analysis, they found that the EPS index positively influences the reduction of CO_2 emissions in developed countries and long-term increases in a country's development lead to a decrease in CO_2 emissions.

Wang et al. (2022) examined the potential impact of the overall EPS index, the share of RES, GDP *per capita*, and industrial value added on reducing CO_2 emissions exclusively in BRICS countries. They used a single approach to measuring CO_2 emissions. Based on cross-sectional autoregressive distributed lag (CS-ARDL) models, the researchers confirmed the positive impact of the EPS index on CO_2 emissions in the long term. Furthermore, the combined impact of the EPS index and the share of RES is greater than their individual effects.

The impact of the EPS index and additional variables, such as environmental tax, energy tax and the share of renewable energy sources on CO_2 emissions in developing countries was studied by Wolde-Rufael and Mulat-Weldemeskel (2021). They utilised consumption-based accounting to analyse CO_2 emissions, which is not common. Using panel data models, they demonstrated that the effectiveness of environmental policy stringency requires time. The authors also found causality between the increase in the EPS index and the decrease in CO_2 emissions.

Yirong (2022) extensively examined the impact of environmental policy stringency on CO_2 emissions mainly in Asian countries and the USA. To estimate the impact of the overall EPS index and additional determinants such as GDP *per capita*, technological innovations and population on CO_2 production, nonlinear ARDL panel models were used. The main conclusion of the study is that increasing environmental policy stringency leads to a reduction in CO_2 emissions in the long term.

The impact of environmental policy stringency instruments on greenhouse gas emissions in Western and Central European countries was examined by Dmytrenko et al. (2024). The study utilised panel data models that considered the separate effects of market-based and non-market-based instruments. Based on these models, the authors concluded that the policies implemented in Europe play a crucial role only in Western countries. The most significant factor contributing to the reduction of greenhouse gases in both groups was R&D expenditure.

Based on the existing literature, it is evident that there is a lack of analyses focusing exclusively on European countries. Moreover, few studies analyse the impact of the EPS index on carbon dioxide emissions measured using both approaches (PBA, CBA). Additionally, a novel aspect of this article is the examination of the impact of the introduction of the ETS on the effectiveness of the EPS index. Finally, the separate impact of EPS index subgroups on CO_2 emissions was also considered, which is rare in the existing literature.

3. Data

The aim of this study is to investigate whether environmental policy instruments and additional determinants influence the reduction of CO_2 emissions, measured using PBA and CBA. The analysis encompasses annual data from 1995 to 2020 for 21 European countries that are members of the OECD, namely: Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, the Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom. These countries were selected for analysis due to data availability.

The variables selected for the analysis are shown in Table 1, which provides information regarding the abbreviation used, the full name of the variable, the unit of measurement and the data source. Table 1 is divided into two parts: the first one presents the dependent variables and the second the explanatory variables.

Table 1. Variables selected to research

Symbol	Variable Name	Unit	Data Source
Dependent variables			
PBA	CO_2 production measured by PBA	Tonnes *per capita*	World Bank
CBA	CO_2 production measured by CBA	Tonnes *per capita*	Our World in Data
Explanatory variables			
GDP	Gross domestic product *per capita* in nominal prices	US Dollar	World Bank
FDI	FDI	% of GDP	World Bank
RES	Share of energy consumption from RES	Percentage of total energy consumption	World Bank
KOFGI	KOF Globalization Index	Percentage of globalisation (0-100%)	ETH Zurich University

EPS	EPS Index	Points, ranging from 0 to 6	OECD
TECH	Technology support of EPS	Points, ranging from 0 to 6	OECD
MARKET	Market instruments of EPS	Points, ranging from 0 to 6	OECD
NON-MARKET	Non-market instruments of EPS	Points, ranging from 0 to 6	OECD

Source: author's work.

Table 1 lists the variables used for modelling CO_2 production. The dependent variables are CO_2 production, measured using both CBA and PBA, expressed in tonnes *per capita*. Data on CO_2 production measured by CBA were obtained from Our World in Data, while data on production measured by PBA from the official World Bank website. To describe the impact of the environmental policy stringency on CO_2 emissions, the main EPS Index and its three subgroups were utilised: technology support EPS, market-based EPS instruments and non-market-based EPS instruments. Additional explanatory variables used include GDP *per capita* in nominal prices expressed in US dollars, FDI as a percentage of GDP and the consumption of electricity from RES as a percentage of its total consumption. These data were also sourced from the official World Bank website. Furthermore, to account for globalisation, the KOF Globalization Index, developed by the Federal Institute of Technology (ETH) Zurich was used. This index takes percentage values from 1 to 100, reflecting the degree of globalisation in a given country.

The EPS index was created for international comparative research on policies aimed at reducing environmental pollution. It consists of three subgroups of environmental policy instruments: market-based, non-market-based and technology support. The EPS index ranges from 0 to 6, with data obtained from the OECD.

The components of market-based instruments (Kruse et al., 2022) are: ETS, Renewable Energy Exchange Instruments, CO_2 tax, nitrate tax and sulphur oxide. However, the non-market-based instruments include (Kruse et al., 2022): nitrate emissions, sulphur oxide emissions, particulate matter emissions and sulphur content in diesel.

The latest update, which introduced the technology sub-index, added two new categories. The first category is ‘upstream’, which includes public expenditures on R&D and the discovery of zero-emission technologies that may be currently unprofitable. The second category, ‘downstream’, encompasses support for the existing RES in the form of subsidies. This subgroup aims to facilitate the operation of the existing technologies. The motivation for creating the third technology subgroup was the distinct nature of these instruments compared to the market-based and non-market-based ones. According to the International Energy Agency data (2021), it is estimated that half of the technologies that will contribute to zero emissions by 2050 are currently in the prototype phase.

One of the greatest challenges regarding CO_2 emissions is the method of measurement. Currently, the two most popular methods are the previously mentioned PBA and CBA. Kozul-Wright and Fortunato (2012) indicate that the reduction in CO_2 emissions in developed countries often results from outsourcing, i.e. relocating environmentally harmful activities to countries with less stringent regulations. In such cases, the PBA does not account for production outside the country, leading to an apparent reduction in emissions. Research conducted in the UK by Barrett et al. (2013) shows the need to apply CBA in territorial CO_2 emission measurements, especially in highly developed countries. Unfortunately, data on emissions measured using CBA are often inconsistent or lack reliability. Therefore, Peters (2008) suggests combining both approaches to diversify research and demonstrate the effectiveness of climate policies.

In most studies, only one method of measuring CO_2 is considered, most commonly PBA (Drastichová, 2018; Vavrek & Chovancova, 2016), and less frequently CBA (Sanyé-Mengual et al., 2019; Wolde-Rufael & Mulat-Weldemeskel, 2021). Studies that incorporate both approaches are the least common (Franzen & Mader, 2018).

4. Methodology

Panel data contain information about multiple units (cross-sectional data) over different time periods (time series). Unlike cross-sectional or time series data, models estimated using panel data allow for the relaxation of assumptions that are implicitly made in cross-sectional data analysis (Maddala, 2006, p. 643). In cross-sectional data analysis, it is often assumed that unobserved factors either do not affect the dependent variable or remain constant. However, with panel data, these unobserved factors can be modelled using fixed or random effects, which account for variations among units over time. Panel data also allow the model to be estimated on an incremental basis, allowing for the avoidance of estimator bias that arises from omitting time-invariant explanatory variables. These variables form part of the unit-specific effect and are removed when calculating first differences (Dańska-Borsiak, 2011).

The first model to be analysed is the fixed effects model. The form of this model is as follows:

$$y_{it} = \eta_i + x_{it}\beta + \nu_{it}, \tag{1}$$

where:

y_{it} – dependent variable for the *i*-th unit in the *t*-th period,

x_{it} – vector of explanatory variables for the *i*-th unit in the *t*-th period,
η_i captures specific factors for the *i*-th unit that are constant over time,
β – the vector of parameters,
ν_{it} – the random component with a normal distribution.

Moreover, the model has a key assumption that allows for the identification of parameters:

$$\mathrm{E}[\nu_i | x_i, \alpha_i] = 0. \tag{2}$$

This means that random component ν_i is not correlated with explanatory variables x_i and fixed effects α_i. The model, in contrast to the classical linear regression model, has 'i' specific intercept terms that account for the effects for each unit. It is also important to note that this model is consistent even when the heterogeneous specific component is correlated with one or more explanatory variables.

The second model, which assumes that individual effects α_i are random variables rather than fixed, is the random effects model. The random effects model can be described by the following equation:

$$y_{it} = x_{it}\beta + (\eta_i + \nu_{it}) = x_{it}\beta + u_{it}, where\ \eta_i + \nu_{it} = u_{it}. \tag{3}$$

The model also assumes that both random components are uncorrelated with the observed explanatory variables:

$$E[u_{it} | x_i] = 0. \tag{4}$$

This assumption excludes the estimation of the model through the ordinary least squares (OLS) method.

The Hausman test applied to panel data, is used to chose between fixed effects and random effects models. The random effects model is based on the assumption that group effects are uncorrelated with exogenous variables (Greene, 2000, pp. 301–303). In other words, this test assists in selecting the model specification, particularly in deciding between random effects or fixed effects models. The hypothesis framework for this test is as follows:

$$H_0 : E[\epsilon_i | x_{it}] = 0 \; vs \; H_1 : E[\epsilon_i | x_{it}] \neq 0. \tag{5}$$

The null hypothesis supports the use of the random effects model; rejecting it in favour of the alternative hypothesis, on the other hand, suggests the application of the fixed effects model.

To ensure the normality of the dependent variable's distribution and to facilitate the conduct of statistical tests, a logarithmic transformation was applied to the variables, namely CO_2 production using CBA and PBA approaches, GDP *per capita* in US dollars (lnGDP), share of renewable energy consumption (lnRES), and values of the KOF globalizsation index (lnKOF). Two general model formulas were considered in this study: one using the overall EPS index (1) and the other based on its three subgroups (2). Additionally, these two types of models were considered for two measures of CO_2 – PBA and CBA. The formulas for the models used are as follows:

$$lnCO_2 = \beta_0 + \beta_1 lnPKB + \beta_2 lnREC + \beta_3 lnKOF + \beta_7 EPS + \epsilon, \tag{6}$$

$$where\ lnCO_2\ is\ lnPBA\ or\ lnCBA,$$

$$lnCO_2 = \beta_0 + \beta_1 lnPKB + \beta_2 lnREC + \beta_3 lnKOF + \beta_4 TECH + \beta_5 MARKET + \beta_6 NONMARKET + \epsilon, \tag{7}$$
$$where\ lnCO_2\ is\ lnPBA\ or\ lnCBA.$$

In order to investigate whether the introduction of climate policies increased the impact of EPS on CO_2 production, models 1 and 2 were estimated on data subsets covering the following periods:

A) years 1995–2020;

B) years 1995–2008, i.e. the period before the introduction of the ETS;

C) years 2008–2020, i.e. directly after the introduction of the ETS.

For example, the PBA_A_1 model is interpreted as the model with the overall EPS index, estimated based on data from 1995–2020, where the dependent variable is CO_2 production *per capita* measured using the PBA approach.

To verify whether the group effect in the random effects models is statistically significant, the Breusch-Pagan test (1980) can be applied. The null hypothesis supports the use of the classical OLS estimator, as the variance of the individual effect is equal to zero, while the alternative hypothesis suggests the significance of individual effects.

5. Empirical results

The choice between the fixed effects estimator or the random effects estimator was based on the results of the Hausman test for pairs of models estimated on the same datasets and identical sets of explanatory variables. The significance level for the test is set at 0.05. The test results are presented in Table 2.

Due to the long time series in the utilised dataset, the possibility of autocorrelation was tested. A suitable test was conducted and models robust to autocorrelation were estimated (Appendix 1), demonstrating that both the sign and significance of the parameters are nearly identical.

Table 2. Hausmann test results

Model	*p*-value	Conclusion
PBA_A_1	0.558	Random effect
PBA_B_1	0.860	Random effect
PBA_C_1	0.674	Random effect
PBA_A_2	0.781	Random effect
PBA_B_2	0.951	Random effect
PBA_C_2	0.826	Random effect
CBA_A_1	0.436	Random effect
CBA_B_1	0.669	Random effect
CBA_C_1	0.519	Random effect
CBA_A_2	0.637	Random effect
CBA_B_2	0.772	Random effect
CBA_C_2	0.811	Random effect

Source: author's work.

Table 2 provides a detailed description of model pairs created based on the previously mentioned criteria, such as the dataset, the dependent variable and the inclusion of either the overall EPS or its subgroups. Based on Table 2, we can conclude that at a significance level of 0.05, in all cases, there is no basis for rejecting the null hypothesis stating that the random effects estimator is a more appropriate model. Based on the conducted Hausman test, the Balestra-Nerlove estimator can be used to estimate the parameters of the 12 random effects models.

To verify the appropriateness of using the random effects estimator over the classical OLS method, the Breusch-Pagan test was applied. The conclusion along with the *p*-value is presented in Table 3.

Table 3. Breush-Pagan test results

Model	*p*-value	Conclusion
PBA_A_1	0	Significant individual effects
PBA_A_2	0	Significant individual effects
CBA_A_1	0	Significant individual effects

CBA_A_2	0	Significant individual effects
PBA_B_1	~0	Significant individual effects
PBA_B_2	~0	Significant individual effects
CBA_B_1	~0	Significant individual effects
CBA_B_2	~0	Significant individual effects
PBA_C_1	~0	Significant individual effects
PBA_C_2	~0	Significant individual effects
CBA_C_1	~0	Significant individual effects
CBA_C_2	~0	Significant individual effects

Source: author's work.

For all models in which the Breusch-Pagan test was conducted, the *p*-value was close to zero. This indicates that the individual effect was significant in all cases.

The values of the individual parameters for the models estimated on the dataset covering the years 1995–2020, along with their statistical significance and the coefficient of determination are presented in Table 4.

Table 4. Models estimated on a dataset from the years 1995–2020

Variable	PBA_A_1	PBA_A_2	CBA_A_1	CBA_A_2
lnGDP	0.122 ***	0.128 ***	0.196 ***	0.201 ***
lnRES	-0.217 ***	-0.209 ***	-0.205 ***	-0.198 ***
lnKOFGI	0.269 **	0.188	-0.472 **	-0.479 **
EPS	-0.079 ***	-	-0.027 *	-
TECH	-	-0.012 **	-	0.004
MARKET	-	-0.088 ***	-	-0.045 ***
NONMARKET	-	-0.019 ***	-	-0.009
Constant	0.378	0.683	2.976 ***	2.965 ***
Coefficient of determination	0.631	0.658	0.336	0.345

Note. *, ****** and *** – the statistical significance of parameters at the significance levels of 1%, 5%, and 10%, respectively.
Source: author's work.

The aggregated impact of all three subgroups is represented by the EPS variable, which shows statistical significance in all examined models. In the model estimated on data covering the years 1995–2020 (PBA_A_1), the value of this parameter was -0.079, indicating that an increase in the stringency of policies included in the EPS index leads to a decrease in *per capita* CO_2 production (PBA). In the model estimated on data covering the years 1995–

2020 (CBA_A_1), the parameter value was -0.027, suggesting that an increase in the stringency of policies included in the EPS index results in a reduction of *per capita* CO_2 production (CBA).

The parameter for the EPS technological support variable (TECH) in the model estimated on data for the years 1995–2020 (PBA_A_2) is -0.012 and is statistically significant. This indicates that increased support for renewable energy sources and expenditures on R&D translates into a reduction in *per capita* CO_2 emissions. The parameter for the EPS technology support variable (TECH) in the model estimated on data for the years 1995–2020 (CBA_A_2) is 0.004, but statistically insignificant.

Another analysed variable is MARKET, representing the effect of market-based EPS instruments. The parameter for the variable describing the effect of market-based EPS instruments (MARKET) in the model estimated on data for the years1995–2020 (PBA_A_2) is -0.088 and is statistically significant. This means that increasing the stringency of instruments such as the ETS, raising the CO_2 or nitrate tax rate, leads to a decrease in *per capita* CO_2 production. The parameter for this variable describing the effect of market-based EPS instruments (MARKET) in the model estimated on data for the years 1995–2020 (CBA_A_2) is -0.045 and statistically significant.

The last subgroup of the EPS index encompasses the non-market instruments (NONMARKET). Based on Table 4, it can be stated that the variable in the model estimated from data for the years 1995–2020 (model PBA_A_2) is statistically significant with a value of -0.019. This indicates that increasing the stringency of instruments such as limits on nitrate, sulfur oxide or suspended particulate emissions leads to a decrease in *per capita* CO_2 emissions. The variable in the model estimated from data for the years 1995–2020 (model CBA_A_2) was -0.009 but statistically insignificant.

The impact of the logarithmic gross domestic product *per capita*, expressed in nominal prices in US dollars (lnGDP), was statistically significant, ranging from 0.122 to 0.201. This means that as the gross domestic product *per capita* increases, the production of CO_2 *per capita* also increases.

Another statistically significant variable in all models is lnRES, which ranged from -0.217 to -0.198. The parameter values are negative, indicating that the share of RES positively affects the reduction of CO_2 production *per capita*.

The last variable present in each model is lnKOF. In two models estimated on data for the years 1995–2020 (CBA_A_1, CBA_A_2), this parameter is statistically significant and positive. This indicates that as globalisation increases in European countries, the production of CO_2 *per capita* rises. In one model (PBA_A_1), the parameter is statistically significant but has a negative value. This suggests that as globalisation increases in European countries, the production of CO_2 *per capita* decreases.

Table 5 presents the values of individual parameters for models, where the dependent variable is CO_2 production measured using production-based accounting. Their statistical significance and coefficient of determination is also provided. The values of the parameters were estimated on datasets for the years 1995–2008 and 2008–2020.

Table 5. PBA models estimated on datasets from the years 1995–2008 and 2008–2020

Variable	PBA_B_1	PBA_C_1	PBA_B_2	PBA_C_2
lnGDP	0.089 ***	0.123 ***	0.099 ***	0.129 ***
lnRES	-0.133 ***	-0.351 ***	-0.134 ***	-0.318 ***
lnKOFGI	0.189 **	-1.35 ***	0.172 *	-0.449
EPS	-0.023 **	-0.051 ***	-	-
TECH	-	-	-0.017 **	-0.004
MARKET	-	-	-0.036 **	-0.049 ***
NONMARKET	-	-	-0.002	-0.054 ***
Constant	0.799 **	7.826 ***	0.807 **	3.878 *

Coefficient of determination	0.231	0.632	0.251	0.654

Note. As in Table 4.
Source: author's work.

The aggregated impact of all three subgroups is represented by the EPS variable. In the models before the introduction of the ETS, in the years 1995–2008 (model PBA_B_1), the parameter value was -0.023, while after its introduction, in the years 2008–2020 (model PBA_C_1), it was -0.051. This indicates that the policy related to the ETS was effective, as the overall stringency resulted in a greater reduction in *per capita* CO_2 production than before 2008, the year in which the scope of the ETS was significantly expanded.

In the models, before the introduction of the ETS, in the years 1995–2008 (model PBA_B_2), the value of the TECH parameter was -0.017, and after its introduction, in the years 2008–2020 (model PBA_C_2), it was -0.004, but this was not statistically significant. This may suggest that the impact of technology support policies on reducing *per capita* CO_2 production weakened.

The next variable analysed is MARKET. In the models before the introduction of the ETS from 1995–2008 (PBA_B_2), the value of the MARKET parameter was -0.036, and after its introduction, in the years 2008–2020 (model PBA_C_2), it was -0.049. In both models, the parameter was statistically significant, suggesting that this subgroup of environmental policies influenced the reduction of *per capita* CO_2 emissions after the policy tightening associated with the ETS expansions post-2008.

Moving to the last subgroup of the EPS index, the non-market instruments (NONMARKET), in the models before the introduction of the ETS, in the years 1995–2008 (PBA_B_2), the value of the NONMARKET variable was –0.002 but statistically insignificant, whereas after its introduction, in the years 2008–2020 (model PBA_C_2), it was -0.054. This indicates that the subgroup of environmental policies based on non-market instruments began to have an effect after the increased stringency of the ETS in 2008.

Table 6 shows the values of the individual parameters for the models, where the dependent variable is CO_2 production measured using consumption-based accounting, along with their statistical significance and coefficient of determination. The estimations concerned datasets covering the years 1995–2008 and 2008–2020.

Table 6. CBA models estimated on datasets from the years 1995–2008 and 2008–2020

Variable	CBA_B_1	CBA_C_1	CBA_B_2	CBA_C_2
lnGDP	0.097 ***	0.435 ***	0.107 ***	0.409 ***
lnRES	-0.096 ***	-0.349 ***	-0.095 ***	-0.304 ***
lnKOFGI	-0.221	-1.872 ***	-0.228	-0.564
EPS	0.054 **	-0.003	-	-
TECH	-	-	0.011	0.012
MARKET	-	-	-0.021	-0.008
NONMARKET	-	-	0.024 ***	-0.076 ***
Constant	2.469 ***	6.973 ***	2.477 ***	1.7
Coefficient of determination	0.225	0.567	0.235	0.604

Note. As in Table 4.
Source: author’s work.

The aggregated impact of all three subgroups is represented by the EPS variable. In the models before the introduction of the ETS, in the years 1995–2008 (model CBA_B_1), the parameter value was 0.054, and after its introduction, in the years 2008–2020 (model CBA_C_1), it was 0.003, but it was not statistically significant. This indicates that the policy negatively impacted the reduction of CO_2 before the increased stringency of the ETS system introduced in 2008. After 2008, it had no impact on production.

In the models before the introduction of the ETS, in the years 1995–2008 (model CBA_B_2) and after its introduction, in the years 2008–2020 (model CBA_C_2), the TECH parameter was not statistically significant. This suggests that EPS technology support policies did not affect CO_2 production *per capita* measured using CBA in any of the studied periods.

Interestingly, in the models before the introduction of the ETS, in the years 1995–2008 (CBA_B_2), the value of the MARKET variable was -0.021, and after its introduction, in the years 2008–2020 (model CBA_C_2), it was –0.008; however, in both models, the variable was statistically insignificant. This suggests that the changes in the ETS did not significantly impact the reduction of CO_2 emissions measured using CBA.

In the models before the introduction of the ETS, in the years 1995–2008 (CBA_B_2), the value of the NONMARKET parameter was 0.024, and after its introduction, in the years 2008–2020 (model CBA_C_2), it was -0.076. Both parameters were statistically significant, suggesting that non-market instruments began positively impacting the reduction of CO_2 emissions after the changes to the ETS system in 2008.

In all the analysed models, the impact of the logarithm of GDP *per capita*, expressed in nominal US dollars (lnGDP), was statistically significant. The models estimated based on data from the years 1995–2020 (PBA_B_1, PBA_B_2, CBA_B_1, CBA_B_2) had lower parameter values than those from 2008-2020 (PBA_C_1, PBA_C_2, CBA_C_1, CBA_C_2). This suggests that after the changes to the ETS system in 2008, the influence of GDP on CO_2 production *per capita* was greater.

Another statistically significant variable in all models is the logarithm of the share of RES in the total energy consumption. Models estimated based on data before the introduction of the ETS (PBA_B_1, PBA_B_2, CBA_B_1, CBA_B_2) had higher parameter values than those after the introduction of the ETS (PBA_C_1, PBA_C_2, CBA_C_1, CBA_C_2). This indicates that after 2008, the impact of the share of RES on CO_2 production *per capita* was greater.

The last variable present in each model is lnKOF. It is worth noting that the sign of the parameter in the years 1995-2008 (PBA_B_1, PBA_B_2) is opposite to that in the years 2008-2020 (PBA_C_1). This difference suggests that after 2008, globalisation began to positively influence *per capita* CO_2 emissions. Similarly, models estimated based on data before the introduction of the ETS in 2008 (CBA_B_1, CBA_B_2) had higher values than those after the introduction of the ETS (CBA_C_1, CBA_C_2), but they were not statistically significant. This suggests that after the changes to the ETS system in 2008, globalisation began to positively influence the reduction of *per capita* CO_2 emissions.

5.1. Robustness check

To verify the robustness of the parameters obtained by using the random effects estimator, an alternative estimator for panel data that accounts for lags was conducted.[1] The estimation results are presented in the Table 7.

Table 7. Random effects with autocorrelation correction

Variable	PBA_A_1	PBA_A_2	CBA_A_1	CBA_A_2
lnGDP	0.0621**	0.0712***	0.161***	0.163***
lnREC	-0.259***	-0.253***	-0.228***	-0.227***
lnKOFGI	0.181	0.148	-0.001	-0.0526
TECH		-0.00177		-0.00888
MARKET		-0.042***		-0.0157
NONMARKET		-0.010**		-0.00268
EPS	-0.032***		-0.021*	
Constant	1.344**	1.406**	1.269	1.469*

Note. As in Table 4.
Source: author’s work.

[1] In STATA, models were estimated with a correction for residual autocorrelation.

In all models incorporating autocorrelation correction, parameters lnGDP and lnREC retain the same sign and exhibit very similar levels of statistical significance. The lnKOFGI parameter also demonstrates the same direction of change as in the random effects models. The most significant finding from these new models pertains to the results for parameters associated with environmental stringency (TECH, MARKET, NONMARKET, and EPS). In models where the EPS index is included in its entirety, the parameter associated with this variable displays the same direction of change and a comparable level of statistical significance. In the remaining models, where the impact of environmental policies is captured separately, the parameters for these variables also exhibit a similar direction of change and statistical significance. Only in model CBA_A_2 does the parameter associated with the MARKET variable lack clear statistical significance.

6. Conclusions

The objective of this study was to examine the impact of strict environmental policies on the production of CO_2 *per capita*, measured using both PBA and CBA. Furthermore, the study examined whether EU policies affect the reduction of CO_2 production. Based on the above, several hypotheses were formulated and empirically tested with fixed and random effects using panel data models. The main hypothesis posited that the environmental policy instruments described in the EPS index significantly influence the reduction of *per capita* CO_2 emissions. However, the study inconclusively confirmed this thesis, despite the significance of the parameters corresponding to these variables in many models.

The second hypothesis was that the choice of the CO_2 measurement method depending on the place of production (PBA) or consumption (CBA), influences the effectiveness of environmental policies in reducing *per capita* CO_2 emissions. This study demonstrated that the choice of the CO_2 measurement method is significant, as in the vast majority of PBA models, the impact of the implemented policies was greater than in the CBA models.

Next, the study attempted to determine whether the changes made to the ETS system in 2008 in the EU influenced the effectiveness of environmental policies in reducing *per capita* CO_2 emissions in European OECD countries. For this purpose, models were constructed for two periods: one covering the years 1995–2008 and the other 2008–2020. In the models with the PBA dependent variable, it was found that the changes introduced to the ETS system increased the effectiveness of the policies, with the exception of the technology subgroup. In the models with the CBA dependent variable, the effectiveness was much lower, as the hypothesis was only proven for the non-market instruments subgroup.

The final hypothesis posited that the various subgroups of the EPS index, namely market-based, non-market-based and technology support, have differing impacts on CO_2 production. The breakdown of the overall EPS index proved accurate and the influence of each subgroup varied depending on the model formula and the analysed time period. In the CBA models, the non-market instruments subgroup had the greatest impact on reducing CO_2 emissions, while in the PBA models the market-based instruments subgroup had the most significant impact. It is also crucial to note that the technology subgroup was statistically insignificant in the PBA models and showed no significance in the CBA models. This may be due to the fact that this is a relatively new subgroup of policy instruments, with effects that are expected to contribute to zero emissions only by 2050.

The final hypothesis was that the different subgroups of the EPS indicator, i.e. market, non-market and technology support, affect carbon production in a different way. The breakdown of the overall EPS indicator proved to be accurate, with the impact of the individual subgroups depending on the model formula and the time period analysed. In the CBA models, the non-market instrument subgroup had the greatest impact on CO_2 reduction, while in the PBA models, it was the impact of the market instrument subgroup. It is also key to note that the technology subgroup was found to be insignificant in the PBA models and showed no significance in the CBA models. This may be due to the fact that it is a relatively new subgroup of policy instruments and is based on technologies that will only contribute to zero-carbon in 2050. As demonstrated by the analyses conducted on the obtained models, the choice of the dependent variable is a key factor in determining the strength and direction of the influence of climate policies and other determinants. Evaluating the impact of policies reveals a significant difference in the parameter results between the CBA and PBA models. Climate policy instruments, particularly those included in the EPS, appear to better explain CO_2 emissions measured using PBA. Additionally, the choice of the dependent variable seems to affect the significance of the parameters. Models measuring CO_2 emissions using production-based accounting generally show statistical significance more frequently compared to those using CBA. Based on the obtained results, it can be assumed that policies may not fully achieve their intended role and the reduction in CO_2 production may be the result of outsourcing, which involves relocating environmentally harmful activities to countries with less stringent regulatory frameworks.

The models estimated using data from the years 1995–2008 and 2008–2020 allow for the assessment of the impact of important changes introduced to the ETS system. Although the system was established in 2005, the changes introduced in 2008 significantly increased the stringency of this policy. As a result of these changes, there was a substantial reduction in CO_2 emissions by entities covered by the system. It is important to note that the method of measuring CO_2 played a crucial role, as policies within the market-based and non-market-based subgroups had a much greater impact on reducing CO_2 emissions measured using PBA after 2008. In the CBA analysis, most results regarding the impact of specific EPS index subgroups on CO_2 emissions were statistically insignificant.

The obtained results may serve as a warning to legislators, prompting deeper reflections on the necessary changes. One of the most significant current challenges is enforcing responsibility for goods consumed in Europe, the production of which contributes to environmental pollution in countries such as India and China. One idea that could help address this problem is the introduction of additional border fees in Europe that would compensate for the harmful effects a product caused during its production process. An interesting tool currently being developed is the Carbon Border Adjustment Mechanism (CBAM). Its role may become significant in the near future due to its impact on enforcing the consequences of outsourcing.

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