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Frontier analysis of eco-efficiency gaps: Evidence from 22 European countries

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Résumé / Abstract

FR
Cette étude estime et compare l'éco-efficacité, définie comme le rapport entre le produit intérieur brut et les émissions de gaz à effet de serre, de 22 pays européens entre 2000 et 2018. L'étude identifie la Suède, le Danemark, l'Italie, la Norvège et le Luxembourg comme les pays les plus éco-efficaces. Ces pays, comparativement aux autres pays Européens, produisent la plus grande quantité de biens et services par unité d'émissions de gaz à effet de serre. L'étude examine également les facteurs technologiques et réglementaires qui expliquent les variations de l'éco-efficacité entre les pays. Les pays qui ont une politique environnementale plus stricte et des taxes énergétiques par unité d'émissions de gaz à effet de serre plus élevées ont tendance à être plus éco-efficaces. Cependant, les gains en matière d'éco-efficacité diminuent à mesure que les réglementations se durcissent et les taxes augmentent.

EN
This study estimates and compares eco-efficiency across 22 European countries from 2000 to 2018. The study derives eco-efficiencies from the ratio of gross domestic product to greenhouse gas emissions, and identifies eco-efficient countries as those that maximize their production of goods and services per unit of greenhouse gas emissions. Specifically, it identifies Sweden, Denmark, Italy, Norway, and Luxembourg as the most eco-efficient countries. Moreover, the paper investigates technological and policy factors that explain variations in eco-efficiency across the countries. Countries with stricter environmental policy and higher energy tax revenue per unit of greenhouse gas emissions tend to be more eco-efficient. However, gains in eco-efficiency diminish as policy stringency and taxes increase.

JEL classification: C01, E23, L60
Keywords: Eco-efficiency; Greenhouse gases; Gross domestic product.

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Abstract

This study estimates and compares eco-efficiency across 22 European countries from 2000 to 2018. The study derives eco-efficiencies from the ratio of gross domestic product to greenhouse gas emissions, and identifies eco-efficient countries as those that maximize their production of goods and services per unit of greenhouse gas emissions. Specifically, it identifies Sweden, Denmark, Italy, Norway, and Luxembourg as the most eco-efficient countries. Moreover, the paper investigates technological and policy factors that explain variations in eco-efficiency across the countries. Countries with stricter environmental policy and higher energy tax revenue per unit of greenhouse gas emissions tend to be more eco-efficient. However, gains in eco-efficiency diminish as policy stringency and taxes increase.

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1. Introduction

Gross Domestic Product (GDP) measures economic output but fails to account for the negative environmental impact caused by production. For instance, it overlooks greenhouse gas (GHG) emissions, a primary contributor to climate change (IPCC, 2013). In response to growing concern about climate change, there has been a shift towards measures of economic performance that include environmental impacts. We develop such measure and use it to evaluate eco-efficiency for a panel of European Countries from 2000 to 2018.

Eco-efficiency[3] (EE hereafter) is defined by the World Business Council for Sustainable Development (WBCSD, 2006) as the production of goods and services with minimal environmental impacts. A key measure of EE is the ratio of GDP to GHG emissions, referred to as carbon productivity (e.g. Kaya and Yokobori, 1993; Pan, 2022). It measures the quantity of goods and services produced (GDP) per unit of GHG emitted, indicating how well a country balances economic performance with negative environmental impacts. In this study, an eco-efficient country is defined as the one achieving the highest output per unit of GHG emissions. Deviations from this optimal level represent eco-inefficiencies or eco-efficiency gaps. GHG emissions are measured using the national inventory concept, which includes emissions from both domestic activities and sales to non-residents.

This paper estimates EEs using OECD, Eurostat, Penn World, and International Energy Agency data. We extend the work of Robaina-Alves et al. (2015), who estimated EE gaps for European countries. We update the time span of the data and considering an alternative estimation framework. A longer time span of data improves the precision of the obtained estimates. The alternative econometric framework enables us to account for country-specific heterogeneity, which, if disregarded, can lead to invalid statistical tests and conclusions based on them.

Furthermore, our analysis examines the role of technological and policy factors in explaining eco-efficiency gaps. While previous studies by Kumbhakar et al. (2022), Liang et al. (2015), Wang et al. (2011), and Lee and Park (2017) have explored the impact of factors such as innovation, stricter environmental regulation, and energy taxes on eco-efficiency and emissions, they have done so individually, without considering their joint impact. This study adopts a joint modeling approach, focusing on three key factors: 1) The Relative Advantage in Environment-related Technologies Index (RAET hereafter), indicating the adoption of environmentally friendly technologies; 2) The Environmental Policy Stringency Index (EPS hereafter), assessing the strictness of a country's environmental policies; and 3) The GHG emission tax rate that measures the economic incentives for improving EE. Finally, we empirically test the hypothesis that an increase in a factor leads to a reduction in eco-efficiency gaps.

To estimate time-varying country-level eco-efficiency gaps, we use the Greene's (2005) fixed effect stochastic frontier model. This model has two advantages: it accounts for heterogeneity

[3] Eco-efficiency is described as "being achieved by the delivery of competitively priced goods and services that satisfy human needs and bring quality of life, while progressively reducing ecological impacts and resource intensity throughout the life-cycle to a level at least in line with the Earth's estimated carrying capacity"(WBCSD, 2006,p.16).

across countries by including country fixed effects. Additionally, this model enables the identification of factors contributing to eco-efficiency gaps across countries. Specifically, it includes an inefficiency term that measures the difference between a country's current GDP per unit of GHG emissions and the highest achievable GDP per unit of GHG emissions. This difference highlights how much a country can improve its GDP relative to its GHG emissions. The inefficiency term also isolates the portion of the gap due to factors that can be managed or improved. This allows us to examine the factors (i.e., RAET, EPS, and GHG emission tax rate) that contribute to variations in the eco-efficiency gaps.

We provide a rank of eco-efficiency gaps for European countries from 2000 to 2018. Sweden, Denmark, Italy, Norway, Luxembourg frequently ranked as the most eco-efficient countries, whereas Poland, Estonia, Slovak Republic, and the Czech Republic generally ranked as the least eco-efficient. We also find that countries with higher EPS Index and GHG emission tax rate tend to exhibit lower EE gaps. However, the efficiency gain diminishes as these variables increase.

Based on our estimates, we calculate the implications of reducing eco-efficiency gaps for the environment in terms of potential carbon savings (i.e. CO_2 equivalent GHG emissions savings). We find that the environmental gains from closing eco-efficiency gaps between best and worst performing countries could lead to a reduction in carbon emissions by 75 million metric tonnes. This reduction is significant, equivalent to the carbon dioxide emissions of 9.7 million U.S. households or eight years of energy consumption for Parisian households.

The rest of this paper is structured as follows: Section 2 outlines the methodology and estimation process. Sections 3 and 4 detail the data and results, respectively. Finally, in Section 5 we provide our conclusions.

2. Methodology

Efficiency analysis rates production or economic entities, like countries, on a scale from 0 to 1, where 1 represents full efficiency. The primary methods for this are Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). DEA is a non-parametric method with no stochastic components, while SFA is parametric, including specific assumptions and stochastic error components. The choice between these methods depends on the objectives of the study and the quality of the data available. In this study, we opted for the panel data stochastic frontier (SF) model with true fixed effects, as introduced by Greene in 2005 since it allows for estimating the impact of specific policy and technological factors on variations in eco-efficiency (EE) aps across our sample countries.[4]

We focus on EE, defined as the ratio of GDP to GHG emissions, to assess how efficiently a country generate economic value per unit of GHG emissions. EE improvement can be achieved by increasing GDP without raising emissions, reducing emissions without lowering GDP, or both. In our analysis, we model EE based on the contributions of labour, capital, and a diverse energy portfolio to maximizing goods and services production per unit of GHG emissions. This

[4] It is important to note that this model has a potential disadvantage. Although the maximum likelihood estimates of model parameters are consistent, the estimates of error variances remain inconsistent unless both the number of time periods and panel units increase indefinitely (incidental parameters problem) (Kutlu et al. 2019).

energy mix, including nuclear, renewable, and traditional energy sources, directly impacts a country's EE. Proper management of these resources influences the GDP a country can produce per GHG unit, reflecting its EE and contribution to a low-carbon economy. We also include a time trend variable to account for shifts in the production function and technological advancements over time.[5]

We employ Greene's (2005) fixed-effects panel stochastic frontier model to analyze factors influencing the evolution of GDP relative to GHG emissions, beyond countries' control, such as climate-related conditions. The model incorporates country fixed effects to control for these external factors. Additionally, SFA identifies deviations from the optimal GDP per GHG emission unit. It attributes these deviations not only to random noise or country-specific effects but also to inefficiencies. Inefficiency here means suboptimal resource utilization, achieving less output than possible. This approach enables benchmarking by comparing each country's EE against those achieving best practices with similar inputs, thus identifying underperformance due to gaps between potential and actual output.

Our model captures three key components: 1) The unobserved country-specific effect μ_i accounts for fixed characteristics of each country; 2) The time-varying inefficiency u_{it} reflects inefficiency levels of a country over time; 3) The statistical noise v_{it} represents random variation. The estimation of our model relies on assumptions about the distribution of these components, as detailed in the works of Kumbhakar and Lovell (2000), Greene (2005), and Kumbhakar et al. (2015). The true fixed effect stochastic frontier (SF) model employed in our study is written as follows:

$$ln(Y)_{it} = \underbrace{\beta_0 + \sum_{j=1} \beta_j \, ln\, X_{jit} + \ timetrend}_{Frontier} + \mu_i + v_{it} - u_{it}(\mathbf{z}_{it}) \tag{1}$$

$$v_{it} \sim N\left(0, \sigma_v^2\right)$$

$$u_{it}(\mathbf{z}_{it}) \sim N^{+6}\left(\overbrace{0, \sigma_u^2(\mathbf{z}_{it})}^{pre-truncation\ moments}\right) \text{where } \sigma_u^2(\mathbf{z}_{it}) = \sigma_u^2 \exp\left(\theta_0 + \theta^{'} \mathbf{z}_{it}\right).$$

In Equation 1, *i* indexes countries and *t* indexes years. The dependent variable *Y* denotes the output emissions ratio (GDP/GHG), that is, EE. **X** is a vector of dependent variables which consists of energy, which is further broken down into nuclear, renewable, and brown energy[7] sources, labour and capital inputs. The vector of coefficients, **β**, reflects the contribution of each variable to EE. The country-specific fixed effect is denoted by μ, capturing time-invariant

[5] Instead of analyzing the share of fossil fuel energy or manufacturing's GDP contribution to explain GHG emissions and EE, our study directly examines energy inputs—categorised as brown, nuclear, and renewable. This approach, coupled with country-specific fixed effects, indirectly captures each country's economic structure, providing a comprehensive analysis of energy use and emission sources.

[6] In a standard normal distribution, variance changes do not affect the mean. But when truncated, a rise in $\sigma_u^2(\mathbf{z}_{it})$ correlates with an increased mean of the truncated u_{it}.

[7] The brown energy is the sum of coal, peat, oil shale, crude, oil products, natural gas, electricity, and heat.

characteristics of each country. The term v represents the conventional random noise, assumed to be normally distributed, which accounts for statistical noise. The inefficiency term, u, measures the loss from maximum potential output, implying that the observed level of output is at most equal to the potential level. This inefficiency is always non-negative and is modeled to follow a non-negative half-normal distribution(denoted as N^{+})[8].

Additionally, this study investigates the factors that may explain differences in EE across countries. We model the variance in eco-inefficiency distribution using variables included in vector **z**[9], as described by Kumbhakar et al. (2015). These variables comprise the Relative Advantage in Environment-related Technologies (RAET) index, the Environmental Policy Stringency (EPS) index, and the energy tax revenue per unit of emission (GHG emission tax rate). We explore these factors to understand their impact on the variance in EE gap across different countries.

Eq. (1) is estimated using Maximum Likelihood (ML) estimator, which is based on a nonlinear optimization, resulting in sample average eco-inefficiency. Finally, country-year specific eco-inefficiency score are obtained using conditional mean estimator proposed by Jondrow et al. (1982). The corresponding country-specific *EE* scores are then calculated as $exp(-inefficiency)$ (Kumbhakar and Lovell, 2000).

Regarding the impact of a change in the determinants (variables included in vector $\boldsymbol{z}$), on EE gaps marginal changes are calculated using a post estimation procedure. Marginal effect represents the derivative of eco-inefficiency with respect to its determinant and provides insight into how changes in the determinant affect the EE gaps of a country.

3. Data

Our dataset includes GDP, GHG emissions, and inputs to production which are labour, capital and diverse energy mix. The dataset cover yearly observations for 22 European countries[10] from 2000 to 2018.

GDP is expressed in chain linked volumes with base year 2017, measured in million Euro. GHG emissions are based on the national inventory concept, rather than the national accounts concept. While the national accounts approach captures emissions linked to the consumption activities of residents only, the national inventory concept also includes emissions from sales to non-residents —for example, fuel sales to foreign drivers. We use emissions data based on the national inventory concept because we aim to measure EE and the impact of policies on GDP per unit of total emissions, not just those attributable to domestic consumption. The inventory data covers emissions of carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), perfluorocarbons (PFCs), hydrofluorocarbons (HFCs), sulphur hexafluoride (SF_6) and nitrogen trifluoride (NF_3). To construct a single emissions indicator, all gases are converted into CO_2-

[8] $N^{+}(.)$ in Eq.(1) indicates that η and u have a one-sided and non-negative distributions originated from a standard normal distribution.

[9] The pre-truncation distribution of inefficiency refers to the distribution of inefficiency scores before the zero lower bound (non-negative assumption) is applied. In SFA applications, it is common to parametriseed the pre-truncation distribution of inefficiency term (see e.g., Badunenko and Kumbhakar (2017)).

[10] The countries covered are: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxemburg, Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, and United Kingdom.

equivalent emissions. [11] Both GDP[12] and GHG emissions data are obtained from Eurostat. The independent variables are inputs to production: energy (*E*), capital (*K*), and labour (*L*). Energy data is provided by International Energy Agency (IEA) World Energy Balances[13]. Energy is disaggregated into three categories according to its source (i) nuclear source, (ii) renewable energy, and (iii) brown energy. The latter is defined as the sum of coal, peat, oil shale, crude, oil products, natural gas, electricity,[14] and heat. Data on capital and labour are obtained from Penn World Table and, respectively, measure capital stock at constant 2017 national prices (in million 2017 Euro) and total labour force.

Data sources for determinants of EE gaps included in this study are as follows. Environmental Policy Stringency Index (EPS) is a measure developed by the OECD. This is an internationally comparative and country-specific index which serves as a crucial benchmark to assess the strictness of environmental policies across different countries. The EPS is defined as the extent to which these policies levy an explicit or implicit cost on environmentally harmful behaviors and pollution. The index draws from the stringency levels of 13 policy mechanisms predominantly concerning climate change and air pollution. With a scale ranging from 0, indicating the least stringency, to 6, marking the highest level of stringency, the EPS presents a comprehensive picture of environmental policy enforcement.[15]

The Relative Advantage in Environment-Related Technologies (RAET) index, developed by OECD, measures a country's specialization and competitiveness in environmental innovation compared to the global value. This index essentially captures how much a country leads or lags in the global race for environmental innovation. It is calculated based on the proportion of a country's environment-related inventions to all its inventions, relative to the same ratio globally. An index of one indicates a country's green innovation matches with the global value, while an index above one indicates the country has a relative technological advantage in environment-related technologies. This assessment covers diverse technological domains, such as environmental management and climate change mitigation technologies.

Finally, GHG emissions' tax rate is defined as the ratio of energy tax revenue to unit of GHG emissions. The energy tax revenue is obtained from Eurostat. The base for energy tax is (i) energy products for transport purposes (Unleaded petrol, Leaded petrol, Diesel, Other energy products for transport purposes (e.g., natural gas and fuel oil), (ii) energy products for stationary purposes (light and heavy fuel oil, natural gas, coal, coke, biofuel, electricity

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[11] These GHG emissions arise from various sources: (i) Energy Production: GHGs from the combustion of fossil fuels and other energy generation processes. (ii) Industrial Processes: Emissions from manufacturing activities, such as cement production. (iii) Product use: GHGs released during the use of specific products, like aerosols. (iv) Agriculture: Emissions related to livestock, manure management, fertilizer application, and other agricultural practices. (v) Waste Management: GHGs generated through waste treatment processes, such as emissions from landfills.

[12] GDP is obtained from section annual National Accounts (NAMA_10_GDP) and data on GHG emissions is downloaded from environment and energy section (ENV_AIR_GGE) retrieved April 2021.

[13] https://www.iea.org/subscribe-to-data-services/world-energy-balances-and-statistics.

[14] International Energy Agency (IEA) World Energy Balances includes electricity as a source of energy supply, where electricity presents net of imported and exported electricity from various sources. It is included in the brown energy category since fossil fuels remain the most common source of electricity production.

[15] A high EPS score may directly or indirectly encourage the adoption of more efficient, less polluting operations as they may put explicitly or implicitly price on polluting or environmentally harmful behavior. However, it is crucial to note that the EPS is a measure of policy stringency and not a direct reflection of environmental efficiency or innovation.

consumption and production, district heat consumption and production and other energy products for stationary use), and (iii) GHGs (e.g., the carbon content of fuels, emissions of GHGs including proceeds from emission permits recorded as taxes in the National Accounts (See regulation (EU) No 691/2011 of the European Parliament and of the Council of July 2011 on European environmental economic accounts). GHG emission tax rate can be used as a policy tool to promote EE. A higher GHG emissions' tax rate may incentivize the adoption of cleaner technologies and a transition to less polluting energy sources. This, in turn, can lead to a reduction in emissions and thereby increase long-term EE. The correlation coefficients between EPS index, RAET index, and GHG emission tax rate are presented in Table 1 (below). As one sees, these determinants are not highly correlated. Table 1 in appendix presents the yearly average summary statistics of the sample over the period 2000-2018.

Table 1. Correlation coefficients between the determinants of time-varying EE

	GHG emission tax rate	**ESI**	**RA_ERT**
GHG emission tax rate	1.00		
ESI	0.59	1.00	
RA_ERT	0.07	0.13	1.00

Data source: OECD and Eurostat data.

3. Results

This section presents the estimates of EE scores. Recall that the SF model used in this study is:

$$ln(Y)_{it} = \underbrace{\beta_0 + \sum_{j=1} \beta_j \, ln\, X_{jit} + \; timetrend}_{Frontier} + \mu_i + v_{it} - u_{it}(\boldsymbol{z}_{it})$$

In this section, we present results from various model specifications, each integrating single or combined determinants of EE gaps into the eco-inefficiency component. This allows us to explore how each variable individually, and in combination with others, affect to EE gaps.

4.1. Production frontier and determinants of EE gaps

Table 2 presents the parameter estimates for different models. Models 1-3 each incorporate one of the determinants of EE gaps. Model 4 is estimated including all these three determinants. As models 3 and 4 indicate insignificant impact of RAET on EE gaps[16], we estimate model 5 including only the two statistically significant determinants (our preferred model). EE's elasticities with respect to all inputs are all different from zero except nuclear energy (in Models 4 and 5). Labour has the largest positive impact on EE. EE decreases with brown energy, suggesting that energy use increases emission more than increasing the GDP. The estimate of technical change, at about 1% per year on average, is also statistically significant.

[16] These two regression models are reported in Table 2 in appendix.

Regarding the determinants of EE gaps, the regression results presented in Table 2 reveal that the impacts of policy variables such as the EPS index and GHG emission tax rate on EE gaps are statistically significant. Indeed, our results suggest a positive link between these variables and narrowing EE gaps. However, the RAET index does not seem to have a statistically significant impact on EE gaps across different models. This suggests that the RAET index may not accurately capture the adaption of environmentally friendly technologies, leading to its inconclusive impact on improvements of EE gaps.

Table 2 below summarizes the sample average EE scores spanning the years from 2000 to 2018 across several model specifications. As mentioned earlier, EE scores are quantified on a scale from zero to one, where a score of one represents an eco-efficient country that optimally balances GDP maximization with the reduction of GHG emissions, thereby decreasing environmental damage.

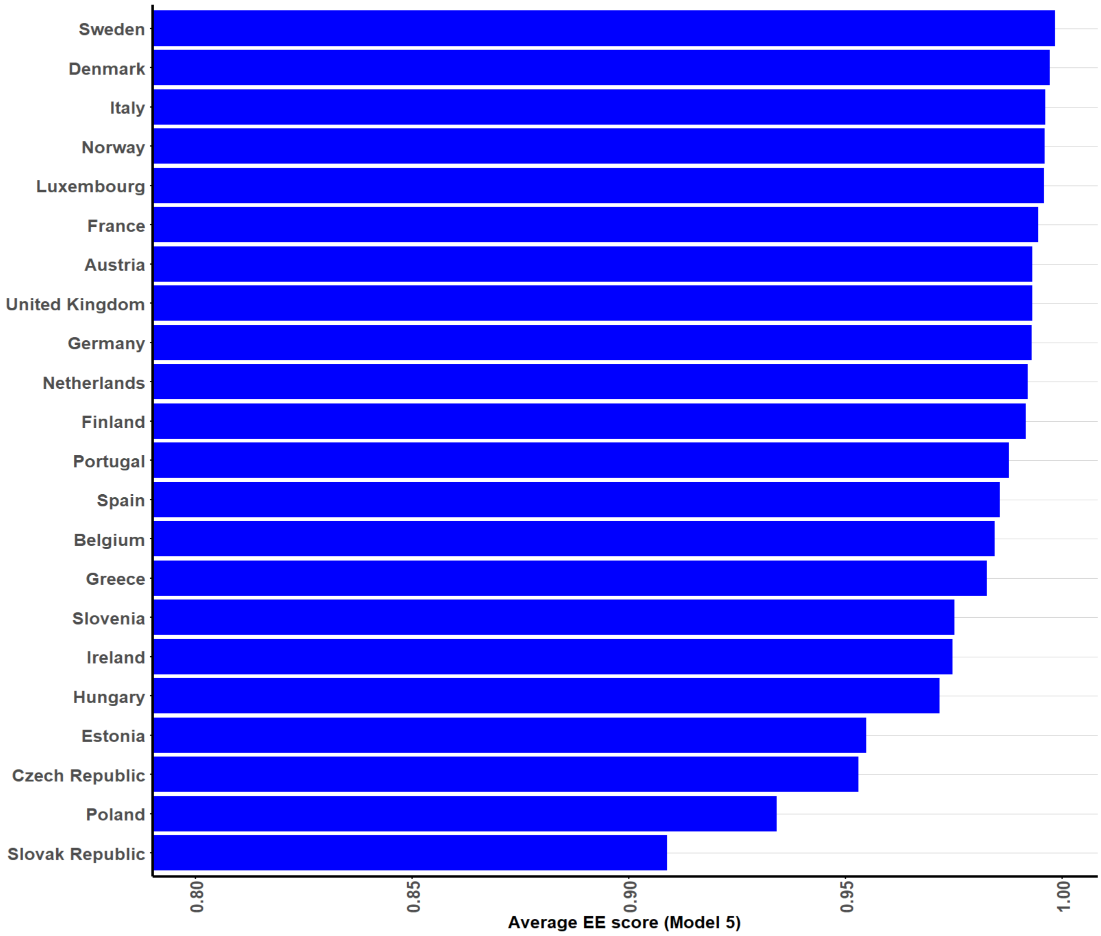
Table 2. Production frontier and determinants of EE gaps

	Model1	Model2	Model3	Model4	Model5
Dependent variable	EE	EE	EE	EE	EE
Frontier					
Ln Nuclear energy	0.046*	0.050*	0.083***	0.036	0.036
	(0.026)	(0.027)	(0.028)	(0.026)	(0.026)
Ln Renewable energy	0.071***	0.071***	0.084***	0.068***	0.068***
	(0.014)	(0.015)	(0.016)	(0.014)	(0.014)
Ln Brown energy	-0.410***	-0.414***	-0.359***	-0.431***	-0.432***
	(0.033)	(0.034)	(0.038)	(0.033)	(0.033)
Ln Labour	0.618***	0.590***	0.590***	0.641***	0.641***
	(0.056)	(0.058)	(0.070)	(0.055)	(0.055)
Ln Capital	0.036*	0.076***	0.046*	0.050**	0.049**
	(0.019)	(0.021)	(0.027)	(0.019)	(0.019)
Time trend	0.013***	0.012***	0.016***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Intercept	-5.069***	-5.151***	-5.307***	-5.404***	-5.392***
	(0.768)	(0.813)	(0.937)	(0.772)	(0.770)
Determinants for EE gaps					
ln (GHG emission tax rate)	-3.612***			-3.181***	-3.176***
	(0.557)			(0.550)	(0.550)
ln (ESI)		-3.382***		-2.024***	-1.984***
		(0.596)		(0.645)	(0.626)
ln (RA_ERT)			-0.097	0.127	
			(0.278)	(0.443)	
Intercept	-19.847***	-3.181***	-5.553***	-17.055***	-17.040***
	(2.398)	(0.360)	(0.424)	(2.321)	(2.324)
Number of observations	418	418	418	418	418
Number of countries	22	22	22	22	22
Mean of EE	0.978	0.963	0.953	0.980	0.980
Log likelihood	670.11	647.57	618.45	675.53	675.49

Standard errors are reported in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$. The dependent variable is eco-efficiency (EE) expressed in natural log. GHG emissions tax rate is defined as the energy tax revenue per unit of emission. ESI is the environmental policy stringency index. RA_ERT is relative advantage in environment-related technologies index. Source: Results of authors' analysis based on data from OECD, Eurostat, Penn World Table, and the International Energy Agency.

Figure 1 provides a breakdown by country of the average EE scores for the period 2000-2018, ordering the countries from the most eco-efficient (highest scores) at the top to the least. This ranking illustrates that countries lower on the graph have more opportunities to enhance their EE gap. It is important to note that while full EE may not have been achieved by all, there is a trend towards the efficiency frontier. Many countries are approaching this boundary, reflecting a general advancement towards greater EE over the observed period.

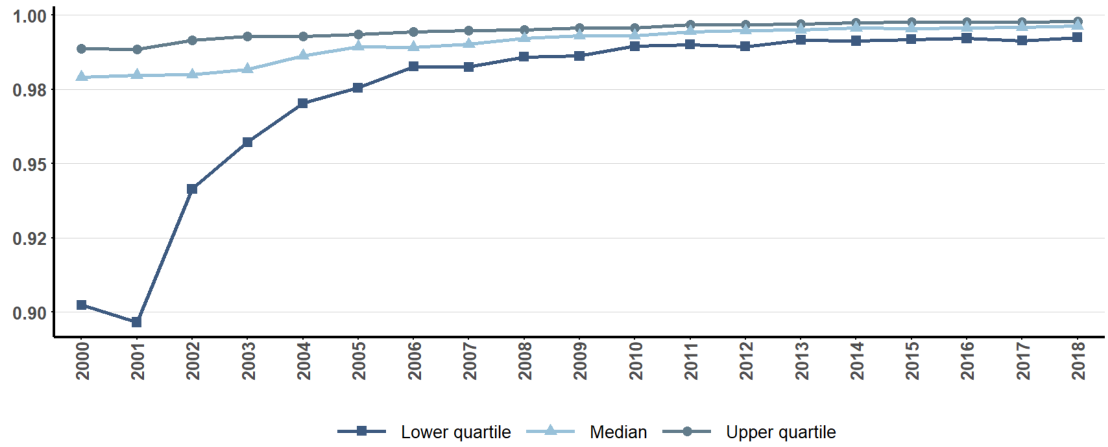
Figure 1. Country ranking of EE scores (2000-2018)



Note: Values present the average eco-efficiency (EE) scores by country from 2000 to 2018. Data source: Results of authors' analysis based on data from OECD, Eurostat, Penn World Table, and the International Energy Agency.

Figure 2 below illustrates the evolution of EE scores from 2000 to 2018, featuring the first and third quartiles along with the median yearly scores from model 5 for each year across the sampled countries. This figure shows that the gap between the quartiles is narrowing, suggesting a trend toward convergence in EE. Countries previously lagging in efficiency are making gains and approaching the performance of their more efficient counterparts, signaling a collective advancement toward improved EE within the sample.

Figure 2. EE score trends from Model 5 (2000-2018)



Note: The values represent the first and third quartiles, along with the median yearly eco-efficiency (EE) scores for each year from 2000 to 2018 across the sampled countries. Data source: Results of authors' analysis based on data from OECD, Eurostat, Penn World Table, and the International Energy Agency.

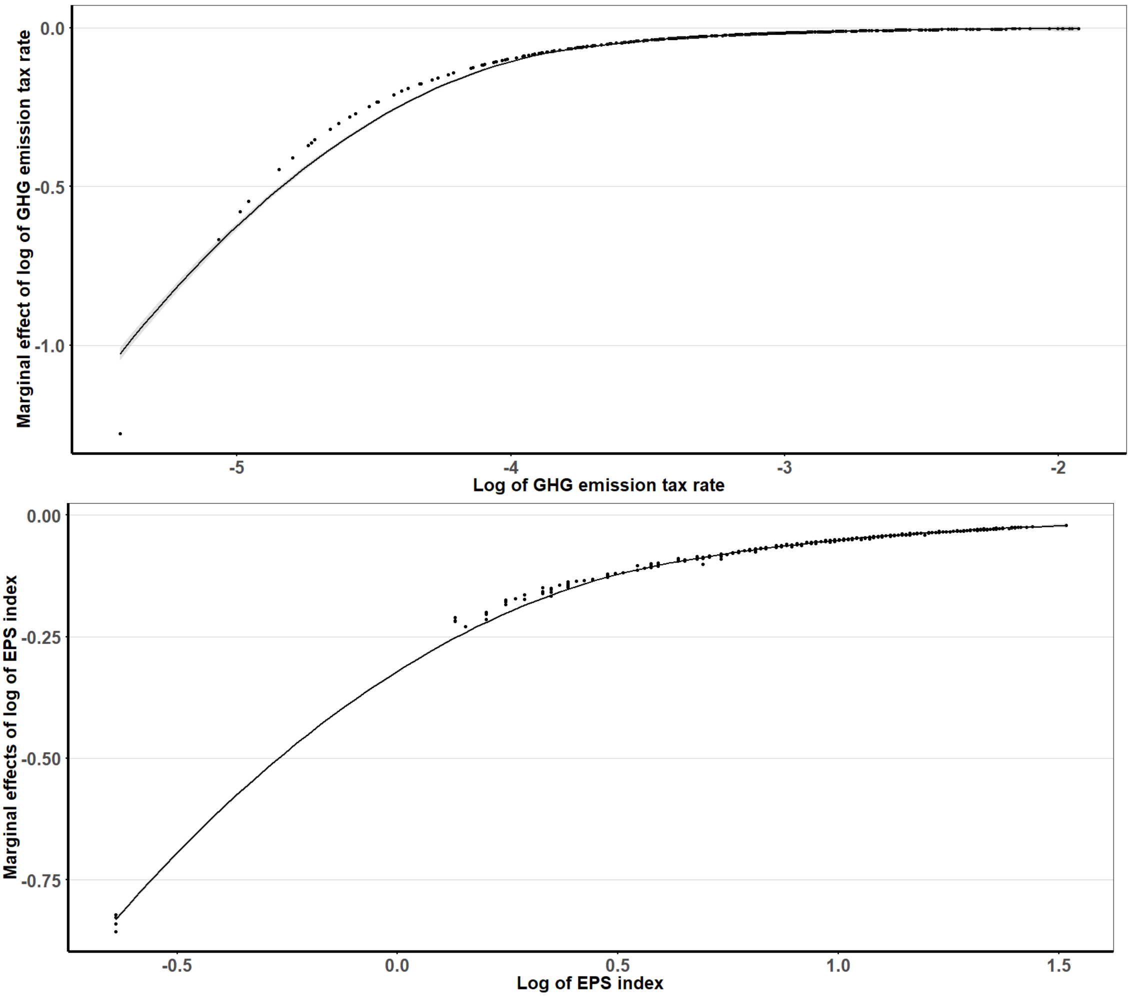
Figure 1 in appendix provides a historical progression of the EE scores for the countries that rank at the bottom in Figure 1. Over time, countries such as Sweden, Denmark, Italy, Norway, and Luxembourg have demonstrated high levels of EE. Luxembourg's high EE could potentially be explained by its service-based economy, in which services contribute significantly more to output than manufacturing (Peroni et al., 2024). Since the service sector generally generates lower emissions than manufacturing, this result is plausible. However, our econometric model accounts for this structural characteristic through country fixed effects and controls for the composition of energy sources used in production. Conversely, the Slovak Republic, Poland, and the Czech Republic have ranked among the less eco-efficient countries. To a certain extent, these patterns are consistent with the study by Robaina-Alves et al. (2015), who found that the Czech Republic, Poland, and Estonia were the least eco-efficient countries, while Sweden, Latvia, the UK, Hungary, and Portugal were among the most eco-efficient from 2005 to 2011.

4.2. Marginal effects of determinants of EE gaps

The findings presented in Table 2 show the statistically significant impacts of EPS and GHG emission tax rate on explaining EE gaps across countries. Thus, we assess whether the marginal impact of changes in these factors on EE gaps varies based on their magnitude.[17] Figure 3 below illustrates that increases in GHG emission tax rate and the EPS index initially improve EE gaps, but the efficiency gains tend to decrease at higher levels of these variables. In other words, the efficiency gains from increasing these factors decrease as their magnitude increases.

[17] It is important to acknowledge that the determinants of EE gaps exhibit non-linear relationships with the expected values of inefficiencies. Therefore, the slope coefficients of this variable does not directly correspond to its marginal effect.

Figure 3. Marginal effects



Note: The plot shows, respectively, the marginal effect of GHG emission tax rate and ESP index on EE gaps. The continuous line represents a trend smoothed by Locally Estimated Scatterplot Smoothing, highlighting the overall pattern. Data source: Results of authors' analysis based on data from OECD, Eurostat, Penn World Table, and the International Energy Agency.

4.3. Quantifying potential for carbon saving

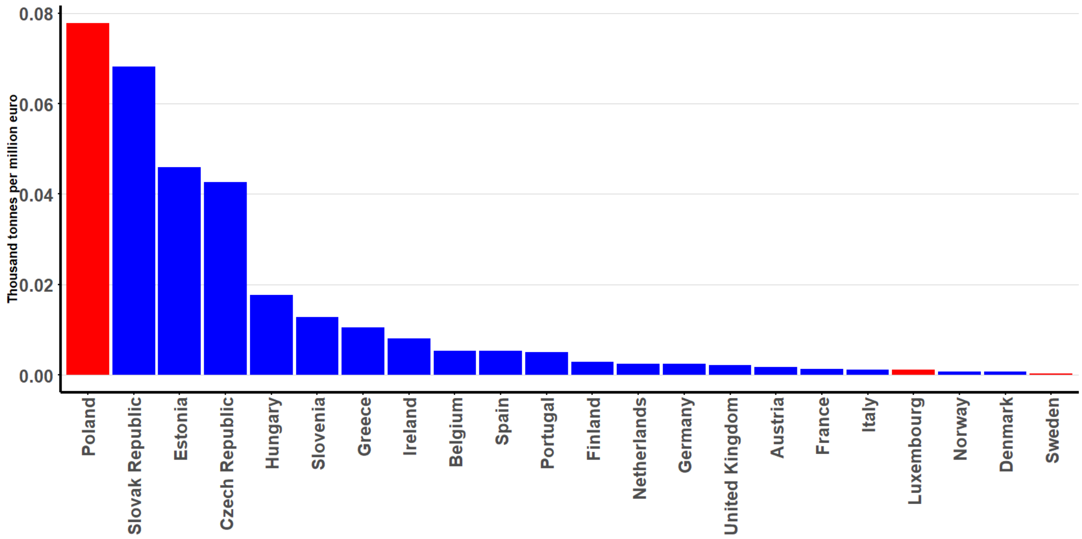
This section calculates potential carbon savings in terms of reduced CO2 equivalent GHG emissions by addressing EE gaps. We assess this potential using two measures: 1) savings for every million euros of GDP, showing the efficiency of emission reductions relative to each unit of economic output, and 2) aggregate savings, which present the total reduction in emissions across different countries, corresponding to the total GDP.

Figure 4 below displays the potential yearly average carbon saving per million euro of GDP across countries from 2000 to 2018. This potential is calculated using the average EE gap and the yearly average carbon intensity for each country, expressed as CO2 equivalent GHG emissions per million euro of GDP. The formula is written as:

$$\text{Yearly average potential carbon saving} = \text{Yearly average carbon intensity} \times (\text{Average EE gap})$$

The data in Figure 4 ranks countries based on their potential for carbon savings, from highest to lowest. Poland has the highest potential for yearly carbon savings per million euro of GDP, approximately 0.08 thousand tonnes. It is followed by the Slovak Republic, Estonia, and the Czech Republic. On the other hand, countries like Sweden, Denmark, Norway, Luxembourg, and Italy show minimal potential for equivalent carbon savings. For Luxembourg specifically, the figure suggests a very small saving (well below 0.01 thousand tonnes per million euro), which is consistent with its service-dominated, already low-carbon economy.

Figure 4. Average annual potential for carbon savings per GDP unit



Note: Values present the average annual potential carbon saving in terms of CO2 equivalent GHG emissions savings (in thousands tonnes) per million Euro of GDP achievable through the elimination of EE gaps. These averages are calculated over the period from 2000 to 2018. Y-Axis presents carbon savings measured in Tonnes per Million of GDP. Data source: Results of authors' analysis based on data from OECD, Eurostat, Penn World Table, and the International Energy Agency.

Figures 5 and 6 illustrate the potential annual carbon savings (in total) each country could achieve by completely eliminating their EE gaps, presented in million tonnes and as a percentage of their average annual emissions, respectively.

To compile this data in Figure 5, the potential carbon savings for each country are first calculated by considering their respective EE gaps and total yearly GHG emissions. The formula used is:

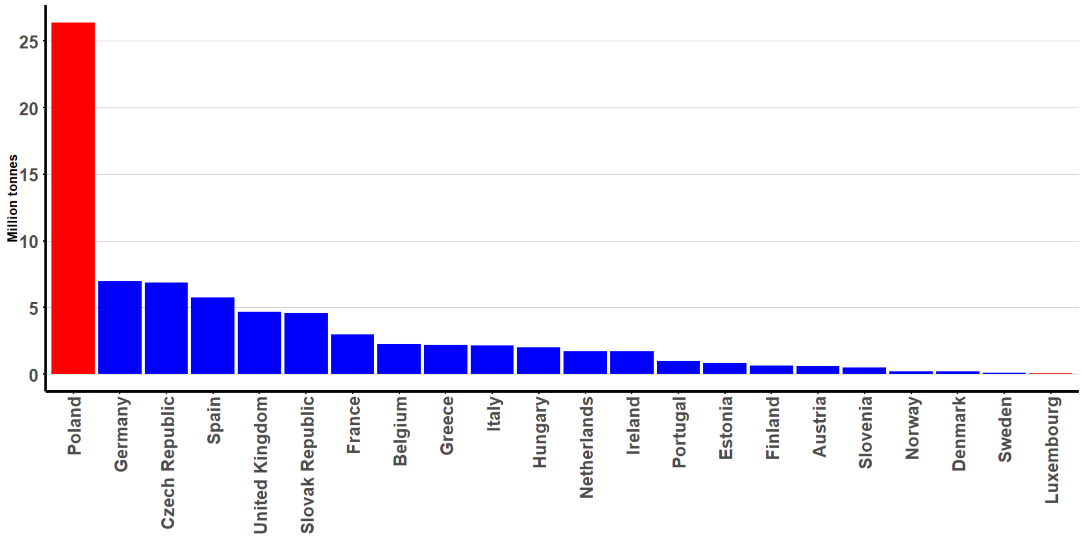
$$\text{Yearly average potential carbon saving} = Average\ (\text{CO2 equivalent GHG emissions} \times \text{EE gap})$$

Figure 5 below reveals a significant variation in potential CO2 equivalent GHG savings across different countries. Poland stands out with the highest potential for environmental improvements and emissions reductions through addressing its substantial EE gap, followed by Germany and the Czech Republic.[18] Research suggests that annual savings on CO2

[18] This likely results from a combination of relatively higher EE gap GHG emissions.

equivalent GHG emissions could average around 75 million tonnes. To illustrate the scale of these savings, according to the United States Environmental Protection Agency's energy calculator, this amount is equivalent to eliminating CO2 emissions from the annual energy consumption of over 9.7 million homes, or more than 8 years of total household energy use in Paris as of 2019, assuming one household per house according to data from statista.com. It is important to note that while these calculations highlight direct carbon savings, they do not account for indirect cost savings or the positive externalities related to reduced air pollution-related illnesses and mortality or the overall improved well-being of the population. A more comprehensive assessment of GHG emission reduction would incorporate these broader impacts, although they are beyond the scope of this current analysis.

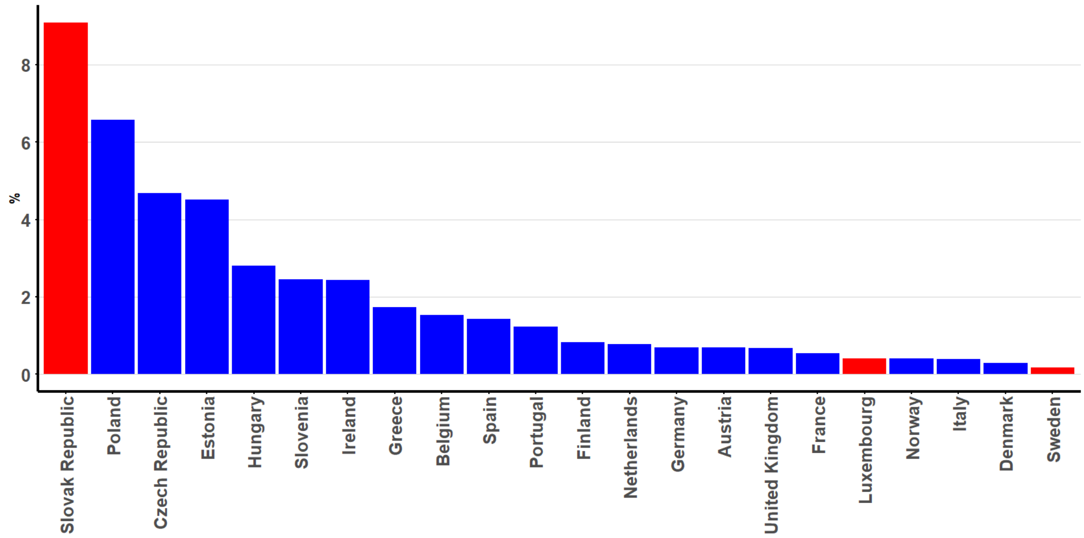
Figure 5. Average annual total potential for carbon saving



Note: Values present the average annual potential carbon saving in terms of CO2 equivalent GHG emissions savings (in thousands tonnes) achievable through the elimination of EE gaps by country. These averages are calculated over the period from 2000 to 2018. Y-Axis presents carbon savings measured in Million Tonnes. Data source: Results of authors' analysis based on data from OECD, Eurostat, Penn World Table, and the International Energy Agency.

Finally, Figure 6 presents the potential savings as a share of each country's total emissions if all EE gaps were eliminated. It identifies the Slovak Republic as the leader in percentage terms of average annual emission savings, followed by Poland and the Czech Republic. In contrast, Sweden, Denmark, Italy, Norway, and Luxembourg have the lowest potential for savings when viewed as a percentage of their average annual emissions. For Luxembourg, the forecast saving represents only a fraction of one percent of its current annual emissions—among the lowest in the sample. This limited saving reflects the country's service-oriented economy and the fact that many EE gains have already been captured.

Figure 6. Average annual GHG emissions savings potential by country



Note: Values represent the average annual potential carbon saving in terms of CO2 equivalent GHG emissions savings achievable by eliminating EE gaps by country, measured as a percentage of the country's total emissions. These averages are calculated over the period from 2000 to 2018. Data source: Results of authors' analysis based on data from OECD, Eurostat, Penn World Table, and the International Energy Agency.

5. Conclusions

While Gross Domestic Product (GDP) is a widely used measure of economic performance, it fails to account for the environmental impacts of production, such as emmissions of greenhouse gasses (GHG). By focusing on eco-efficiency (EE), a measure of economic performance that includes GHG emmissions, we assess how 22 European countries balance production and environmental costs. Countries that maximize their economic output per unit of GHG emitted are considered eco-efficient. Deviation from this maximum level of output per unit of GHG represents EE gap or eco-inefficiency, which we estimated using Greene's true fixed-effect stochastic frontier model (Greene, 2005).

The results highlight varying levels of EE across countries. The average EE scores, calculated over the period from 2000 to 2018, ranged from 0.91 to 0.99 across the 22 countries. Sweden, Denmark, Italy, Norway, and Luxembourg were generally ranked as the most eco-efficient countries. In contrast, the Slovak Republic, Poland, and the Czech Republic ranked as the least eco-efficient counties. Luxembourg's strong performance may reflect its service-based economic structure, which tends to produce lower emissions. However, this factor is accounted for in the analysis through country fixed effects and controls for energy mix.

We also analysed which factors explain variations in EE gaps across countries. More precisely, countries with higher energy tax revenue or a higher Environmental Policy Stringency (EPS) index have lower EE gaps. However, the positive impact of these factors on EE declines as their levels increase, indicating factors' diminishing returns in efficiency gains.

Finally, we calculated potential carbon savings (i.e. CO2 equivalent GHG emissions savings) from elimination of EE gaps. The largest savings stem from closing EE gaps in Poland, Germany and the Czech Republic. Environmental gains from closing all eco-efficiency gaps could lead to a reduction in carbon emissions by 75 million metric tonnes.As a final note, for Luxembourg—a service-based economy—our analysis currently presents results for all sectors; however, Luxembourg is predominantly services-oriented. Conducting the analysis at the industry level with a focus on services would therefore yield more relevant insights into the effectiveness of policies aimed at improving EE. Because the service sector relies less on emissions-intensive inputs and more on labour and digital infrastructure, the impact of specific policy measures on EE can differ from those in energy-intensive sectors such as manufacturing. Accordingly, further work could concentrate on the service sector alone to capture the effects of policy measures on EE gains, thereby allowing the results to more accurately reflect Luxembourg's economic structure.

References

Badunenko, O., Kumbhakar, S.C., (2017), "Economies of scale, technical change and persistent and time-varying cost efficiency in Indian banking: do ownership, regulation and heterogeneity matter?", *European Journal of Operational Research*, vol.260, pp. 789–803.

Greene, W. H. (2005), "Fixed and Random Effects in Stochastic Frontier Models", *Journal of Productivity Analysis*, vol. 23, pp. 7–32.

International Energy Agency (2017), "Tracking Clean Energy Progress 2017, Energy Technology Perspectives 2017, Excerpt Informing Energy Sector Transformation", [Online], Available from:https://www.ourenergypolicy.org/wp-content/uploads/2017/05/TrackingCleanEnergyProgress2017.pdf [Accessed 10 July 2020].

Jondrow, J., Lovell, C. A. K., Materov, I. S. and Schmidt, P. (1982), "On the estimation of technical inefficiency in the stochastic frontier production function model", *Journal of Econometrics*, vol.19, pp. 233 – 238.

Kaya, Y., and Yokobori, K. (1993), "Environment, Energy, and economy: Strategies for sustainability", United Nations University Press. Conference Title: 'Global environment, energy, and economic development' held at the United Nations University25-27 October 1993. Available at :https://archive.unu.edu/unupress/unupbooks/uu17ee/uu17ee00.htm

Kumbhakar, S. C. and Lovell, C. A. K. (2000), "Stochastic Frontier Analysis", Cambridge: Cambridge University Press.

Kumbhakar, S., Wang, H. J. and Horncastle, A. (2015), "A Practitioner's Guide to Stochastic Frontier Analysis Using Stata", New York, NY: Cambridge University Press.

Kumbhakar, S., Badunenko, O., Willox, M. (2022), "Do carbon taxes affect economic and environmental efficiency? The case of British Columbia's manufacturing plants", *Energy Economics*, Vol.115, 106359.

Kutlu, L., Tran, K. C., and Tsionas, M. G. (2019), "A time-varying true individual effects model with endogenous regressors", *Journal of Econometrics*, vol. 211(2), pp. 539-559.

Lee, P., and Park, Y. J. (2017), “Eco-efficiency evaluation considering environmental stringency”, *Sustainability*, 9(4), 661.

Liang, Wan., Biao, Luo., Tieshan Li., Shanyong and Wang., Liang Liang. (2015), “Effects of technological innovation on eco-efficiency of industrial enterprises in China”, *Nankai Business Review International*, vol. 6(3), pp. 226–239.

Pan, J. (2022), “Climate Change Economics: Perspectives from China”, *Springer Nature*. ISBN 978-981-19-0220-8.

Peroni, C., DiMaria C-H. & Amjadi, G. (2024). LuxKLEMS revisited: Productivity trends and drivers in Luxembourg. Rapport annuel 2024-2025. Conseil National de la Productivité, Luxembourg.

Robaina-Alves, M., Moutinho, V., Macedo, P. (2015), “A new frontier approach to model the eco-efficiency in European countries”, *Journal of Cleaner Production*, vol. 103, pp. 562–573.

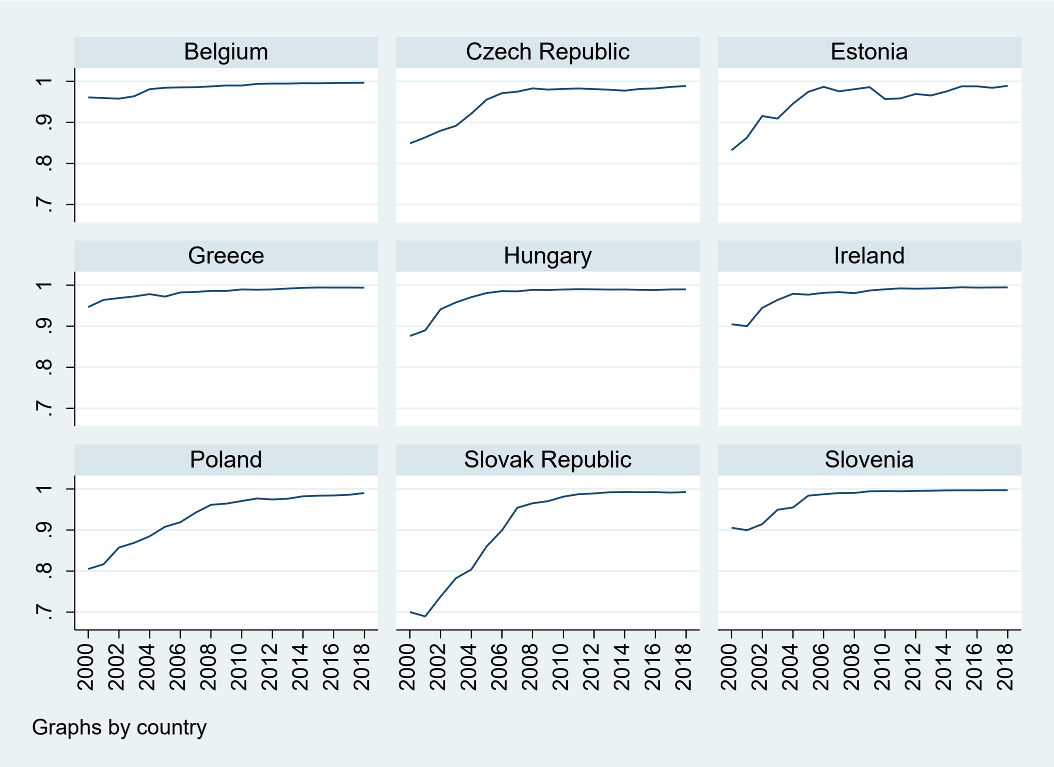
Safitri, V.A., Sari, L. and Gamayuni, R.R. (2020), “Research and Development (R&D), Environmental Investments, to Eco-Efficiency, and Firm Value”, *The Indonesian Journal of Accounting Research*, 22(3).

Wang, Y., Liu, J., Hansson, L., Zhang, K. and Wang, R., (2011), “Implementing stricter environmental regulation to enhance eco-efficiency and sustainability: a case study of Shandong Province’s pulp and paper industry, China”, *Journal of cleaner production*, vol.19(4), pp.303-310.

World Business Council for Sustainable Development (2006), “eco-efficiency LEARNING MODULE” [Online]. Available from:
https://docs.wbcsd.org/2006/08/EfficiencyLearningModule.pdf [Accessed 04 MAy 2021].

Appendix

Figure 1. EE by country (2000- 2018)



Data source: Results of authors' analysis based on data from OECD, Eurostat, Penn World Table, and the International Energy Agency.

Table 1. Descriptive statistics: Averages (2000–2018)

Country	GDP	GHG	GDP/GHG	Labour	Capital	Nuclear Energy	Renewable Energy	Brown Energy	ETax	ETax/GHG	RA_ERT	EPS
Austria	333112	85767	3.9	4070900	2133086	.05	8974	23546	4600	.054	1.18	2.64
Belgium	398215	137304	2.95	4454119	2516599	11315	2953	41924	5699	.0429	.903	2.51
Czech Republic	159862	141776	1.14	5097367	1893509	6695	3202	33765	2837	.0203	1.12	2.62
Denmark	264931	64826	4.21	2824363	1189636	.05	4009	14321	5637	.0898	1.58	3.34
Estonia	19537	19581	.996	622766	142943	.05	773	4667	337	.017	1.11	3.06
Finland	208377	70841	3.01	2483804	906125	5992	9355	19352	3479	.0511	1.08	3.17
France	2103019	525284	4.04	2.69e+07	1.33e+07	111922	20582	126470	32063	.0622	1.05	3.31
Germany	2899863	984220	2.97	4.08e+07	1.59e+07	33781	30178	261608	47606	.0486	1.22	2.85
Greece	199697	120165	1.67	4435887	2162222	.05	2111	24871	3776	.0334	1.14	2.24
Hungary	109633	68170	1.63	4158553	998076	3846	2238	19862	1884	.0282	.946	2.75
Ireland	209005	66286	3.19	1935045	949355	.05	698	13280	2405	.0369	.618	2.3
Italy	1736583	521160	3.37	2.46e+07	1.49e+07	.05	20270	148184	38530	.0763	.897	3.06
Luxembourg	48085	12626	3.83	348725	185736	.05	163	3795	836	.0662	1.26	3.06
Netherlands	666916	216305	3.1	8706847	3537663	1011	3576	72261	11168	.0521	.869	2.79
Norway	315483	55967	5.64	2527719	1144347	.05	12766	15894	4135	.074	1.11	3.05
Poland	356209	405030	.879	1.50e+07	1900835	.05	6851	88951	7348	.0181	1.2	2.35
Portugal	188479	76858	2.47	4916396	2289062	.05	4739	19004	3088	.0406	1.22	2.35
Slovak Republic	66542	46973	1.45	2203094	554747	4228	1214	12180	1194	.0264	1.23	2.18
Slovenia	37610	19247	1.97	955429	381536	1479	972	4567	969	.0514	.678	2.11
Spain	1060793	391396	2.74	1.88e+07	8456963	15411	12887	99819	14481	.0377	1.06	2.25
Sweden	406530	63662	6.51	4571558	2086103	16898	16584	15932	7430	.118	.972	3.28
United Kingdom	2084791	643152	3.34	2.97e+07	1.12e+07	19017	8687	174470	37481	.0599	.939	2.69

Note: Units of measurement for variables are as follows: GDP in M€ (Million Euros), GHG in Kt (Kilotons), Labour in No. (Number), Capital in M€ (Million Euros), Nuclear Energy, Renewable Energy, and Brown Energy in Mtoe (Million Tons of Oil Equivalent), ETax in M€ (Million Euros), ETax/GHG in M€/kt (Million Euros per Kiloton). RA_ERT and EPS are indices. Data source: OECD, Eurostat data, Penn World, and International Energy Agency.

Table 2. Production frontier and determinants of EE gaps

	Model6	Model7
Dependent variable	EE	EE
Frontier		
Ln Nuclear energy	0.046* (0.026)	0.050* (0.027)
Ln Renewable energy	0.071*** (0.014)	0.071*** (0.015)
Ln Brown energy	-0.410*** (0.033)	-0.416*** (0.034)
Ln Labour	0.618*** (0.056)	0.590*** (0.058)
Ln Capital	0.036* (0.019)	0.077*** (0.021)
Time trend	0.013*** (0.001)	0.012*** (0.001)
Intercept	-5.069*** (0.770)	-5.142*** (0.813)
Determinants for EE gaps		
$\boldsymbol{ln}(\textbf{GHG emission tax rate})$	-3.612*** (0.560)	
$\boldsymbol{ln}(\boldsymbol{ESI})$		-3.365*** (0.592)
$\boldsymbol{ln}(\boldsymbol{RA\_ERT})$	-0.002 (0.456)	-0.151 (0.293)
Intercept	-19.845*** (2.424)	-3.167*** (0.359)
No. Observations	418	418
No. Countries	22	22
Mean of EE	0.978	0.963
Log likelihood	670.11	647.70

Note: Standard errors are reported in parentheses.* p<0.10, ** p<0.05, *** p<0.01. Dependent variable eco-efficiency (EE) is in natural log. GHG emission tax rate is defined as the energy tax revenue per unit of emission. ESI is the environmental policy stringency index. RA_ERT is relative advantage in environment-related technologies index. Data source: Results of authors' analysis based on data from OECD, Eurostat, Penn World Table, and the International Energy Agency.