Towards the green transition in the European regions. Assessing eco-efficiency in greenhouse gas emissions

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Abstract

Purpose – This paper aims to assess eco-efficiency in greenhouse gas (GHG) emissions, which are a major driver of global warming, across European Union regions and examine its determinants.

Design/methodology/approach – In line with the European Green Deal's (EGD) green transition objectives, eco-efficiency is evaluated as the potential of regions to reduce GHG emissions while maintaining gross domestic product (GDP). Data envelopment analysis, truncated regression and bootstrapping techniques are used to ensure robust and reliable results.

Findings – Nordic and Western regions rank among the most eco-efficient, whereas Central and Eastern regions lag behind. Innovation capacity, capital city status, institutional quality (quality of government and social capital) and population size contribute to higher eco-efficiency, whereas large industrial sectors hinder progress towards the green transition.

Practical implications – The green transition requires place-based policies that promote technological upgrading, industrial diversification and innovation to achieve emission reductions compatible with sustained economic growth. Strengthening governance quality and social capital can further improve policy outcomes and long-term eco-efficiency.

Originality/value – Eco-efficiency is assessed at the regional level using GHG emissions as an indicator of ecological performance, in keeping with the territorial focus and policy objectives of the EGD. A second-stage analysis is conducted to identify the factors that drive regional eco-efficiency.

Keywords Eco-efficiency, European Green Deal, European Union, Greenhouse gas emissions, Green transition, European regions

Paper type Research paper

1. Introduction, motivation and background

Accelerated global warming and environmental degradation caused by human activities have heightened social concern in recent decades. The 2015 Paris Agreement, signed by 196 countries, aims to limit global warming to below 2°C above pre-industrial levels by 2050. The European Union (EU) roadmap towards the green transition, outlined in the European Green Deal (EGD), seeks to reduce greenhouse gas (GHG) emissions – the main driver of

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global warming – by 55% by 2030 (relative to 1990) and reach carbon neutrality by 2050. Achieving these goals requires ambitious climate policies across Member States (European Commission, 2020), supported by roughly €600bn from the Next Generation EU recovery plan and the EU's seven-year budget (Maucorps *et al.*, 2023).

A successful green transition is also closely linked to economic activity (O'Donovan, 2024). Green growth aims to make production more resource-efficient, cleaner and more resilient without hindering economic development (Cheba *et al.*, 2022). However, the EU exhibits substantial regional disparities in ecological performance and economic dynamism, and not all regions face the same environmental urgency or level of readiness for reform. This means that the impacts of the transition will vary widely (Rodríguez-Pose and Bartalucci, 2024). Moreover, the shift towards a low-carbon economy will reshape industrial structures and consumption patterns, posing major challenges for areas dependent on carbon-intensive sectors such as coal, fossil fuels, steel and cement (Maucorps *et al.*, 2023).

The immediacy of the green transition, along with policymakers' growing demand for empirical evidence to inform the design of more effective environmental policies, has recently stimulated academic research in the European regional context, traditionally understudied. In this regard, Peiró-Palomino *et al.* (2025) report a positive relationship between regional air quality and social capital, while Grashof and Basilico (2025) demonstrate that technological specialization influences green diversification. Other recent regional-level studies have focused on the impacts of climate change by developing indicators of environmental well-being and investigating their determinants (Vaccaro *et al.*, 2025).

Accurate measurement is therefore essential for a successful green transition; without reliable information on regional performance, resources for environmental action cannot be allocated efficiently. Eco-efficiency indicators address this need by providing clear and accessible metrics for both policymakers and practitioners. Broadly speaking, eco-efficiency refers to the capacity to produce more goods and services while consuming fewer natural resources and reducing environmental impacts, thereby integrating both economic and ecological performance (OECD, 1998; UN, 2009).

Eco-efficiency has been widely studied at the national level. Previous research has primarily focused on developed economies, examining the determinants of eco-efficiency and its convergence patterns. For instance, Camarero *et al.* (2014) find evidence of convergence clubs across OECD countries, indicating persistent heterogeneity between core and peripheral EU countries. Peiró-Palomino and Picazo-Tadeo (2019) highlight the role of economic development in explaining cross-country differences, showing that higher income levels are associated with improved eco-efficiency. Sectoral analyses have also been conducted. Pishgar-Komleh *et al.* (2021), focusing on agriculture, report substantial inefficiencies linked to input overuse and emphasize the importance of technological improvements to enhance sustainability. In the energy sector, Tenente *et al.* (2020) find notable disparities in eco-efficiency across electricity generation systems, largely driven by differences in energy mix and the adoption of cleaner technologies. By contrast, regional-level studies remain scarce due to data limitations, an issue now addressed by emerging data sources such as the Emissions Database for Global Atmospheric Research (EDGAR), which is used in this study.

While the empirical literature on eco-efficiency at the regional level remains limited, closely related strands provide useful insights into its potential drivers. In this regard, a large body of work on urban economics highlights how agglomeration economies, higher human capital and knowledge spillovers enhance productivity and technological adoption, which may translate into lower environmental impact (Duranton and Puga, 2004; Glaeser, 2011). Moreover, studies on environmental governance emphasize the role of institutional capacity and policy enforcement in shaping environmental outcomes, often finding that subnational variation in governance quality is a key determinant of ecological performance (Fredriksson and Millimet, 2002; Damania *et al.*, 2003). Lastly, the literature on green growth and innovation shows that technological change and structural transformation towards services contribute to decoupling economic activity from emissions (OECD, 2011; Aghion *et al.*, 2016). By bringing these perspectives together, this paper helps bridge the gap between the literature on regional economic performance and eco-efficiency.

This paper applies data envelopment analysis (DEA) to construct an eco-efficiency indicator based on GHG emissions for 231 EU regions in 2023. It makes three main contributions. First, it updates regional analysis beyond studies such as Bianchi *et al.* (2020), whose data ended in 2014 and relied on non-environmental inputs; and Peiró-Palomino *et al.* (2025), who focused primarily on air quality. In doing so, it addresses an important gap in the literature, as most existing evidence on eco-efficiency remains concentrated at the national or sectoral level, potentially overlooking substantial within-country heterogeneity in environmental and economic performance. Second, drawing on EDGAR data, it assesses regional eco-efficiency based on GHG emissions, thereby aligning more closely with the objectives of the EGD and extending previous country-level GHG-based analyses (Picazo-Tadeo *et al.*, 2014). This approach provides a more policy-relevant measure of environmental performance, directly linked to climate change mitigation targets. Third, in a second-stage analysis, it examines the determinants of eco-efficiency, focusing on the role of economic, demographic and institutional factors as potential drivers.

The results reveal substantial regional disparities in eco-efficiency across the EU, contrasting with a growing body of studies that focus exclusively on ecological performance while abstracting from economic outcomes. For instance, several contributions construct indicators of environmental quality based on measures such as air pollution concentrations, carbon emissions or broader environmental indices, and analyse their determinants across regions (e.g. Peiró-Palomino *et al.*, 2025; Vaccaro *et al.*, 2025). While these approaches provide valuable insights into the spatial distribution of environmental conditions, they fail to account for the level of economic activity that generates environmental pressures. As a result, regions with low emissions or better environmental indicators may appear to perform well, even if this reflects lower levels of production rather than more environmentally efficient use of resources. By contrast, the eco-efficiency framework adopted in this paper explicitly incorporates economic performance together with environmental pressures, thereby capturing the ability of regions to decouple economic activity from environmental impact. This distinction is crucial for policy purposes, as it allows identifying regions that achieve both high economic output and low environmental intensity, rather than simply low levels of pollution. In particular, Nordic and Western regions generally achieve the highest levels of performance, whereas Central and Eastern regions tend to lag behind. Moreover, pronounced intra-country variation highlights the importance of subnational analysis for effective policy design. The second-stage results indicate that innovation capacity, capital city status, larger population size and stronger institutional frameworks enhance eco-efficiency, whereas a larger industrial base exerts a negative effect.

Following this introduction, Section 2 outlines the empirical framework; Section 3 presents the eco-efficiency results; Section 4 examines their determinants; and Section 5 concludes with policy recommendations.

2. Empirical framework

2.1 Data, sample and sources

The data set comprises 231 NUTS2-level EU regions [1], which serves as the standard territorial unit for implementing major regional policies, including the European Cohesion Policy. Eco-efficiency is evaluated using regional gross domestic product (GDP) as a proxy for economic performance; GDP is expressed in constant € (2015 prices) and calculated as the average for the years 2021–2023, based on Eurostat data [2]. The use of a three-year average mitigates potential distortions arising from outliers or measurement errors, thereby enhancing the robustness and reliability of the analysis.

Ecological performance is proxied by regions' GHG emissions, encompassing fossil carbon dioxide (CO2) that is the most widespread GHG released from fossil fuel combustion (coal, oil and gas), deforestation and industrial processes; methane (CH4) from agriculture (notably livestock), landfills, and fossil fuel extraction; nitrous oxide (N2O) from agricultural fertilizers, fossil fuel combustion and certain industrial processes; and fluorinated gases (Fgases), synthetic compounds used in refrigeration, air conditioning, electronics manufacturing and industrial applications. Emissions of CH4, N2O and Fgases are expressed in CO2-equivalents using global warming potential values from the Intergovernmental Panel on Climate Change Fifth Assessment Report (IPCC-AR5). The data are also three-year averages (2021–2023) sourced from EDGAR [3]. The emission estimates cover six sectors, including agriculture, buildings, energy, industry, transport and waste [4]. Detailed sectoral activities and methodological procedures are provided in Crippa *et al.* (2024).

The variables used in the second stage to examine the determinants of eco-efficiency include economic, demographic and institutional factors, as well as geographical location, which is included as a control variable. Table 1 provides a description of GDP, GHG emissions and the second-stage variables, along with their sources. Table 2 presents selected descriptive statistics.

2.2 Methodology

2.2.1 The assessment of eco-efficiency with data envelopment analysis. This research adopts the formal definition of eco-efficiency proposed by Kuosmanen and Kortelainen (2005), as the ratio between an indicator of economic performance – measured by GDP – and an indicator of ecological performance – proxied by a composite indicator of GHG emissions, including CO2, CH4, N2O and Fgases. Formally:

$$\text{Ecoefficiency} = \frac{\text{Economic performance}}{\text{Ecological performance}}$$

$$= \frac{\text{GDP}}{\left(w_{CO2}CO2 + w_{CH4}CH4 + w_{N2O}N2O + w_{Fgases}Fgases\right)} \tag{1}$$

where w_{CO2}, w_{CH4}, w_{N2O} and w_{Fgases} represent the weights assigned to each of the four GHGs in constructing the ecological performance indicator.

Eco-efficiency improves as economic performance rises relative to ecological performance, reflecting a region's ability to generate greater economic value with lower emissions. A key advantage of this indicator is its simplicity and ease of interpretation for both policymakers and the general public. Furthermore, it accurately reflects the overarching objective of European environmental policies, as outlined in the EGD, to promote economic development while minimizing environmental impact [5].

This concept of eco-efficiency is operationalized by the use of DEA, a non-parametric technique introduced by Charnes *et al.* (1978) to evaluate productive performance. DEA constructs a technological frontier representing best practices based on observations within a sample; each observation – regions in this case study – is then evaluated against this frontier. An advantage of DEA in the context of this research is that the weightings assigned to the

Table 1. Variables, description and sources

Variable	Description	Source
Economic performance		
Gross domestic product (GDP)	GDP (millions constant € at 2015 prices). Average 2021–2023	Eurostat
Ecological performance		
Fossil carbon dioxide (CO2)	Emission of CO2 (ktons). Average 2021–2023	EDGAR
Methane (CH4)	Emission of CH4 (ktons of CO2-equivalents from the IPCC-AR5). Average 2021–2023	EDGAR
Nitrous oxide (N2O)	Emission N2O (ktons of CO2-equivalents from the IPCC-AR5). Average 2021–2023	EDGAR
Fluorinated gases (Fgases)	Emission of Fgases (ktons of CO2-equivalents from the IPCC-AR5). Average 2021–2023	EDGAR
Second-stage variables		
Innovation	European Regional Innovation Scoreboard (EU=100). Average 2021–2023	European Commission
Industrial sector	Industrial gross value added (GVA) over total GVA (%). Average 2021–2023	ARDECO
Trade openness	Sum of regional exports and imports over GDP (%). Year 2013	Thissen *et al.*, (2019)
Capital city	Dummy equal to 1 if the region hosts de capital city of the country	Eurostat
Population	Inhabitants at 1th January (thousands). Average years 2021–2023	Eurostat
Elderly population	Population aged 65 and over (%). Average years 2021–2023	ARDECO
Institutional quality	Simple average of quality of government and social capital (0–10 scale)	ESS and QoG institute
Quality of government	Standardized EQI Index (0–10 scale), including impartiality, control of corruption and quality of public services. Average 2017 and 2021	QoG institute
Social capital	Simple average of the standardized (0–10 scale) values of social trust and active citizenship. Average 2010 and 2015	ESS and EU-SPI
Northern	Dummy equal to 1 if the region belongs to a Northern European Union's country, including Denmark, Estonia, Finland and Sweden	Eurostat
Southern	Dummy equal to 1 if the region belongs to a Southern European Union's country, including Cyprus, Greece, Italy, Malta, Portugal and Spain	Eurostat
Western	Dummy equal to 1 if the region belongs to a Western European Union's country, including Austria, Belgium, Germany, France, Ireland, Luxemburg and The Netherlands	Eurostat
Central-Eastern	Dummy equal to 1 if the region belongs to a Central or Eastern European Union's country, including Bulgaria, Czechia, Croatia, Hungria, Lithuania, Latvia, Poland, Romania, Slovakia and Slovenia	Eurostat
Other variables		
Sectoral specialization	A region is classified as industrial if the industrial GVA share (NACE Rev. 2 sections B–E) exceeds the mean plus half a standard deviation (25.9%). It is classified as service-oriented if the services GVA share (NACE Rev. 2 sections G–S) exceeds the mean plus half a standard deviation (74.1%). Regions that do not meet either of the two criteria above are classified as mixed. Finally, a region is classified as agricultural if the GVA share of agriculture (NACE Rev. 2 section A) exceeds the mean plus half a standard deviation (4.3%)	ARDECO

Note(s): ARDECO: Annual Regional Database of the European Commission; EDGAR: Emissions Database for Global Atmospheric Research; EQI: European Quality of Government Index; ESS: European Social Survey; EU-SPI: European Union Social Progress Index; Eurostat: European Statistical Office; IPCC AR5: Intergovernmental Panel on Climate Change, Assessment Report 5; QoG Institute: Quality of Government Institute. NACE: Nomenclature des Activités Économiques dans la Communauté Européenne

Table 2. Descriptive statistics

Variable	Measurement unit	Mean	SD	Max.	Min.
Economic performance					
Gross domestic product (GDP)	Millions of constant € at 2015 prices	58,596.0	72,012.4	717,775.1	1,311.1
Ecological performance					
Fossil carbon dioxide (CO2)	Ktons of CO2	11,462.4	9,273.5	49,712.6	40.8
Methane (CH4)	Ktons of CO2-equivalents	1,891.3	2,038.0	17,429.1	23.0
Nitrous oxide (N2O)	Ktons of CO2-equivalents	886.8	806.7	4,363.6	4.0
Fluorinated gases (Fgases)	Ktons of CO2-equivalents	325.8	352.5	3,314.8	3.4
Second-stage variables					
Innovation	Index number (EU = 100)	92.15	29.75	156.20	19.30
Industrial sector	% of industrial GVA over total GVA	22.07	8.60	68.51	4.76
Trade openness	(Exports + imports)/GDP	1.567	0.991	9.055	0.473
Capital city	Dummy variable	0.112	–	–	–
Population	Thousands of inhabitants	1,899.7	1,639.8	12,353.3	30.2
Elderly population	% of population aged 65 and over	21.57	2.97	29.74	12.96
Institutional quality	Index from 0 to 10	4.51	1.83	8.49	0.68
Quality of government	Index from 0 to 10	5.02	2.26	10	0
Social capital	Index from 0 to 10	4.00	1.63	8.94	0.75
Northern	Dummy variable	0.082	–	–	–
Southern	Dummy variable	0.242	–	–	–
Western	Dummy variable	0.411	–	–	–
Central-Eastern	Dummy variable	0.265	–	–	–

four GHG emissions in constructing the composite indicator of ecological performance are endogenously determined based on the “benefit-of-the-doubt” principle (Cherchye *et al.*, 2007). Accordingly, each GHG receives a weight that puts the region evaluated in the most favourable position in terms of eco-efficiency when compared to all regions in the sample with the same structure of weightings. Moreover, DEA does not require assuming a specific functional form for the technology, as it is constructed directly from the data [6].

Assessing eco-efficiency using DEA requires assuming the existence of an underlying, unknown environmental technology – the GHG-generating technology set (GGTS) – which represents all technologically feasible combinations of GDP and GHG emissions given the state of knowledge. Formally, the GGTS is defined as:

$$\text{GGTS} = [\text{GDP}, (\text{CO2}, \text{CH4}, \text{N2O}, \text{Fgases})] \in \mathcal{R}^5 | \text{GDP can be obtained with emisisions } (\text{CO2}, \text{CH4}, \text{N2O}, \text{Fgases}). \quad (2)$$

The GGTS is assumed to satisfy the following properties (Picazo-Tadeo *et al.*, 2012):

- generating GDP unavoidably emits GHG;
- lower GDP can always be achieved with the same level of GHG emissions;
- GHG emissions can always be increased for a given GDP; and
- any convex combination of feasible GDP and GHG emissions is also feasible.

Accordingly, GHG emissions are formally treated as environmental inputs (Korhonen and Luptacik, 2004; Kuosmanen and Kortelainen, 2005; Zhang *et al.*, 2008), an approach that can be justified by viewing environmental quality as a form of natural capital serving as a production factor. Under this view, higher emissions represent greater use of the assimilative capacity of the environment, i.e. a depletion of environmental services that are implicitly required for production activities [7].

Building on this characterization of the environmental technology and using the DEA-based CCR proportional measure of performance proposed by Charnes *et al.* (1978), the assessment of the eco-efficiency of a region r' – from the $r = 1, \ldots, 231$ regions in the sample – requires solving the following emissions-oriented linear dual programme (Cooper *et al.*, 2007):

$$\text{Minimize}_{\theta_{r'}^{CCR}, z_r} \; \theta_{r'}^{CCR} \tag{3}$$

Subject to:

$$GDP_{r'} \leq \sum_{r=1}^{231} z_r GDP_r \tag{3i}$$

$$\theta_{r'}^{CCR} \quad GHG_{r'}^{n} \geq \sum_{r=1}^{231} z_r GHG_r^{n} \qquad n = CO2,\; CH4,\; N2O,\; Fgases \tag{3ii}$$

$$z_r \geq 0 \qquad r = 1, \ldots, \; 231 \tag{3iii}$$

where GDP_r and GHG_r^n represent the GDP and emission of GHG n in region *r*, respectively; z_r is a set of intensity variables accounting for the weightings of each region *r* in constructing the technological frontier against which region *r'* is benchmarked. Furthermore, constant returns to scale are assumed, which is a common practice in eco-efficiency analyses (Kortelainen and Kuosmanen, 2004, p. 14; also see Picazo-Tadeo *et al.*, 2011).

The GHG-oriented eco-efficiency score for region r' computed from expression (3), namely, $\widehat{\theta}_{r'}^{CCR}$, measures its potential to reduce all four GHG emissions proportionally while maintaining GDP level. The score ranges from 0 to 1, where 1 indicates full eco-efficiency and lower values reflect greater potential for emission reductions. For instance, a score of 0.75 implies that the observed GDP could be maintained with only 75% of current GHG emissions; i.e. region r' could proportionally cut CO2, CH4, N2O and Fgases by 25%.

2.2.2 The Simar and Wilson approach to explaining eco-efficiency. To identify the determinants of eco-efficiency across EU regions, this research uses the approach proposed by Simar and Wilson (2007) in a second-stage analysis, which combines bootstrapping with truncated regression. Notably, this method models an underlying data-generating process consistent with the two-stage estimation framework and explicitly addresses the serial correlation and potential bias of eco-efficiency scores arising from their computation with DEA from a common sample of regions. Specifically, Simar and Wilson's algorithm #2 is applied, which corrects the potential bias through bootstrapping and allows valid statistical inference in the second-stage truncated regression. This approach, thus, yields consistent estimators while properly accounting for the complex statistical properties of DEA-based eco-efficiency scores (Simar and Wilson, 2007, pp. 42–43).

Adapting the Simar and Wilson's algorithm #2 to the GHG emissions-oriented framework of this research enables the study of the determinants of the eco-efficiency scores computed from expression (3) for the 231 EU regions in the sample ($\widehat{\theta}_r^{CCR}$). This procedure involves the following steps:

(1) Use maximum likelihood and eco-inefficient regions (with $0 < \widehat{\theta}_r^{CCR} < 1$) from programme (3) to obtain coefficient estimates $\widehat{\boldsymbol{\beta}}$ of $\boldsymbol{\beta}$ and an estimate $\widehat{\sigma}$ of the

variance parameter σ, in the two-sided truncated regression (at 0 from the left and at 1 from the right) of $\hat{\theta}_r^{CCR}$ on a set of covariates $\mathbf{x}_r$.

(2) Loop over Steps 2.1–2.4 B_1 times to get a set of B_1 bootstrap estimates $\hat{\theta}_r^{CCRb}$ for each region $r = 1,\ldots,231$, with $b = 1,\ldots,B_1$:

(2.1) For each region $r = 1,\ldots,231$ draw an artificial error $\tilde{\varepsilon}_r$ from the two-sided truncated $N(0, \hat{\sigma})$ distribution, with left-truncation at $-\mathbf{x}_r\hat{\boldsymbol{\beta}}$ and right-truncation at $1 - \mathbf{x}_r\hat{\boldsymbol{\beta}}$.

(2.2) Calculate artificial eco-efficiency scores $\tilde{\theta}_r^{CCR}$ as $\mathbf{x}_r\hat{\boldsymbol{\beta}} + \tilde{\varepsilon}_r$, again for each region $r = 1,\ldots, 231$.

(2.3) Generate $r = 1, \ldots, 231$ artificial regions with GDP quantities $\widetilde{GDP}_r = GDP_r$, and GHGs emissions $\widetilde{GHG}_r^n = \left(\hat{\theta}_r^{CCR}/\tilde{\theta}_r^{CCR}\right)GHG_r^n$, with $n = CO2$, $CH4$, $N2O$ and Fgases.

(2.4) Use the $r = 1, \ldots, 231$ artificial regions generated in Step 2.3 as the reference set in a DEA programme analogous to programme (3) to yield $\hat{\theta}_r^{CCRb}$ for each $r = 1, \ldots, 231$ original region.

(3) For each region $r = 1,\ldots,231$, calculate a bias-corrected eco-efficiency score $\hat{\theta}_r^{CCRbc}$ as $\hat{\theta}_r^{CCR} - \left[(1/B_1)\sum_{b=1}^{B_1}\hat{\theta}_r^{CCRb} - \hat{\theta}_r^{CCR}\right]$.

(4) Run by maximum likelihood a two-sided truncated regression (at 0 from the left and at 1 from the right) of $\hat{\theta}_r^{CCRbc}$ on a set of covariates $\mathbf{x}_r$ to obtain coefficient estimates $\hat{\hat{\boldsymbol{\beta}}}$ of $\boldsymbol{\beta}$, as well as an estimate $\hat{\hat{\sigma}}$ of the variance parameter σ.

(5) Loop over Steps 5.1–5.3 B_2 times to get a set of B_2 bootstrapped estimates $\left(\hat{\hat{\boldsymbol{\beta}}}^b, \hat{\hat{\sigma}}^b\right)$, with $b = 1,\ldots,B_2$:

(5.1) For each region $r = 1, \ldots, 231$ draw an artificial error $\tilde{\tilde{\varepsilon}}_r$ from the two-sided truncated $N\left(0, \hat{\hat{\sigma}}\right)$ distribution, with left-truncation at $-\mathbf{x}_r\hat{\hat{\boldsymbol{\beta}}}$ and right-truncation at $1 - \mathbf{x}_r\hat{\hat{\boldsymbol{\beta}}}$.

(5.2) Calculate artificial eco-efficiency scores $\tilde{\tilde{\theta}}_r^{CCR}$ as $\mathbf{x}_r\hat{\hat{\boldsymbol{\beta}}} + \tilde{\tilde{\varepsilon}}_r$, again for each region $r = 1, \ldots, 231$.

(5.3) Use maximum likelihood to run a two-sided truncated regression (at 0 from the left and at 1 from the right) of $\tilde{\tilde{\theta}}_r^{CCR}$ on a set of covariates $\mathbf{x}_r$ to obtain coefficient estimates of $\hat{\hat{\boldsymbol{\beta}}}^b$ and $\hat{\hat{\sigma}}^b$.

(6) Lastly, calculate standard errors and confidence intervals for $\hat{\hat{\boldsymbol{\beta}}}$ and $\hat{\hat{\sigma}}$ from the bootstrap distributions of $\hat{\hat{\boldsymbol{\beta}}}^b$ and $\hat{\hat{\sigma}}^b$.

3. Assessing greenhouse gas eco-efficiency across European Union regions

The results for GHG eco-efficiency are in Table 3 [8]. Average eco-efficiency is 0.183, meaning that the same level of GDP could be ideally produced with just under 20% of the GHG currently emitted [9]. Figure 1 illustrates the distribution of eco-efficiency scores. A few regions score above 0.8, whereas most fall between 0.1 and 0.4, indicating generally low performance. This reflects the heterogeneity of EU regions in terms of economic issues (e.g.

Table 3. European Union's regions eco-efficiency

Eco-efficiency	Regions All regions (231)	Northern (19)	Southern (56)	Western (96)	Central-Eastern (60)
Mean	0.183	0.313	0.151	0.241	0.078
SD	0.180	0.261	0.097	0.202	0.091
Max.	1	1	0.530	1	0.466
Min.	0.012	0.057	0.018	0.057	0.012
Top 10 performers	Bruxelles-Capitale (BE10); Berlin (DE30); Hovedstaden (DK01); Stockholm (SE11); Hamburg (DE60); Noord-Holland (NL32); Wien (AT13); Ile-de-France (FR10); Darmstadt (DE71); Aland (FI20)				
Bottom 10 performers	Yugoiztochen (BG34); Severoiztochen (BG33); Dytiki Makedonia (EL53); Severozápad (CZ04); Sud-Vest Oltenia (RO41); Severen Tsentralen (BG32); Severozapaden (BG31); Sud-Muntenia (RO31); Sud-Est (RO22); Dél-Dunántúl (HU23)				

Note(s): Number of regions per geographical area in parentheses

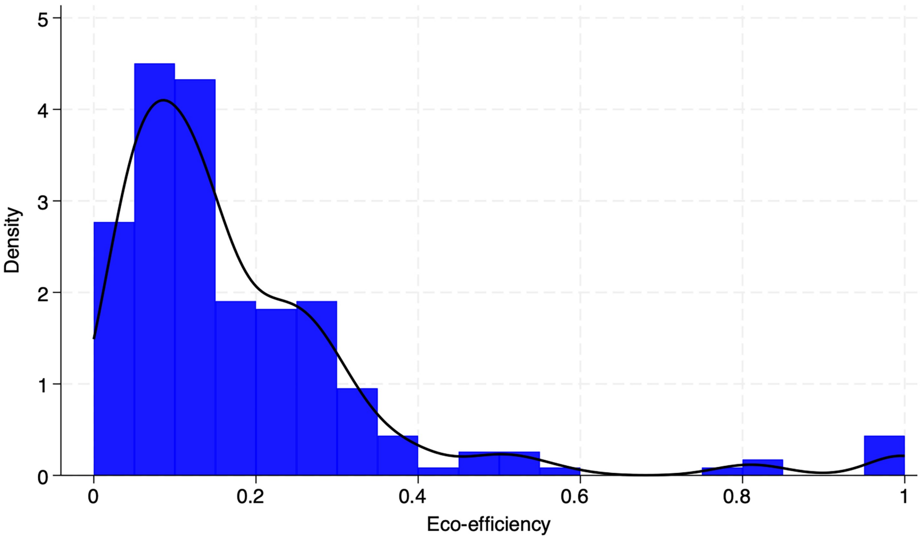

Figure 1. Distribution of European Union scores of eco-efficiency
Note: Histogram (bars) and Gaussian kernel-density function (line)

level of development, innovation capacity and productive structure), as well as demographics and institutional frameworks. The relationship of these features with eco-efficiency is examined in the second stage. Furthermore, low average performance is a finding consistent with recent evidence on the environmental performance of European regions reported by Peiró-Palomino *et al.* (2025) and Vaccaro *et al.* (2025).

The top-performing regions are mainly located in Northern and Western Europe and often include the country's capital city – e.g. Stockholm in Sweden, Bruxelles-Capitale in Belgium, Berlin in Germany, Vienna in Austria, Noord-Holland with Amsterdam and Île-de-France hosting Paris. These regions concentrate high value-added, low-polluting service activities and some of them shape the technological frontier, serving as benchmarks for best practices [10]. By contrast, the regions with the lowest performance are primarily located in South and, particularly, Central-Eastern countries that joined the EU in the 2000s – including Yugoiztochen, Severoiztochen, Severen Tsentralen and Severozapaden in Bulgaria; Sud-Vest Oltenia, Sud-Muntenia and Sud-Est in Romania; Severozápad in the Czech Republic; in addition to Dytiki Makedonia in Greece. Energy and polluting industries play an important role in these regions, while agriculture remains important in some of them.

Figure 2 provides an overview of eco-efficiency across all EU regions in the sample, further corroborating the previously highlighted patterns. Average eco-efficiency scores by geographical area are 0.313 for Northern regions, 0.241 for Western regions, 0.151 for Southern regions and only 0.078 for Central and Eastern regions (Table 3). At first glance, this overall picture does not seem to differ substantially from previous analyses based on other measures of ecological performance, such as air, water or soil quality (Vaccaro *et al.*, 2025; Peiró-Palomino *et al.*, 2025). However, a closer examination of the map reveals some differences with respect to these prior studies. The main reason is the nature of the eco-efficiency indicator computed in this research, which goes beyond simpler measures by assessing ecological performance relative to the economic value generated in each region. For instance, the indicators of air quality presented by Peiró-Palomino *et al.* (2025) and Vaccaro *et al.* (2025) have a marked country-level behaviour, showing a comparatively more limited within-country variability. In addition, some regions identified as having high air quality in the two mentioned works, such as those in Finland, Sweden or Denmark, occupy intermediate positions when their economic

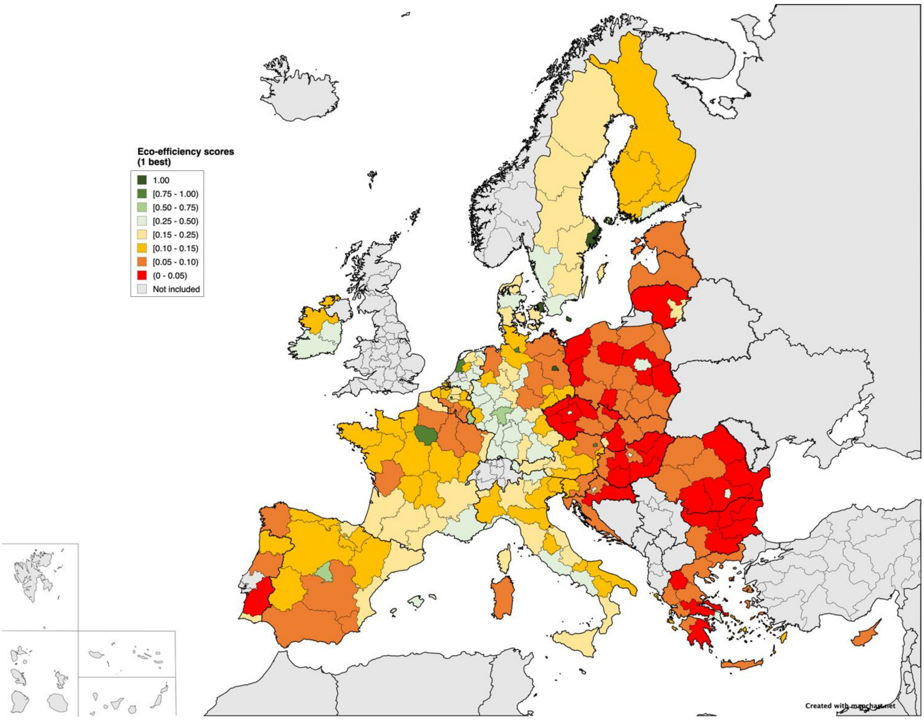

Figure 2. Eco-efficiency in the European Union regions

performance is considered. A similar pattern is observed in some regions of Germany – including Mecklenburg-Vorpommern, Brandenburg and Dresden – which perform well ecologically but rank among the lowest in eco-efficiency due to low economic performance. By contrast, regions such as Bruxelles-Capitale, Île-de-France and Berlin – which host the Belgian, French and German capitals, respectively – produce significant emissions, yet perform well when these are evaluated relative to regional economic output.

To further examine the role of sectoral specialization in explaining eco-efficiency, this research uses a metafrontier analysis, enabling performance comparisons across groups of regions with different structural characteristics, such as industrial versus service-oriented regions. Essentially, this approach involves constructing a global benchmark or metafrontier – as already done – that represents the overall best practices across all regions, alongside group frontiers capturing the best practices within each group. Comparing eco-efficiency scores relative to both the metafrontier and the group frontiers allows for the calculation of the so-called metatechnology ratios, which indicate which group technology is more eco-efficient in reducing GHG emissions while maintaining GDP. Accordingly, this approach helps disentangle differences in eco-efficiency across regions that arise from technological constraints associated with sectoral specialization from those driven by other contextual factors, such as economic dynamism, demographic structure or institutional context. The analysis builds on the seminal work of O'Donnell *et al.* (2008) and its extension to eco-efficiency assessment by Beltrán-Esteve and Picazo-Tadeo (2015), to which readers are referred for methodological details.

For empirical purposes, in a first scenario, the regions in the sample were classified as industrial, service or mixed according to their average sectoral contribution to gross value added (GVA) over 2021–2023. A region was considered as industrial when the GVA share of sectors B–E in the NACE Rev. 2 classification (European Commission, 2008) exceeded the sample mean by more than 0.5 standard deviations (25.9%). Service regions were identified analogously based on sectors G–U (74.1%), while the remaining regions were classified as mixed. When industrial regions are benchmarked against other industrial regions, they display an average group eco-efficiency of 0.436, implying a potential GHG reduction of 56.4% without compromising GDP. Service regions exhibit an average group eco-efficiency of 0.313, suggesting a potential GHG reduction of 68.7%. Although these averages are not directly comparable to each other, since they are computed using different technological frontiers, the results indicate that service-oriented regions operate farther from their group frontier. This suggests that, once considered the difference of productive structures, other contextual factors play a stronger role in explaining eco-inefficiency in service regions than in industrial regions. On the other hand, the average metatechnology ratios are 0.276 for industrial regions and 1 for service regions, indicating that service-sector technology is more eco-efficient [11]. Moreover, these figures mean that the technology of services coincides with the metafrontier, thus also representing the overall benchmark of best practices across all groups.

In a second scenario, agricultural regions – defined as those with a share of sector A in the NACE Rev. 2 classification more than 0.5 standard deviations above the sample mean (4.3%) – are distinguished from non-agricultural regions that do not meet this criterion. Average group eco-efficiency is 0.391 and 0.218 for agricultural and non-agricultural regions, respectively; this means that the latter operate further away from their group frontier than the former. Furthermore, metafrontier results suggest that the technology of non-agricultural regions is more eco-efficient.

3.1 Robustness checks

To assess the sensitivity of regional eco-efficiency scores and rankings to the computation method, four alternative indicators of eco-efficiency were constructed using different approaches. The rankings obtained from these alternative indicators were then compared with the baseline CCR-based ranking.

The methodology used in the baseline scenario is deterministic and assesses eco-efficiency relative to a technological frontier constructed from best observed practices in a sample of regions, rather than the true technology. Consequently, the resulting eco-efficiency scores are subject to sampling variability and may be upwardly biased, as the estimated frontier necessarily represents a weak subset of the true technology. The first alternative indicator is therefore a bias-corrected version of the CCR indicator computed following Simar and Wilson (1998), denoted as θ^{CCRbc}. The second indicator assumes variable returns to scale, whereby each region is evaluated relative to a region – observed or virtual – of similar size, giving rise to the ϕ^{BCC} eco-efficiency indicator (see Banker *et al.*, 1984). The third indicator is based on the non-radial slacks-based measure (SBM) of performance pioneered by Tone (2001), which calculates eco-efficiency scores as the simple average of the individual maximum feasible reductions of CO2, CH4, N2O and Fgases while maintaining GDP. Notably, this alternative indicator – which is denoted as φ^{SBM} – does not impose proportionality; it also ranges from 0 to 1, with higher values indicating better performance. The fourth alternative indicator is calculated as the ratio of GDP to total GHG emissions, obtained by aggregating CO2 – measured in kilotons – with CH4, N2O and Fgases, all three expressed in kilotons of CO2-equivalents. This ratio is then normalized between 0 and 1 using a min–max scaling procedure, yielding the $\mathrm{NEEff}^{\mathrm{Ratio}}$ eco-efficiency indicator.

The distributions of these alternative indicators of eco-efficiency closely resemble that of the baseline CCR indicator (Figure 3). However, for robustness purposes, what truly matters are the rankings generated by the different eco-efficiency measures. In this regard, the Spearman's rank correlations across pairs of indicators mostly exceed 0.9 and are statistically significant at the 1% level (Table 4). This indicates that regional rankings are largely consistent across indicators,

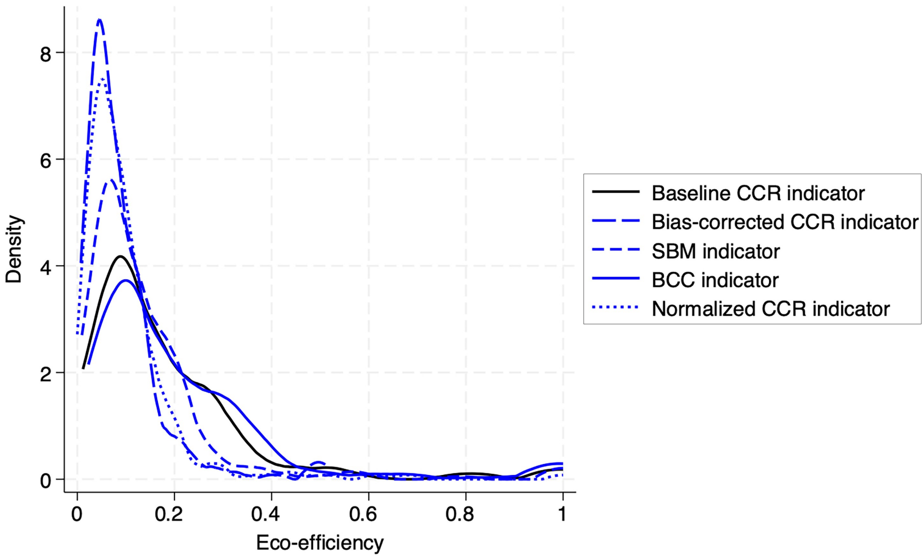

Figure 3. Distribution of baseline and alternative indicators of eco-efficiency
Note: Gaussian kernel-density functions

Table 4. Spearman ranks correlation (*ρ-Spearman*) across eco-efficiency indicators

Eco-efficiency indicator	Baseline CCR indicator (θ^{CCR})	Bias-corrected CCR indicator (θ^{CCRbc})	BCC indicator (ϕ^{BCC})	SBM indicator (φ^{SBM})	Normalized eco-efficiency ratio ($NEEff^{RATIO}$)
Baseline CCR indicator (θ^{CCR})	1				
Bias-corrected CCR indicator (θ^{CCRbc})	0.972***	1			
BCC indicator (ϕ^{BCC})	0.980***	0.957***	1		
SBM indicator (φ^{SBM})	0.986***	0.960***	0.961***	1	
Normalized eco-efficiency ratio ($NEEff^{RATIO}$)	0.910***	0.890***	0.883***	0.942***	1

Note(s): *** means statistical significance at 1%

with top- and bottom-performing regions largely coinciding. Such consistency reinforces the reliability of the results and strengthens the conclusions of this research.

As a final robustness check, the metafrontier analysis was replicated using two alternative classifications of EU regions based on their productive structures. In the first, more restrictive framework, a region is classified as industrial, service-oriented or agricultural if the sector's GVA share exceeds the sample mean by more than 0.75 standard deviations, thus capturing strong specialization. The second, more lenient criterion uses a threshold of the mean plus 0.25 standard deviations. The main results and overall conclusions from the baseline scenario remain virtually unchanged in these alternative frameworks.

4. Exploring the drivers of eco-efficiency

The second-stage analysis investigates the drivers of eco-efficiency. The selection of potential explanatory variables is grounded in a conceptual framework that links eco-efficiency to regions' economic and structural characteristics, as well as to demographic and institutional contexts. From a theoretical perspective, eco-efficiency is closely related to the concept of environmental productivity. In this sense, the literature on technical change (Acemoglu *et al.*, 2012; Aghion *et al.*, 2016) and green growth (OECD, 2011) emphasizes that technological progress and innovation play a central role in reducing the environmental impact of production activities. Accordingly, territories with higher innovation capacity are expected to develop and adopt cleaner technologies and more environmentally efficient production processes, thereby improving eco-efficiency. To capture this feature, this paper uses the Regional Innovation Scoreboard developed by the European Commission (2025).

A second set of determinants relates to structural characteristics of the economy. The composition of economic activity, particularly the relative importance of the industrial sector, might be a driver of environmental performance, as industrial activities tend to be more energy- and emission-intensive (Grossman and Krueger, 1995; Cole and Elliott, 2003; Dinda, 2004), thereby complementing the earlier discussion on the environmental contrasts between service-based and industrial structures. The importance of the industrial sector is measured as the share of industry and energy in regional GVA. Trade openness may also affect eco-efficiency through multiple channels. While increased trade can lead to a "pollution haven" effect, it can also foster the diffusion and adoption of cleaner technologies and more eco-efficient practices (Antweiler *et al.*, 2001; Cole, 2004; Frankel and Rose, 2005). Moreover, trade openness can influence emissions through scale effects and embodied pollution (Afesorgbor and Demena, 2022). These competing mechanisms suggest that the net effect of openness is ultimately an empirical question. In this research, trade openness is measured by the trade-to-GDP ratio.

Another important determinant of eco-efficiency may be whether a region hosts the national capital. Despite higher emissions associated with concentrated economic and human activity, as well as higher income and consumption levels, capital cities also display characteristics that may help mitigate environmental pressures. Regions hosting the national capital tend to concentrate high value-added services, more productive firms and frontier technologies within sectors, which leads to lower environmental intensity conditional on economic structure (Aghion *et al.*, 2016). They also typically exhibit stronger institutional capacity and more effective policy enforcement, which can further enhance environmental performance (Rodríguez-Pose and Garcilazo, 2018). Moreover, proximity to central governments may strengthen administrative capacity and policy implementation, while more developed public infrastructure can contribute to greater resource efficiency (Duranton and Puga, 2004; Glaeser and Kahn, 2010; Glaeser, 2011). To account for these features, all models include a dummy variable equal to 1 if the region hosts the national capital.

Demographics can also play an important role in shaping eco-efficiency. Population size and density are closely linked to agglomeration economies, which can enhance productivity and resource efficiency through scale effects, knowledge spillovers and shared infrastructure (Duranton and Puga, 2004; Glaeser and Kahn, 2010). By contrast, larger populations are typically associated with greater mobility and human activity that can increase emissions (Cole and Neumayer, 2004). At the same time, demographic structure – such as the share of the elderly population – may influence environmental outcomes through differences in consumption patterns, energy use and preferences regarding environmental quality (Menz and Welsch, 2010; Zhao *et al.*, 2025). As the proportion of older adults rises, health awareness and pro-environmental preferences reinforce social demand for environmental goods and regulations (Alberini and Chiabai, 2007). Furthermore, ageing shifts consumption habits towards energy-intensive services such as healthcare and residential care, alters mobility patterns, and reduces average household size (Xu, 2024). The net effect of aging on environmental performance is context-dependent, with empirical evidence remaining mixed (e.g. Wang *et al.*, 2024; Li *et al.*, 2025; Zhao *et al.*, 2025).

Regarding institutional factors, both government quality and social capital – representing formal and informal institutions, respectively – are considered as potential determinants of eco-efficiency. Theoretical and empirical contributions highlight that effective governance enhances the design, implementation and enforcement of environmental regulations, thereby reducing pollution intensity (Fredriksson and Millimet, 2002; Damania *et al.*, 2003; Lisciandra and Migliardo, 2017; Peiró-Palomino *et al.*, 2025). Quality of government is measured using the European Quality of Government Index (EQI), developed by the University of Gothenburg (Charron *et al.*, 2014), which captures several dimensions that are essential for achieving higher eco-efficiency, including control of corruption, impartiality and quality of public services. Social capital reflects cultural values and is measured as the average of social trust and active citizenship, using data from the European Social Survey (ESS) and the EU Social Progress Index (EU-SPI). Evidence shows that higher social capital is linked to better environmental performance (Farrow *et al.*, 2017; Jo and Carattini, 2021), as cooperative behaviour and reciprocal expectations foster compliance with environmental norms and collective action to protect natural resources (Kountouris and Remoundou, 2016). Peiró-Palomino *et al.* (2025) provide empirical evidence for the EU regions.

Overall, this framework provides a theoretical basis for the selection of potential explanatory variables for eco-efficiency and aligns the empirical analysis with established strands of the literature on environmental economics, urban economics and institutional analysis. To complement this group of explanatory factors, a set of dummies captures the geographical location of regions – including Northern, Southern, Western and Central-Eastern Europe. These variables account for the spatial patterns of eco-efficiency, as illustrated in Figure 1.

Table 5 reports truncated regression estimates based on algorithm #2 of Simar and Wilson (2007) [12]. High correlations across some explanatory variables (e.g. innovation, industrial sector, capital city or institutional quality) make the interpretation of the estimated coefficients from the truncated regression difficult. This issue is addressed by sequentially introducing the regressors, which enables tracking the evolution of the estimated coefficients.

Model 1 incorporates only economic variables, with innovation showing a statistically significant positive effect at the 1% level. This result aligns with the notion that higher innovation capacity might be associated with the use of cleaner and more efficient technologies. This positive association remains robust across all models, suggesting that other factors beyond the sectoral structure, population and institutions shape this relationship. Furthermore, regions hosting the national capital exhibit significantly higher eco-efficiency, and this effect remains robust after controlling for other covariates. This relationship likely results from a set of unobserved characteristics not fully captured by standard controls, such as stronger administrative capacity, more developed infrastructure, as well as more productive firms and frontier technologies within sectors, as noted above. A larger industrial sector has a negative and statistically significant impact on eco-efficiency, indicating that regions with a stronger industrial base face greater environmental challenge. Trade openness is consistently statistically insignificant, suggesting that it is not systematically associated with regional eco-efficiency once other factors are controlled for. This finding may suggest that the opposing trade-related mechanisms offset each other.

Model 2 incorporates demographic variables, revealing a positive and statistically significant effect of population size at 1% level. Although larger populations may generate higher emissions through increased mobility and energy use, the eco-efficiency measure adjusts for economic output, which appears to offset these pressures. By contrast, the share of the elderly population shows no significant association with regional eco-efficiency in the EU regional context.

Model 3 includes institutional quality, capturing the combined effects of quality of government and social capital, which are further examined separately in Models 3a and 3b. All institutional indicators exhibit a positive and statistically significant effect on regional eco-efficiency, highlighting the critical role of governance, social trust and civic engagement in promoting sustainable economic growth.

Lastly, Model 4 introduces geographic dummies, with Southern regions serving as the reference group. Once economic, demographic and institutional variables are included, the geographic effects are generally statistically insignificant, as the spatial patterns of innovation capacity, industrial sector and institutional quality largely overlap with the geographic dummies, absorbing their explanatory power. Statistically significant disparities are observed only for Central and Eastern regions (at 5% level), where eco-efficiency is markedly lower. It is also noteworthy that the negative effect associated with the industrial sector disappears once geographical controls are included, suggesting that spatial patterns of sectoral specialization are effectively captured by these geographical variables.

In summary, results from the second-stage analysis indicate that innovation capacity, population and the quality of institutions – government effectiveness and social capital – are key drivers of regional eco-efficiency, whereas industrial intensity constitutes a significant constraint. Trade openness and population ageing have no statistically significant effect.

Table 5. Determinants of the eco-efficiency of European Union regions

Variable	Model 1	Model 2	Model 3	Model 3a	Model 3b	Model 4
Constant	−0.2858*** (0.0634)	−0.3002*** (0.1033)	−0.2479*** (0.0949)	−0.2805*** (0.1023)	−0.2317** (0.0979)	−0.1871* (0.1028)
Economic variables						
Innovation	0.0037*** (0.0004)	0.0036*** (0.0004)	0.0022*** (0.0005)	0.0027*** (0.0006)	0.0027*** (0.0004)	0.0019*** (0.0005)
Industrial sector	−0.0030** (0.0012)	−0.0024** (0.0012)	−0.0024** (0.0011)	−0.0028** (0.0011)	−0.0021* (0.0011)	−0.0016 (0.0010)
Trade openness	−0.0060 (0.0095)	0.0037 (0.0087)	0.0081 (0.0080)	0.0083 (0.0092)	0.0041 (0.0082)	0.0047 (0.0081)
Capital city	0.0760*** (0.0239)	0.0562** (0.0259)	0.0723*** (0.0263)	0.0722** (0.0285)	0.0599** (0.0258)	0.0951*** (0.0281)
Demographic variables						
Population		0.0169*** (0.0042)	0.0186*** (0.0042)	0.0196*** (0.0046)	0.0161*** (0.0041)	0.0152*** (0.0040)
Elderly population		−0.0016 (0.0032)	−0.0033 (0.0031)	−0.0022 (0.0032)	−0.0043 (0.0031)	−0.0042 (0.0030)
Institutional variables						
Institutional quality			0.0234*** (0.0071)			0.0258*** (0.0095)
Quality of government				0.0136* (0.0071)		
Social capital					0.0201*** (0.0059)	
Geographic variables						
Northern						−0.0643 (0.0470)
Western						−0.0255 (0.0301)
Central-Eastern						−0.0845** (0.0366)
Sigma	0.0811***	0.0793***	0.0767***	0.0789***	0.0786***	0.0743***
Wald Chi^2	82.53***	85.74***	98.47***	87.21***	99.67***	103.57***
Number of observations						
Bias-corrected DEA	231	231	231	231	231	231
Truncated regression	231	231	229	229	230	229

Note(s): Bootstrap replications: 1,000 for bias-corrected eco-efficiency scores, and 5,000 for truncated regressions. Bootstrapped standard errors in parentheses. *, **, *** indicate significance at 10, 5 and 1%, respectively. The reference geographical category is Southern

Coefficients from truncated regressions, however, cannot be interpreted directly; only their sign and statistical significance are meaningful. To evaluate the magnitude of the relationship between eco-efficiency and the explanatory variables, marginal effects were computed from Models 3, 3a and 3b, which are the parsimonious models including all significant determinants of eco-efficiency (Table 6). The strongest marginal effect corresponds to national capital status, followed by overall institutional quality, particularly social capital and population.

6. Conclusions and policy recommendations

Measuring environmental performance at the regional level has long been challenging. This research assesses eco-efficiency in the emission of GHG across European Union regions. By integrating emissions and economic performance, eco-efficiency offers a robust indicator to inform the design of environmental policies aimed at achieving the green transition objectives of the EGD.

Results reveal significant regional disparities in eco-efficiency: Nordic and Western European regions perform best, whereas Eastern and Central regions lag behind. Considerable within-country heterogeneity is observed, contrasting sharply with studies based solely on ecological indicators. Service-oriented regions tend to exhibit more eco-efficient technologies; however, other contextual factors play a stronger role in explaining eco-inefficiencies than in industrial regions. The second-stage analysis shows that innovation capacity, national capital status, larger populations and the quality of institutions are all positively associated with eco-efficiency, whereas a large industrial base exerts a negative effect. These findings are novel for the EU and hold important implications for the green transition agenda, as they adopt a regional perspective, focus on GHG emissions directly linked to global warming and assess relative eco-efficiency rather than absolute emissions.

These results also yield important implications for the design of environmental policies in the EU. The less-developed regions of Central-Eastern Europe exhibit the highest GHG emissions relative to GDP, reflecting their concentration in polluting industries and supporting the "pollution haven" hypothesis (Martínez-Zarzoso *et al.*, 2017). By contrast, service-oriented regions engaged in high-value activities generate lower emissions relative to their economic performance. Advancing the green transition therefore requires targeted efforts in less eco-efficient regions to modernize industrial structures and adopt cleaner technologies, accompanied by policies that facilitate workforce adaptation and ensure a just transition. Moreover, fostering development in lagging regions may indirectly enhance eco-

Table 6. Determinants of the eco-efficiency of European Union regions: Marginal effects for statistically significant variables

Variable	Model 3	Model 3a	Model 3b
Innovation	0.0009*** (0.0002)	0.0011*** (0.0001)	0.0011*** (0.0002)
Industrial sector	−0.0010** (0.0004)	−0.0009* (0.0004)	−0.0011** (0.0004)
Capital city	0.0311*** (0.0114)	0.0258** (0.0112)	0.0295** (0.0116)
Population	0.0080*** (0.0017)	0.0069*** (0.0017)	0.0080*** (0.0018)
Institutional quality	0.0097*** (0.0021)		
Quality of government		0.0055* (0.0029)	
Social capital			0.0086*** (0.0025)

Note(s): Delta-method standard errors in parenthesis; ***, ** and * stand for statistical significance at 1, 5 and 10%, respectively efficiency. High-quality governance is also essential for efficient resource allocation and the implementation of robust environmental policies. Social capital further promotes eco-efficiency, although its persistence makes it difficult to modify; consequently, regions with low social capital may require additional targeted support. Furthermore, fostering cooperation and the transfer of knowledge between high- and low-performing EU regions can facilitate the dissemination of best practices, technologies and governance methods, thereby enhancing overall eco-efficiency.

Despite its contributions, this research has some limitations. It assumes that all regions could reach the technological frontier regardless of their structural characteristics. However, structural heterogeneity – e.g. between industrial and service-based regions, as highlighted by the metafrontier analysis – may exist and potentially influence eco-efficiency. Furthermore, the algorithm used in the second stage to investigate the drivers of eco-efficiency cannot accommodate panel data or address endogeneity using external instruments; therefore, the results might reflect correlations rather than causal effects. These limitations open several avenues for future research, including the estimation of regional eco-efficiency and its drivers using parametric methods to test the sensitivity of the results to the analytical approach; the expansion of the analysis to include different types of industrial activities, such as energy-intensive, traditional and high value-added industries; the extension of the study to a finer regional scale to identify best practices across different types of regions and to inform policymaking; and the exploitation of the temporal dimension of the data set on emissions to assess environmental performance over time and its determinants (e.g. technological change and catch-up effects), as well as to analyse convergence patterns across regions.

Notes

[1.] This research adopts the NUTS2 2021 classification, which comprises 242 regions. Ultraperipheral regions were excluded from the sample due to their distinct characteristics; additionally, two more regions were omitted due to data unavailability.

[2.] Data accessed on 24 February 2025 from the Eurostat website https://ec.europa.eu/eurostat

[3.] Data accessed on 26 February 2025 from https://edgar.jrc.ec.europa.eu

[4.] Emissions from international shipping and aviation are excluded from the database due to their transboundary nature. Similarly, emissions from domestic shipping, domestic aviation and offshore fuel extraction are not allocated at the NUTS2 regional level.

[5.] This indicator does not account for conventional production inputs – typically energy, labour and capital. Including these inputs would be necessary to calculate eco-productivity (e.g. Beltrán-Esteve and Picazo-Tadeo, 2017). However, the central concern in this case study is to compare a region’s economic output with its environmental impact, regardless of its origin, including any inefficient use of production factors.

[6.] An alternative approach to DEA would be to assume a particular functional form and estimate eco-efficiency using parametric methods (see Orea and Wall, 2017).

[7.] While this approach facilitates the integration of environmental degradation into standard production frameworks, it has been criticized on the grounds that emissions are treated as freely disposable inputs, thereby neglecting their technological linkage to desirable outputs and the fact that their reduction typically involves economic or technological trade-offs. Dyckhoff and Allen (2001), as well as Seiford and Zhu (2002), provide a critical review of the advantages and limitations of alternative approaches to modelling undesirable resultants of production in DEA-based environmental models.

[8.] The calculations have been carried out with Stata 18 and the package developed by Badunenko and Mozharovskyi (2016).

[9.] The GDP-weighted average eco-efficiency, which assigns different levels of importance to regions based on their economic size, is 0.297. Comparing the unweighted and GDP-weighted averages indicates that larger regions tend to be more eco-efficient than smaller ones.

[10.] Following a referee's suggestion, eco-efficiency was recalculated after excluding from the sample regions hosting national capitals, to assess the extent to which they influence the results. The average eco-efficiency score increased to 0.338, and the regional ranking changed only slightly compared with that obtained when all 231 regions were included. The Spearman rank correlation coefficient between the two rankings is 0.944, which is statistically significant at the 1% level.

[11.] Whereas most studies argue that the expansion of the service sector contributes to lower environmental pressures due to reduced energy intensity (Glaeser and Kahn, 2010), some authors highlight indirect effects through consumption, outsourcing of emissions and global value chains, which may offset these gains (e.g. Stern, 2004). The environmental advantage of service-based economies is thus an open empirical question.

[12.] The models have been estimated with Stata 18 software and the package developed by Badunenko and Mozharovskyi (2019).

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