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Eco-efficiency changes of the electricity and gas sectors across 28 European countries: A value-based data envelopment analysis productivity approach

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ABSTRACT

This paper assesses the relative eco-efficiency changes in the electricity and gas sector (E&G)' production and consumption chains in 28 European countries. We propose a novel robustness assessment for the productivity index, specifically adjusted to value-based data envelopment analysis. Overall, results indicate that total factor productivity gains have been mainly driven by the catch-up effect across all chains of the E&G sector. When a more demanding perspective concerning negative environmental externalities is adopted, we find that the number of European countries that achieved productivity gains across all chains decreases. Besides, results depict the existence of lower productivity gains for the direct production chain when compared with the direct and indirect supply chains of the E&G sector. Germany, Luxembourg, and Belgium were consistently viewed as innovators across all chains, according to the environmental perspective. Several Eastern Europe countries usually viewed as policy laggards that resisted adopting the ambitious European decarbonization targets, showed total factor productivity gains in the supply chain of the E&G sector under a more environmental demanding perspective. Czechia was the only country with productivity losses across all chains, due to increasing coal-fired electricity generation in the time horizon assessed. The current partial return to coal as a source of electricity, due to the geopolitical tensions between Russia and Europe, brings additional challenges to the enhancement of the eco-efficiency of the European E&G sector.

1. Introduction

The electricity and gas (E&G) sector is of paramount importance both to the economy and to the environment, motivating a pervasive interest in the assessment of energy systems, explicitly addressing their eco-efficiency [1], including country-level analyses of European countries [2,3]. Eco-efficiency is intrinsically related to sustainability as it couples at least two of its pillars, i.e., economics and the environment [4]. In this context, Data Envelopment Analysis (DEA) can be especially useful because it allows for the integration of multiple axes of sustainability evaluation into a single indicator, thereby facilitating policy decision making [5].

The DEA methodology has been largely employed in the evaluation of the efficiency of the energy sector, as reviewed by Ref. [1]. Ref. [6] tackled two of the shortcomings identified in the articles examined by Ref. [1] and suggested how to mitigate them. They applied the Directional Distance Function (DDF) model with the Economic Input-Output Life Cycle Assessment (EIO-LCA) tool to address the eco-efficiency evaluation of the E&G industry of 28 European countries between 2010 and 2014. Later, Ref. [7] employed the Value-Based DEA (VBDEA) approach in the conversion of decision-makers' (DMs') preferences into value functions in the eco-efficiency evaluation of the E&G sector. One of the key innovations in their work was the use of value functions inspired by Ref. [8], but with the zero-state as the reference state.

VBDEA is an efficiency assessment method that combines the additive model of DEA with Multiple Criteria Decision Aiding (MCDA) [9]. By extending the traditional additive DEA method, VBDEA allows converting inputs and outputs into value scales. This can be particularly convenient not only for taking into consideration the preferences of the DMs but also for easily handling negative or null data.

Despite the fact that VBDEA can be useful in a variety of situations (e.g., Refs. [7,10–15]), no prior work has addressed productivity change within the VBDEA framework in the E&G sector, nor has it contrasted or explored the impact of distinct stances toward the environment by using

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value functions that model different perspectives concerning environmental impact. This work aims to fill this void.

In classical DEA, the Malmquist Index and the Luenberger Productivity Indicator have been established to appraise changes in efficiency over time [16]. These productivity indices are obtained from the efficiency scores computed with DEA models and allow measuring total factor productivity (TFP). TFP can be decomposed into Technical Change and Efficiency Change [17]. Technical Change evaluates shifts in the production frontier, also known as “frontier shifts”. Efficiency Change assesses changes in the position of a Decision-Making Unit (DMU) regarding the efficient frontier (the catching-up effect).

The Malmquist-Luenberger Productivity Index (MLPI) is commonly used to assess environmental efficiency and productivity change over time when desirable and undesirable factors coexist. Concerning specifically the electricity sector, Ref. [18] studied the progress of productivity in Illinois electric utilities by developing an input-based Malmquist productivity index based on Shephard’s input distance function. Also, Ref. [19] estimated the MLPI to measure the productivity in Japan’s steam power-generation sector in 1978–2003. Similarly, Ref. [20] used the MLPI approach and ANOVA to evaluate the dynamics of productivity changes in the Australian electricity industry. In a similar vein, Ref. [21] suggested a new slacks-based DEA measure to compute the meta-frontier MLPI to gauge the productivity change in three different categories of 48 Iranian thermal power plants over eight years. Later, Ref. [22] developed a new approach by integrating the slacks-based measure to enhance the MLPI through a material balance condition, using data from Iranian gas-fired power plants from 2003 to 2010.

The model used in this work follows the rationale of the Luenberger Productivity Indicator because it matches better the non-oriented and non-radial nature of VBDEA and has other advantages over the Malmquist Index [16,23,24]. Since the Luenberger indicator is a difference-based measure whereas the Malmquist index is a ratio-based measure, it does not have the same well-known issues related to infeasibility; the Luenberger indicator does not account for slacks; and it also does not have the validity issues associated with the production of undesirable outputs [25].

Hence, the present work introduces three main contributions: it proposes the use of the VBDEA productivity index for assessing which factors are behind the relative eco-efficiency changes of the E&G sector, thus allowing to further understand if efficiency enhancements were the result of pure efficiency (movements toward the frontier) or technology improvements (frontier shifts); it develops a novel robustness assessment for the productivity indicator; and it applies the model to data from the E&G sector of 28 European countries, illustrating the effect of using different value functions for the factors representing negative externalities to the environment from a “neutral” perspective and nonlinear value functions for an “environmentally demanding” perspective.

The remainder of this paper is organized as follows: Section 2 further describes the methodological approaches used and developed in this study; Section 3 presents the data employed to demonstrate the usefulness of the proposed methodology; Section 4 presents the value functions representing different evaluation perspectives in this context; Section 5 presents the results; Section 6 provides the robustness assessment of the results obtained; Section 7 discusses the results obtained; and Section 8 draws some conclusions.

2. The methodological approach

The next sections provide a description of the VBDEA methodological approach and its main underpinning assumptions.

2.1. VBDEA

The VBDEA model [9,26] tackles both the scaling bias and the absence of interpretation of the scores obtained through the DEA additive model [27]. This is accomplished by combining the DEA and MCDA frameworks, embedding the DMs’ preferences, and translating the performances of the DMUs into value scales.

Consider the set of n DMUs $\{DMU_j : j = 1, \ldots, n\}$ that are being evaluated based on their performance on q criteria. Each DMU_j ($j = 1, \ldots, n$) is thus characterized by a performance vector $(x_{1j}, \ldots, x_{mj}, y_{1j}, \ldots, y_{pj})$ with $q = m + p$ elements, such that x_{ij} $(i = 1, \ldots, m)$ are minimized (inputs and undesirable outputs), and y_{rj} $(r = 1, \ldots, p)$ are maximized (outputs). The transformation of inputs and outputs is based on Multi-Attribute Utility/Value Theory (MAUT/MAVT) [28] and consists of building partial value functions $\{v_c(.), c = 1, \ldots, q\}$ that represent the DM’s preferences. Specifically, each of the partial functions indicates how much the DM values each performance level, according to a [0, 1] value scale, so that the performance of DMU j in criterion c (p_{cj}) has the value 0 in the worst case and the value 1 in the best case. The value function is increasing if the criterion represents a desirable output produced, and it is decreasing if it represents the level of consumption of an input, or an undesirable output. Therefore, the DM wishes to maximize all the value functions. These q functions are aggregated into a global value function according to an additive model,

$$V(DMU_j) = \sum_{c=1}^{q} w_c v_c(DMU_j), \tag{1}$$

where $w_c \geq 0, \forall c = 1, \ldots, q$ and $\sum_{c=1}^{q} w_c = 1$. In the spirit of DEA, each DMU can choose the weight vector that places it in the best possible light when compared to its peers. Namely, the weights (scale coefficients) $w_1, \ldots, w_q$ of the additive value function are set in such a way that each alternative minimizes the value difference to the best alternative, following the min-max regret rule [29].

After converting all the criteria into a value scale, the VBDEA requires two phases. Phase 1 consists of solving the linear program (2) to obtain the efficiency score, d_k^*, and the corresponding weighting vector, w_k^*, for each DMU_k (k = 1, …, n):

$$\begin{aligned}
&\min_{d_k, w} d_k \\
&s.t. \sum_{c=1}^{q} w_c v_c(DMU_j) - \sum_{c=1}^{q} w_c v_c(DMU_k) \leq d_k, j = 1, \ldots, n; j \neq k \\
&\sum_{c=1}^{q} w_c = 1 \\
&w_c \geq 0, \forall c = 1, \ldots, q
\end{aligned} \tag{2}$$

The optimal value of the objective function, d_k^* is the value difference to the best of all DMUs (note that the best DMU will also depend on w), excluding itself from the reference set (i.e., computing a superefficiency score). If d_k^* is negative, then DMU_k under evaluation is efficient, and the more negative the value d_k^*, the more efficient is DMU_k.

VBDEA, like other non-radial models (e.g., the Range Adjusted Measure [30]) makes no assumption about returns to scale and therefore can be considered a benevolent perspective towards efficiency, when the DMUs use a constant returns to scale technology. We can note, however, that since VBDEA is not ratio based and the variables undergo a transformation, it does not allow considering scale in the usual sense.

The VBDEA method can also include a Phase 2, omitted here, to compute the corresponding projected point on the efficient frontier of the DMU_k under evaluation (for further details, see Ref. [9]).

2.2. Productivity index

The TFP indicator for VBDEA is obtained as follows [14][1]:

$$TFP_{t,k}^{t+1} = \frac{1}{2}\left\{-d^{*t}\left(DMU_k^{t+1}\right) - d^{*t+1}\left(DMU_k^{t+1}\right) + d^{*t}\left(DMU_k^{t}\right) + d^{*t+1}\left(DMU_k^{t}\right)\right\} \quad (3)$$

where t refers to year t and $t+1$ refers to a later year, respectively. Here, $d^{*t}(DMU_k^t)$ and $d^{*t}(DMU_k^{t+1})$ represent the (in)efficiency scores of DMU_k in years t and $t+1$, according to the efficiency frontier in year t. Identically, the (in)efficiency scores of DMU_k in years t and $t+1$, are expressed by $d^{*t+1}(DMU_k^t)$ and $d^{*t+1}(DMU_k^{t+1})$, according to the efficiency frontier in year t+1.

Ref. [17] proposed the decomposition of TFP into technical change (TC) and efficiency change (EC). By adapting this decomposition in the framework of the VBDEA, we define formulations (4) and (5):

$$TC_{t,k}^{t+1} = \frac{1}{2}\left\{ -d^{*t}\left(DMU_k^{t+1}\right) + d^{*t+1}\left(DMU_k^{t+1}\right) - d^{*t}\left(DMU_k^{t}\right) + d^{*t+1}\left(DMU_k^{t}\right)\right\}, \quad (4)$$

$$EC_{t,k}^{t+1} = d^{*t}\left(DMU_k^{t}\right) - d^{*t+1}\left(DMU_k^{t+1}\right), \quad (5)$$

Subsequently, the TFP for the VBDEA is also adapted, and it is given as:

$$TFP_{t,k}^{t+1} = TC_{t,k}^{t+1} + EC_{t,k}^{t+1}. \quad (6)$$

Then, the frontier shifts obtained for any DMU are given by the value of the TC and do not necessarily mean that the corresponding DMU moves the frontier of production in a better direction. Thus, the DMUs that move the frontier line, i.e., the “innovators” (see Ref. [17]), are those fulfilling the next three conditions (for a given $\mathrm{DMU_k}$):

$$TC_{t,k}^{t+1} > 0, \quad (7)$$

$$d^{*t+1}\left(DMU_k^{t}\right) < 0, \quad (8)$$

$$d^{*t+1}\left(DMU_k^{t+1}\right) < 0. \quad (9)$$

The proposed index respects the well-known decomposition into TC and EC of the classical Luenberger indicator. Other decompositions have been proposed in the literature, namely considering scale changes as well [31], but these do not apply to VBDEA since it is based on value functions and not the original units of the factors/criteria. This means that if a DMU changes to consume 10% more inputs and produce 10% more outputs, then the overall value of the DMU will change according to the way the DM values these differences.

In order to compute $d^{*t}(DMU_k^{t+1})$ and $d^{*t+1}(DMU_k^{t})$ formulation (2) is modified in a way that enables the analysis of efficiency changes over time. For the computation of $d^{*t+1}(DMU_k^{t})$, we assume that the DMU_k is under evaluation and has values from the year t, and all the other DMUs have values from the year t+1 (see linear problem (10)). To compute $d^{*t}(DMU_k^{t+1})$ we assume that the DMU_k under evaluation has year t+1 values and all other DMUs have year t values (see linear problem (11)).

$$\min_{d_k,w} d_k^{t+1}\left(DMU_k^{t}\right),$$

$$s.t. \sum_{c=1}^{q} w_c v_c\left(DMU_j^{t+1}\right) - \sum_{c=1}^{q} w_c v_c\left(DMU_k^{t}\right) \le d_k^{t+1}\left(DMU_k^{t}\right), j=1,\dots,n; j\neq k$$

$$\sum_{c=1}^{q} w_c = 1,$$

$$w_c \ge 0, \forall c = 1,\dots,q. \quad (10)$$

$$\min_{d_k,w} d_k^{t}\left(DMU_k^{t+1}\right),$$

$$s.t. \sum_{c=1}^{q} w_c v_c\left(DMU_j^{t}\right) - \sum_{c=1}^{q} w_c v_c\left(DMU_k^{t+1}\right) \le d_k^{t}\left(DMU_k^{t+1}\right), j=1,\dots,n; j\neq k,$$

$$\sum_{c=1}^{q} w_c = 1,$$

$$w_c \ge 0, \forall c = 1,\dots,q. \quad (11)$$

2.3. Robustness analysis

Most real-life problems must deal with data uncertainty, which is challenging for DEA models since efficiency outcomes are highly dependent on the data. The VBDEA model can handle both uncertainty and infeasibility [26]. The robustness analysis using VBDEA has been used for examining the robustness of efficiency results considering perturbations in the factors or to investigate the robustness of results attained for all feasible input and output weights and selecting a common vector of weights to capture the stability of results given the multiplicity of possible scenarios [13,15]. Besides, it allows performing a robustness assessment by considering the perturbations in the DMUs' performance within a given interval. To address this concern, Ref. [26] proposed an optimistic and pessimistic efficiency measure that enables classifying each DMU as surely efficient, surely inefficient, or undetermined (potentially efficient), for an established tolerance value.

Let the value of p_{cj} (denoting an input to be minimized or an output to be maximized for DMU_j) be uncertain and varying within the range $p_{cj}(1-\delta) \le p_{cj} \le p_{cj}(1+\delta)$ for a given tolerance δ. Considering that the value functions $v_c(.)$ are increasing for factors to be maximized and decreasing for factors to be minimized, let $v_c^L(DMU_j)$ and $v_c^U(DMU_j)$ denote, respectively, the lowest and highest value obtained by DMU_j for the given tolerance interval:

$$v_c^L\left(DMU_j\right) = \begin{cases} v_c\left(p_{cj}(1-\delta)\right), & \text{if } c \text{ is being maximized} \\ v_c\left(p_{cj}(1+\delta)\right), & \text{if } c \text{ is being minimized} \end{cases} \quad (12)$$

$$v_c^U\left(DMU_j\right) = \begin{cases} v_c\left(p_{cj}(1+\delta)\right), & \text{if } c \text{ is being maximized} \\ v_c\left(p_{cj}(1-\delta)\right), & \text{if } c \text{ is being minimized} \end{cases} \quad (13)$$

Hence, $v_c^L(DMU_j) \le v_c(DMU_j) \le v_c^U(DMU_j)$, for c={1, …, q}.

The optimistic efficiency measure is obtained by assuming the best value of the intervals for the DMU_k under assessment and the worst value of the intervals for all the other DMUs. The opposite is used to calculate the pessimistic efficiency measure.

On the one hand, the best optimal value to this problem is obtained by considering the most favorable version of the objective function (i.e., the lower bound of the interval objective function since it is a minimization problem) and the maximum value range inequality (i.e., the widest version of the feasible region that in inequality constraints should have the lowest value on the left hand side and the upper value on the right hand side of the constraints) [32,33]. On the other hand, the worst optimal value to this problem is computed by considering the less favorable version of the objective function (i.e., the upper bound of the interval objective function since it is a minimization problem) and the minimum value range inequality (i.e., the tightest version of the feasible region that in inequality constraints should have the upper value on the left hand side and the lower value on the right hand side of the constraints) [32,33].

[1] Please note that these formulas are slightly different from the ones presented in Ref. [14] due to a typo.

Hence, we propose the optimistic efficiency measure, $d^{opt*t+1}(DMU_k^t)$, for DMU_k, which allows obtaining the best optimal value, given by linear program (14):

$$\min_{d_k,w} d_k^{opt^{t+1}}\left(DMU_k^t\right), s.t. \sum_{c=1}^{q} w_c v_c^L\left(DMU_j^t\right) - \sum_{c=1}^{q} w_c v_c^U\left(DMU_k^{t+1}\right) \le d_k^{opt^{t+1}}\left(DMU_k^t\right), j=1,\ldots,n; j\ne k, \sum_{c=1}^{q} w_c = 1, w_c \ge 0, \forall c=1,\ldots,q. \tag{14}$$

Also, the optimistic efficiency measure $d^{opt*t}(DMU_k^{t+1})$ for DMU_k is obtained by (15):

$$\min_{d_k,w} d_k^{opt^{t}}\left(DMU_k^{t+1}\right), s.t. \sum_{c=1}^{q} w_c v_c^L\left(DMU_j^{t+1}\right) - \sum_{c=1}^{q} w_c v_c^U\left(DMU_k^{t}\right) \le d_k^{opt^{t}}\left(DMU_k^{t+1}\right), j=1,\ldots,n; j\ne k, \sum_{c=1}^{q} w_c = 1, w_c \ge 0, \forall c=1,\ldots,q. \tag{15}$$

To compute the pessimistic efficiency measure $d^{pess*t+1}(DMU_k^t)$ for DMU_k, which allows obtaining the worst optimal value, we solve (16).

$$\min_{d_k,w} d_k^{pess^{t+1}}\left(DMU_k^t\right), s.t. \sum_{c=1}^{q} w_c v_c^U\left(DMU_j^t\right) - \sum_{c=1}^{q} w_c v_c^L\left(DMU_k^{t+1}\right) \le d_k^{pess^{t+1}}\left(DMU_k^t\right), j=1,\ldots,n; j\ne k, \sum_{c=1}^{q} w_c = 1, w_c \ge 0, \forall c=1,\ldots,q. \tag{16}$$

Analogously, the pessimistic efficiency measure $d^{pess*t}(DMU_k^{t+1})$ for DMU_k is obtained by (17):

$$\min_{d_k,w} d_k^{pess^{t}}\left(DMU_k^{t+1}\right), s.t. \sum_{c=1}^{q} w_c v_c^U\left(DMU_j^{t+1}\right) - \sum_{c=1}^{q} w_c v_c^L\left(DMU_k^{t}\right) \le d_k^{pess^{t}}\left(DMU_k^{t+1}\right), j=1,\ldots,n; j\ne k, \sum_{c=1}^{q} w_c = 1, w_c \ge 0, \forall c=1,\ldots,q. \tag{17}$$

Note that linear programs (14) to (17) are solved after the original performance of the criteria is converted into value scales. The optimistic and pessimistic measures of efficiency $d^{opt*t}(DMU_k^t)$, $d^{opt*t+1}(DMU_k^{t+1})$ and $d^{pess*t}(DMU_k^t)$, $d^{pess*t+1}(DMU_k^{t+1})$ for each DMU_k, are obtained by following a similar reasoning to problems (14), (15) and (16), (17), respectively.

Finally, from the solution to these problems it is possible to obtain the ranges of variation of TFP, EC and TC, respectively.

$$\left[TC_{t,k}^{L^{t+1}}, TC_{t,k}^{U^{t+1}}\right] = \left[\frac{1}{2}\left\{d^{opt*t}\left(DMU_k^{t+1}\right) + d^{opt*t+1}\left(DMU_k^{t+1}\right) - d^{pess*t}\left(DMU_k^t\right) + d^{opt*t+1}\left(DMU_k^t\right), \right\}, \frac{1}{2}\left\{d^{pess*t}\left(DMU_k^{t+1}\right) + d^{pess*t+1}\left(DMU_k^{t+1}\right) - d^{opt*t}\left(DMU_k^t\right) + d^{pess*t+1}\left(DMU_k^t\right)\right\}\right] \tag{18}$$

$$\left[Ec_{t,k}^{L^{t+1}}, EC_{t,k}^{U^{t+1}}\right] = \left[d^{opt*t}\left(DMU_k^t\right) - d^{pess*t+1}\left(DMU_k^{t+1}\right), d^{pess*t}\left(DMU_k^t\right) - d^{opt*t+1}\left(DMU_k^{t+1}\right)\right] \tag{19}$$

$$\left[TFP_t^{L^{t+1}}, TFP_t^{U^{t+1}}\right] = \left[TC_t^{L^{t+1}} + EC_t^{L^{t+1}}, TC_t^{U^{t+1}} + EC_t^{U^{t+1}}\right] \tag{20}$$

As a result, a DMU is surely TFP robust if, following the changes in its criteria, the $TFP_t^{L^{t+1}} > 0$ and $TFP_t^{U^{t+1}} > 0$; whereas it is potentially TFP robust if $TFP_t^{L^{t+1}} < 0$ and $TFP_t^{U^{t+1}} > 0$. Following a similar approach, analogous conclusions can be reached for EC and TC, allowing one to determine whether a DMU is surely, potentially (or not) robust in terms of its TFP, EC and TC for the considered tolerance.

3. Eco-efficiency and productivity change in the E&G sector

Within the context of the E&G sector, this work contributes to the research stream on the assessment of productivity change over time, as well as the research streams on eco-efficiency assessment using VBDEA and input-output (IO) economic models. In particular, the analysis presented in the next sections elaborates on the prior work by Refs. [6, 7], who were the first to combine IO analysis with DEA in the

Table 1
Criteria considered in the Value-Based DEA model.

	Criteria	Units
To be minimized	Jobs in full time equivalent (FTE)	1000 employees
	Nominal Capital Stock (K)	10^6 €
	GHG emissions	1000-ton CO_2 eq.
	Acidifying gas (ACG) emissions	1000-ton SO_2 eq.
	Ozone precursors (O3PR)	1000-ton NMVOC eq.
To be maximized	Gross Value-added (GVA)	10^6 €

Note: GHG – Greenhouse Gas; CO_2 – carbon dioxide; SO_2 – sulphur dioxide; NMVOC - Non-methane volatile organic compounds; € - euro, eq. - equivalent.

eco-efficiency assessment of the E&G sector.

We began the criteria selection process by examining the previous studies of [34] and [35], which combine IO analysis with DEA. In general, these studies use labor and capital as Inputs, pollutant emissions as undesirable Outputs and Gross Value Added (GVA) or Gross Domestic Product as (desirable) Outputs. Based on these examples and following [6], the inputs and outputs used here as criteria in the VBDEA model are presented in Table 1.

Detailed data can be obtained from Ref. [36]. The time horizon selected incorporates the impact of the financial and Fukushima crises and the effect of the Russian annexation of Crimea in May 2014. Table 2 provides data on the descriptive statistics for 2010 and 2014 and shows that, despite the increase in capital stock and GVA, the environmental performance improved over the time horizon of this study for all chains of the E&G sector.

Table 2 also shows that labor, emissions, and GVA from the direct supply chain (i.e., considering sectors directly engaged with the E&G sector) are lower than those from the indirect supply chain of the E&G sector (i.e., using the sectors indirectly linked with the E&G sector). The dependence of all sectors (particularly those involved in the indirect supply chain) on the E&G sector itself explains these findings.

4. Value functions

In VBDEA, the performance of each factor is converted into a value scale, as described in Section 2.1. The value functions are defined individually for each factor, so that the worst level of the original scale on each factor has a value of 0, and the best level has a value of 1. After that, all factors can be treated as criteria to be maximized.

The VBDEA allows using non-linear functions to match the value differences that DMs place on performance improvements. Different procedures to elicit value functions from DMs are available (see Ref. [28]), which have been used in previous studies [10–12]. In this application to the assessment of eco-efficiency in the E&G sector, hypothetical (rather than elicited) value functions that we have called neutral and environmentally demanding are used to illustrate two different perspectives of analysis concerning negative environmental externalities.

To define the domain of each value function, two limits were determined for each criterion, M_c^L and M_c^U, such that $M_c^L < 0.9 \times min\{p_{cj}, j = 1, \ldots, 28\}$ and $M_c^U > 1.1 \times max\{p_{cj}, j = 1, \ldots, 28\}$, for each $c = 1, \ldots, 6$, already taking into account the tolerance $\delta = 10\%$ assigned to the performance values.

Under the neutral perspective, all value functions are linear, being converted into the range [0, 1] through transformation (21a). Such functions entail that the same absolute improvement adds the same value to a DMU, regardless of the starting point.

$$v_c(DMU_j) = \begin{cases} \dfrac{p_{cj} - M_c^L}{M_c^U - M_c^L}, \text{if criterion c is output} \\ \dfrac{M_c^U - p_{cj}}{M_c^U - M_c^L}, \text{if criterion c is input} \end{cases}, j = 1, \ldots, 28; c = 1, 2, 6 \tag{21a}$$

The environmentally demanding perspective uses non-linear value functions (21 b) in the factors associated with pollution (x_{O3PR}; x_{ACG}; x_{GHG}):

Table 2
Descriptive statistics of all DMUs.

Direct Production Chain		*Labour (×1000)*	*K (×10ˆ6 €)*	*GHG (×1000 ton)*	*ACG (×1000 ton)*	*O3PR (×1000 ton)*	*GVA (×10ˆ6 €)*
2010	Minimum	1	404	1206	1	3	70
	Maximum	249	219,861	357,283	652	423	56,033
	Average	47	39,002	47,401	122	82	8108
	Standard deviation	61	54,220	75,520	166	115	12,214
2014	Minimum	1	550	765	1	2	43
	Maximum	250	222,906	352,117	497	407	49,571
	Average	45	44,493	41,284	87	68	8432
	Standard deviation	60	58,483	72,323	129	104	12,222
Direct supply chain							
2010	Minimum	0	–	110	0	0	18
	Maximum	150	–	23,958	47	60	11,077
	Average	20	–	3344	8	7	1489
	Standard deviation	30	–	5914	11	13	2463
2014	Minimum	0	–	5	0	0	16
	Maximum	148	–	21,975	37	54	11,285
	Average	19	–	2861	6	6	1598
	Standard deviation	30	–	5121	9	11	2681
Indirect supply chain							
2010	Minimum	1	–	439	1	1	36
	Maximum	215	–	144,848	232	176	29,249
	Average	36	–	18,334	47	33	4032
	Standard deviation	48	–	29,660	63	47	6208
2014	Minimum	1	–	338	0	1	26
	Maximum	213	–	152,050	185	179	27,997
	Average	35	–	16,418	34	28	4291
	Standard deviation	48	–	30,136	50	43	6535

Source: [6].

Table 3
Performances converted into value scales considering the two perspectives for Direct Production Chain in 2010.

DMU[a]	Factors in original scales						Factors in value scale (Neutral)						Factors in value scale (Environmentally demanding)					
	x_K	x_{Labour}	x_{GHG}	x_{ACG}	x_{O3PR}	y_{GVA}	v_1	v_2	v_3	v_4	v_5	v_6	v_1	v_2	v_3	v_4	v_5	v_6
AT	26,804	27	11,205	11	15	5222	0.894	0.910	0.974	0.985	0.974	0.084	0.894	0.910	0.525	0.576	0.613	0.084
BE	23,578	19	22,317	14	24	6178	0.907	0.937	0.946	0.981	0.955	0.099	0.907	0.937	0.427	0.545	0.545	0.099
BG	3123	32	34,188	376	62	1184	0.989	0.893	0.916	0.499	0.880	0.019	0.989	0.893	0.366	0.134	0.411	0.019
HR	3553	19	5055	15	10	852	0.987	0.937	0.989	0.980	0.983	0.013	0.987	0.937	0.639	0.537	0.668	0.013
CY	1656	2	3884	25	8	291	0.995	0.993	0.992	0.967	0.988	0.004	0.995	0.993	0.676	0.474	0.705	0.004
CZ	26,825	32	57,813	165	113	5775	0.894	0.893	0.857	0.780	0.778	0.093	0.894	0.893	0.291	0.237	0.325	0.093
DK	31,127	11	21,505	16	26	3643	0.877	0.963	0.948	0.978	0.951	0.058	0.877	0.963	0.432	0.525	0.533	0.058
EE	2947	9	14,655	88	19	502	0.989	0.970	0.965	0.883	0.965	0.008	0.989	0.970	0.487	0.316	0.576	0.008
FI	20,742	13	28,047	63	58	4208	0.918	0.957	0.931	0.916	0.888	0.067	0.918	0.957	0.394	0.357	0.420	0.067
FR	101,256	133	41,711	156	139	25,525	0.596	0.557	0.897	0.792	0.725	0.411	0.596	0.557	0.337	0.244	0.295	0.411
DE	179,671	249	357,283	435	423	56,033	0.282	0.170	0.107	0.419	0.155	0.904	0.282	0.170	0.031	0.115	0.136	0.904
EL	11,883	20	48,487	245	148	2909	0.954	0.933	0.880	0.674	0.706	0.046	0.954	0.933	0.316	0.187	0.286	0.046
HU	14,202	39	17,098	27	33	2312	0.944	0.870	0.959	0.964	0.937	0.037	0.944	0.870	0.465	0.463	0.499	0.037
IE	11,565	12	12,932	18	16	2492	0.955	0.960	0.969	0.977	0.971	0.040	0.955	0.960	0.505	0.517	0.602	0.040
IT	219,861	85	117,850	86	122	25,238	0.121	0.717	0.707	0.885	0.759	0.407	0.121	0.717	0.189	0.318	0.314	0.407
LV	3672	12	2483	4	8	618	0.986	0.960	0.995	0.995	0.987	0.009	0.986	0.960	0.740	0.700	0.696	0.009
LT	3880	14	4020	9	7	811	0.986	0.953	0.992	0.988	0.989	0.013	0.986	0.953	0.672	0.596	0.713	0.013
LU	2882	1	1377	1	3	306	0.990	0.997	0.998	0.998	0.997	0.004	0.990	0.997	0.825	0.848	0.830	0.004
MT	404	2	1206	11	6	70	1.000	0.993	0.999	0.985	0.992	0.001	1.000	0.993	0.844	0.570	0.741	0.001
NL	38,221	24	52,108	23	31	7301	0.848	0.920	0.871	0.969	0.943	0.117	0.848	0.920	0.306	0.483	0.511	0.117
PL	42,094	178	168,752	652	359	11,084	0.833	0.407	0.579	0.131	0.283	0.178	0.833	0.407	0.138	0.065	0.160	0.178
PT	15,977	9	12,020	30	22	3343	0.937	0.970	0.972	0.960	0.959	0.053	0.937	0.970	0.515	0.450	0.556	0.053
RO	10,314	124	37,877	350	80	4581	0.960	0.587	0.907	0.534	0.844	0.073	0.960	0.587	0.351	0.143	0.374	0.073
SK	39,948	20	10,122	61	17	2487	0.841	0.933	0.976	0.919	0.970	0.040	0.841	0.933	0.540	0.361	0.596	0.040
SI	6300	8	6469	14	14	835	0.976	0.973	0.985	0.982	0.977	0.013	0.976	0.973	0.604	0.547	0.626	0.013
ES	108,386	60	60,192	153	152	25,533	0.567	0.800	0.851	0.796	0.698	0.411	0.567	0.800	0.285	0.246	0.282	0.411
SE	60,385	28	10,768	18	24	9577	0.759	0.907	0.975	0.976	0.956	0.154	0.759	0.907	0.531	0.512	0.546	0.154
UK	80,800	129	165,796	351	357	18,103	0.678	0.570	0.586	0.532	0.287	0.292	0.678	0.570	0.140	0.143	0.160	0.292

[a] The acronyms for each Member State are given as follows: AT - Austria; BE - Belgium; BG - Bulgaria; CY - Cyprus; CZ - Czech Republic; DE - Germany; DK - Denmark; EE - Estonia; ES - Spain; FI - Finland; FR - France; EL - Greece; HR - Croatia; HU - Hungary; IE - Ireland; IT - Italy; LT - Lithuania; LU - Luxembourg; LV - Latvia; MT - Malta; NL - Netherlands; PL - Poland; PT - Portugal; RO - Romania; SE - Sweden; SI - Slovenia; SK - Slovakia; UK - United Kingdom.

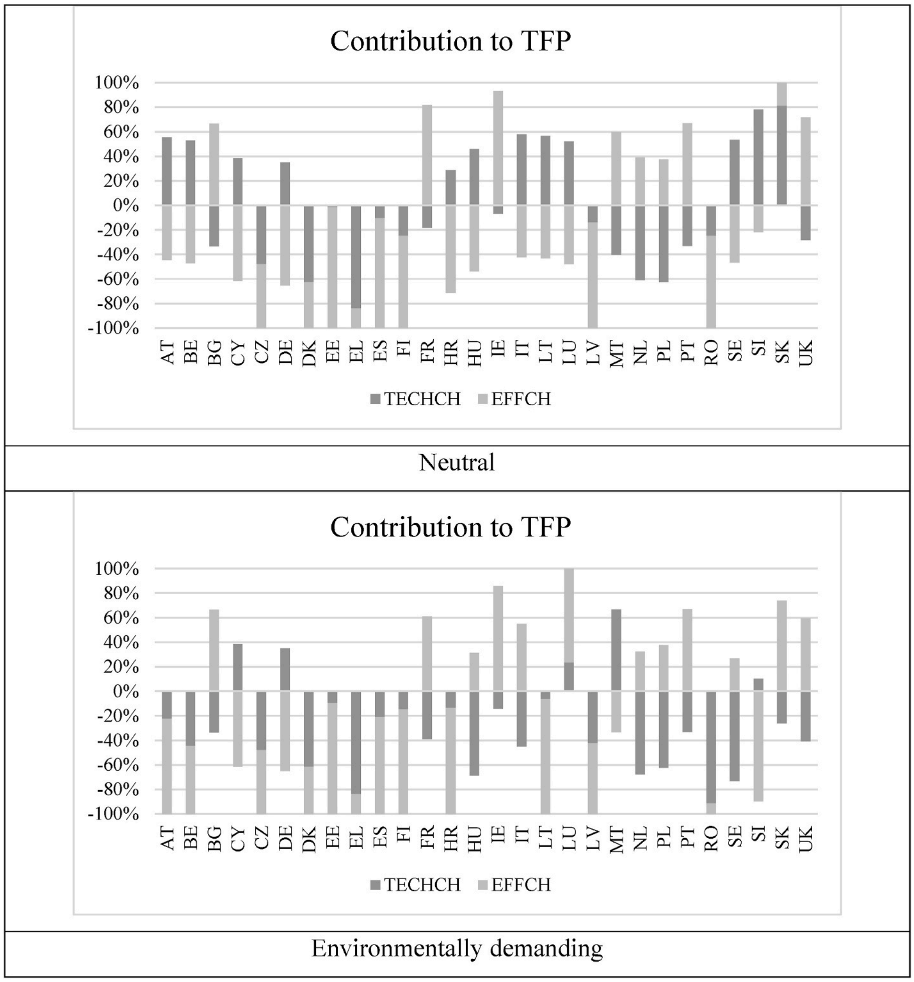

Fig. 1. Contribution of TC (TECHCH) and EC (EFFCH) to TFP in the Direct production chain.

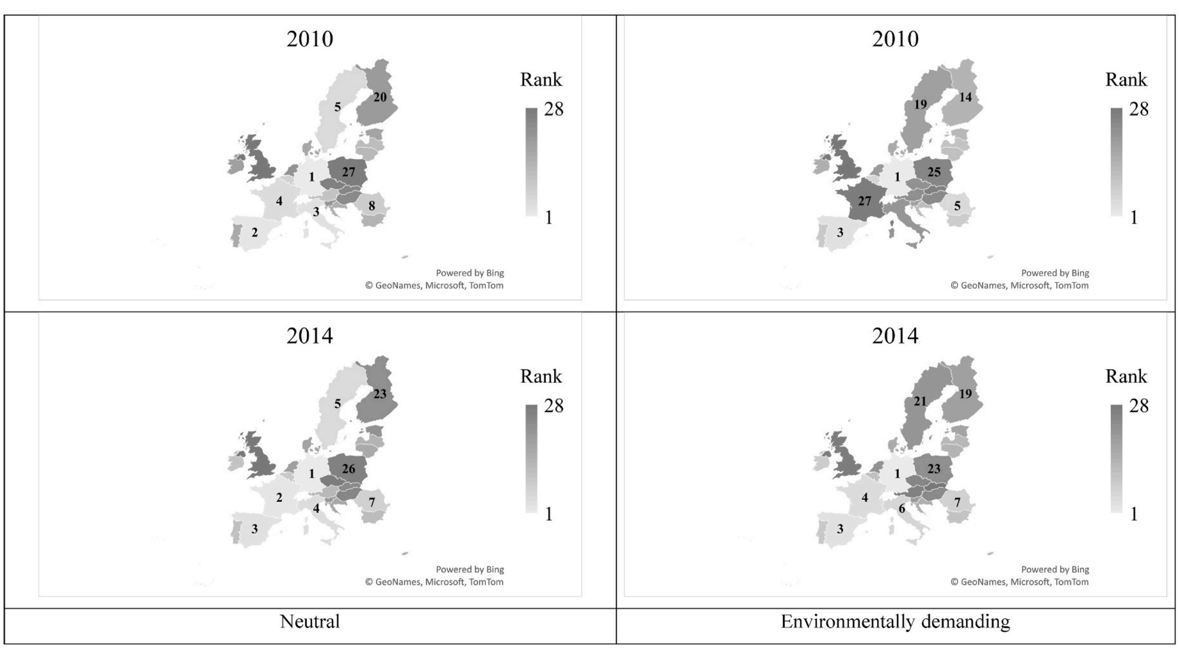

Fig. 2. Ranking of efficiency according to VBDEA in the Direct Production Chain.

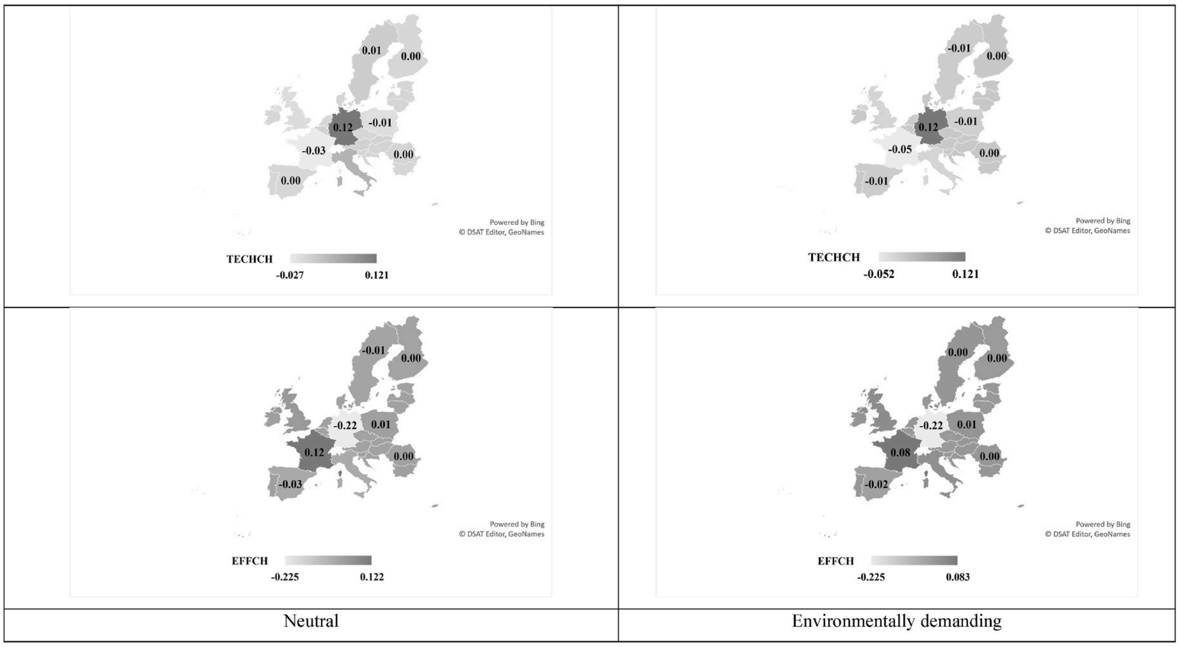

Fig. 3. Tc (TECCH) and EC (EFFCH) across EU28 in the Direct production chain.

Table 4
Correlation and average values of TC, EF and TFP – Direct Production.

Neutral	TC	EC	TFP	Environmental demanding	TC	EC	TFP
TC (correlation)	1.000			TC (correlation)	1.000		
EC (correlation)	−0.930	1.000		EC (correlation)	−0.960	1.000	
TFP (correlation)	−0.770	0.950	1.000	TFP (correlation)	−0.820	0.950	1.000
TFP (average values)	0.005	−0.005	0.000	TFP (average values)	0.000	−0.003	−0.002
TFP>0 (average values)	0.002	0.008	0.010	TFP>0 (average values)	−0.008	0.020	0.012
TFP<0 (average values)	0.007	−0.018	−0.011	TFP<0 (average values)	0.004	−0.014	−0.009

$$v_c(DMU_j) = \frac{\ln\left(M_c^U\right) - \ln\left(p_{cj}\right)}{\ln\left(M_c^U\right) - \ln\left(M_c^L\right)}, j = 1, \ldots, 28; c = 3, 4, 5 \tag{21b}$$

This transformation is applied only to the three undesirable outputs. Its decreasing and convex shape implies that the same absolute improvement adds more value to a DMU if the emissions are low than if the emissions are high. Thus, it demands a greater reduction of these outputs from countries with high levels of emissions to obtain the same increase in value. Eq. (21b) also ensures the performances are converted into the interval [0, 1].

Table 3 shows the original data and the corresponding value functions for the neutral and environmentally demanding perspectives, respectively, focusing on the Direct Production Chain in 2010.

5. Results

Next, we analyze the results regarding the evolution of TFP. A positive TFP indicates gains in productivity across the period under analysis. Changes in TFP are also split into TC and EC. While the former indicates shifts in the production frontier, the latter indicates changes in the position of a DMU relative to the frontier.

Fig. 1 depicts the TFP drivers for the various countries' direct production chains according to distinct value functions[2].

Considering the direct production chain and the value functions that reflect neutrality, fourteen countries face TFP losses, namely (in decreasing order): Germany, Spain, Finland, Poland, Czechia, Estonia, Greece, Romania, the Netherlands, Croatia, Latvia, Cyprus, Hungary, and Denmark (see the top of Fig. 1). The country with the highest TFP gains for the direct production chain is France, which occupied the 4th and 2nd places of the ranking of efficient countries in 2010 and 2014, respectively (see the left-hand side of Fig. 2). Also, according to this

Table 5
Countries viewed as innovators.

TC innovator	Neutral	Environmentally demanding
	DMU	DMU
Direct Production Chain	DE	DE
	-	MT
	LU	LU
	IT	-
	SE	-
	BE	
Direct Supply Chain	DE	DE
	CY	CY
	DK	DK
	IE	IE
	LU	LU
	UK	UK
	BE	-
	SE	-
Indirect Supply Chain	DE	DE
	LU	LU
	SE	SE
	AT	-
	BE	-
	FR	-

[2] The result discussion of the direct and indirect supply chains is given in Appendix A (in Supplementary Material).

perspective, the country with the second highest TFP is the UK, despite being at the bottom of the ranking of inefficient countries in both years—see the left-hand side of Fig. 2. Italy (which was positioned in the 3rd and 4th places of the ranking of efficient countries in 2010 and 2014, respectively) occupies the third place in terms of TFP gains. Ireland and Slovakia rank 4th and 5th, respectively.

If we further examine the reasons behind TFP changes, it can be concluded that sixteen countries had a positive value for TC in the direct production chain of the E&G sector, showing the existence of technological progress across the period under assessment (see top of Figs. 1 and 3 (upper left side)). The biggest frontier shift belongs to Germany; see the upper left side of Fig. 3. Besides, under the neutral perspective, from the top of Figs. 1 and 3 (bottom left side), it is possible to establish that nineteen out of the twenty-eight countries show a negative EC. Nevertheless, EC is highly correlated to TFP gains (see Table 4). One curious result is the one reached in the case of Germany (one of the 14 countries with TFP losses), because this country reaches the worst position in terms of TFP and EC, whereas it manages to attain the biggest frontier shift. Contrarily, France has the highest gains both for TFP and EC, which surpass the worst value attained for TC.

For the value functions that represent an environmentally demanding stance, thus penalizing countries facing higher pollution levels, only nine countries show TFP gains (i.e., Luxembourg, France, UK, Ireland, Malta, Italy, Slovakia, Portugal, and Bulgaria), compared to the previously fourteen countries with positive gains. These findings suggest that, when considering this new perspective, most of the countries face productivity losses (see the bottom of Fig. 1), because this perspective becomes more stringent in terms of environmental outcomes. When compared to the previous perspective, France drops one position in TFP, and rises from the 27th place in terms of efficiency in 2010 to the 4th place in 2014.

If we further evaluate the reasons supporting TFP gains, it can be established that except for Malta, all the countries in this condition had a positive value for EC in the direct production chain of the E&G sector (see bottom of Fig. 1 and bottom of Fig. 3 (bottom right side)). Once again, the biggest frontier shift belongs to Germany—see the upper right side of Fig. 3. Besides, from an environmentally demanding perspective, from Fig. 1 (bottom) and 3 (bottom right side), it is possible to establish that sixteen countries show a negative EC. Nevertheless, EC is highly correlated to TFP gains (see Table 4). Only Germany, Malta, Luxembourg, Cyprus, and Slovenia have positive TC. Then again, Germany attains a curious result (one of the nineteen countries with negative TFP) because this country achieves the worst position in terms of TFP and EC while managing to accomplish the biggest frontier shift. Contrastingly, France has the 2nd highest TFP gain and the 1st position in terms of EC, thus compensating for the worst value achieved for TC.

On average, according to a neutral perspective, the countries improved their performance in 2014 when contrasting their performances against the efficient frontier of 2010 (i.e., they had a positive TC), but endured efficiency losses when compared to their peers in the same year (i.e., they had a negative EC)—see Table 4. However, according to a more environmentally demanding perspective, the countries kept their performance in 2014, when contrasting their performances against the efficient frontier of 2010 (i.e., they had a nearly null TC), but endured efficiency losses when compared to their peers in the same year (i.e., they had a negative EC)—see Table 4.

Furthermore, those countries that experienced TFP gains from a neutral perspective had positive TC and positive EC, whereas those countries that experienced TFP gains from an environmentally demanding perspective had positive EC but negative TC (see Table 4). Finally, on average, according to both perspectives, TFP losses meant that EC was negative, and TC was positive (see Table 4).

Because the TC only represents the shift in the production frontier from that country's perspective, a positive value of this indicator does not necessarily imply that the country shifted the frontier line in a more desirable direction. Hence, we will next determine which countries are responsible for shifting the production frontier, also known as "innovators" [17]. Table 5 shows the countries that were found to be innovators across all chains. In this case, according to the neutral perspective, Germany, Luxembourg, Belgium, and Sweden are innovators across all chains. Under the environmentally demanding stance, the list of innovators remains almost the same, except for Sweden, which no longer becomes an innovator in the direct supply chain. Overall, according to this perspective, the number of innovators diminishes when compared to the neutral perspective.

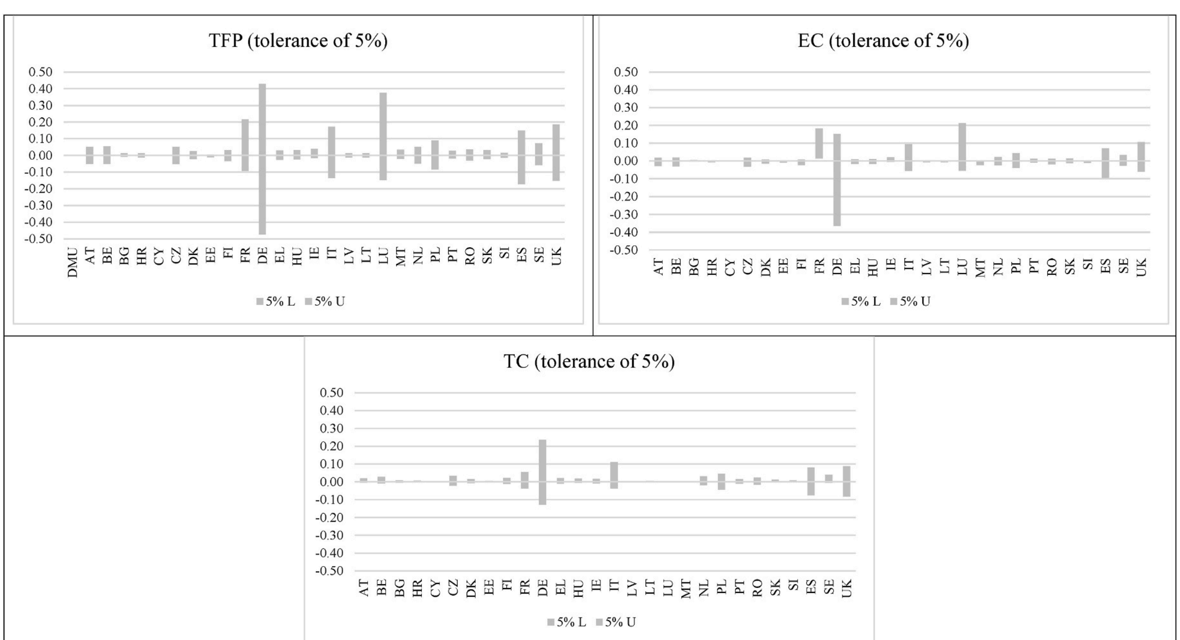

Fig. 4. TC and EC across EU28 in the Direct Production Chain – Environmentally demanding (5%).

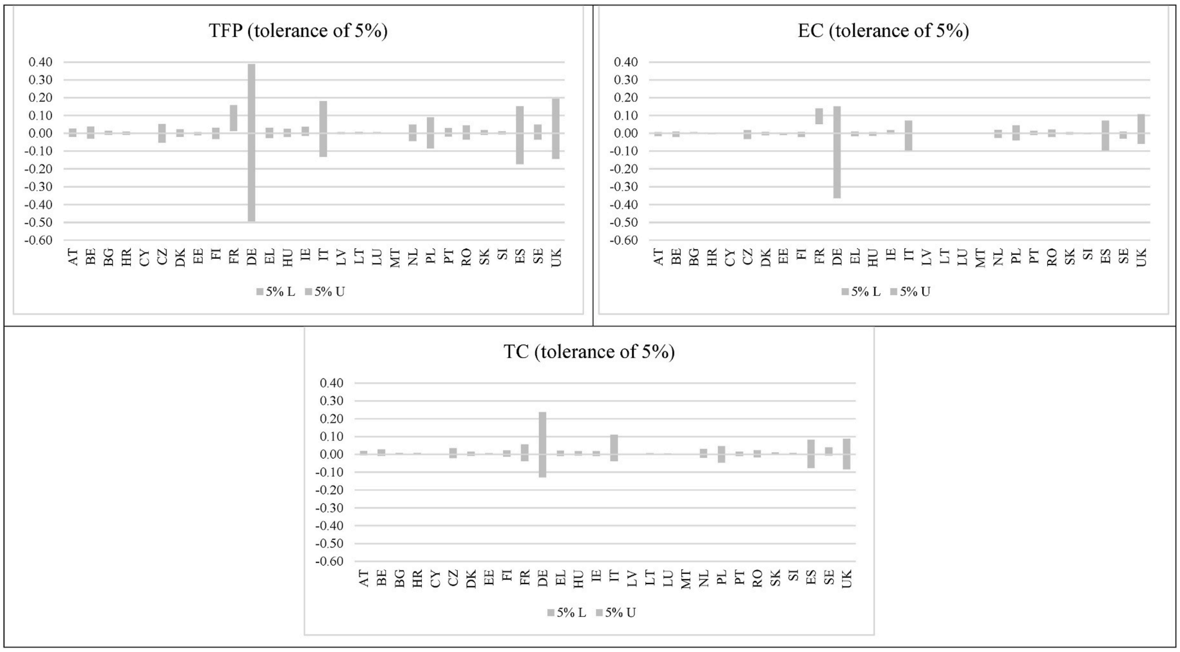

Fig. 5. TC and EC across EU28 in the Direct production chain – neutral (5%).

6. Robustness assessment

We have performed a robustness analysis of the results in the face of uncertain information using linear problems (14) to (17), considering tolerances (δ) of 5% or 10%. This type of analysis enabled us to find whether each country is surely, potentially, or not robust in terms of its TFP, EC, and TC for a given tolerance.

Figs. 4 and 5 show whether each country maintains its status in terms of TFP, EC, and TC for the direct production chain of the E&G sector from an environmentally demanding and neutral perspective, respectively, considering a 5% tolerance. Similar information is depicted in Figs. 1b and 6b in Appendix B (see Supplementary Material) for a tolerance of 10%. Figs. 2b-5b and Figs. 7b–10b, in Appendix B, present analogous results for the remaining direct and indirect supply chains for both tolerances and perspectives.

From the analysis of Figs. 4 and 1b in Appendix B (i.e., from an environmentally demanding perspective), it can be concluded that in the direct production chain, all countries show potential TFP gains for δ = 5% and even δ = 10%. Furthermore, no country will surely suffer TFP losses because of these tolerances. In terms of TC, the conclusion that Malta shows gains is robust for δ = 5%, while the remaining countries will potentially face TC. For δ = 10% all countries can potentially achieve technological progress. In what concerns the EC, only France surely shows efficiency gains for δ = 5%, while the remaining countries only show potentially efficiency gains for this same tolerance. Finally, all countries show potential efficiency gains for δ = 10%.

If the DMs take a neutral stance, only France will surely have TFP gains for a tolerance of 5%, while the remaining countries can only face potential TFP gains (see Fig. 5). For a tolerance of 10%, all countries show potential TFP gains (see Figs. 5b and 6b). Additionally, only Luxemburg surely reaches technological progress for both tolerances, while Malta surely faces negative TC for δ = 5%. Regarding EC, only France and Malta surely get efficiency gains for δ = 5%, whereas for δ = 10% all countries can potentially attain efficiency gains.

Figs. 2b, 4b and 7b and 9b indicate that according to both perspectives, Cyprus consistently shows TFP gains in the direct supply chain for all the tolerances used, while Bulgaria, Estonia, Hungary, Lithuania, Romania, and Slovakia surely have TFP gains for a tolerance of 5%. Bulgaria, Cyprus, Italy, Latvia, Poland, and Slovakia surely face frontier shifts for both tolerances, while Belgium, Croatia, Finland, Germany, Lithuania, the Netherlands, Romania, Spain, and Sweden surely underwent TC for a tolerance of 5%. For that same tolerance, Malta surely faces negative TC. Finally, Cyprus consistently shows efficiency gains for all tolerances, whereas Estonia, Hungary, Lithuania, Malta, and Romania surely have efficiency gains for a tolerance of 5%. For that same tolerance, Latvia surely has efficiency losses.

From the analysis of Figs. 3b and 5b, which show the robustness of results obtained in the indirect supply chain from an environmentally demanding perspective, it can be concluded that all countries show potential TFP gains. In the case of TC, only Malta depicts robust frontier shifts for δ = 5%. In terms of efficiency, for δ = 5%, Germany and Malta, surely show negative gains, whereas Bulgaria, Croatia, Ireland, Lithuania, and Romania surely have efficiency gains. In the remaining situations, all countries present potential gains in efficiency.

Finally, from a neutral perspective (see Figs. 8b and 10b), the robustness of results obtained in the indirect supply chain shows that all countries face potential TFP gains, with Lithuania reaching full robustness when δ = 5%. In the case of EC, only Bulgaria, Ireland, and Lithuania have robust efficiency gains for this tolerance. Luxembourg is the worst country in terms of these indicators, since it surely has efficiency losses with δ = 5% and δ = 10%, while Malta surely shows efficiency losses for δ = 5%.

Regarding TC, for a tolerance of 5% and 10%, Luxembourg and Malta, surely show technological progress, whereas Croatia, Italy, Latvia, and Lithuania surely have positive TC for a tolerance of 5%. In the remaining situations, all countries present potential technological change.

7. Discussion

From an environmental perspective, it is possible to see the impact of a heavy reliance on fossil fuels in the direct production chain, particularly in Germany (the country that reached the highest TFP losses both for the direct production and indirect supply chains between 2010 and 2014) and in Czechia and the Netherlands (both facing TFP losses across all chains). Despite showing the biggest TFP losses in the direct production and indirect supply chains of the E&G sector, Germany ended up being the leader of RES support schemes (particularly feed-in tariffs and feed-in premiums) in 2014, with a total investment in RES of €19.75 billion [37]. Besides, between 2010 and 2014, this country managed to increase RES production and decline both oil and natural gas imports [37]. Therefore, Germany ended up achieving the biggest frontier shifts across all chains of the E&G sector, being a consistent "innovator". Italy, the UK, and France (all of which demonstrated TFP and eco-efficiency gains between 2010 and 2014), as well as Spain contributed approximately € 3 billion to RES [37]. While the first two countries showed TFP and eco-efficiency gains, the third showed losses across all TFP components. The fact that Sweden (a leader both in RES and nuclear power generation) shows TFP losses in the direct production chain in 2010–2014 might be related to the fall of RES production, particularly in 2013 and 2014, due to the decline of electricity demand in the country in these years [37]. Nevertheless, Sweden increased its eco-efficiency due to the limitation of fuel combustion, also showing an inelastic behavior for nuclear power generation [37].

In summary, our findings suggest that, in the direct production chain, the main factor underlying TFP gains was efficiency, i.e., the catching-up effect (irrespective of the perspective considered). Curiously, from an environmental point of view, on average, some countries that showed TFP losses also showed technological progress, whereas some countries that showed TFP gains also showed technological regression. These results might suggest, on the one hand, that some countries (such as Germany, Cyprus, and Slovenia) tried to overcome the reduction in efficiency in the use of their current levels of inputs and technology by triggering technological progress and seeking more productive techniques, some associated with innovations. Specifically, in the case of Germany, this was the result of the phase-out of nuclear power plants that was complemented by RES but also largely by fossil fuels in 2014 [6]. On the other hand, countries like Bulgaria, Hungary, Ireland, Italy, Portugal, Slovakia, and the UK managed to increase their TFP levels just by making better use of their current resources and technologies. In other countries, such as Austria, Belgium, Czechia, Estonia, Spain, Denmark, Greece, Finland, Croatia, Lithuania, Latvia, and Romania, there were losses across all components of TFP in the direct supply chain. Possible reasons for these outcomes might be the European Union (EU) Emissions Trading System crisis due to extremely low CO2 prices, along with changes to the remuneration systems because of the financial crisis, and the phase-out of nuclear power in some countries (particularly in Belgium) after the Fukushima catastrophe.

To further understand the reasons behind TFP in the supply chain of the E&G sector, it is important to know which industries increased and decreased their contributions both directly and indirectly, as well as which countries are mostly responsible for these changes.

The sectors that contributed the most directly to the increase in emissions in the power and gas sectors were A01[3]–crop and animal production; H51–air transport; A03–fishing and aquaculture; H52–warehousing and support activities for transportation; and H49–land transport and transportation via pipeline [6,36]. In this regard, all sectors other than sectors H49 and H52 saw a rise in Italy's emissions [6,36]. It is also worth noting that Italy leads the sector A01 emission levels, most likely because it ranked third globally in terms of the amount of power produced from biomass in 2014, up 98% from 2010 [38], resulting in a positive and robust TC but in an eco-efficiency loss, which ultimately resulted in a TFP loss in the direct supply chain from an environmental perspective.

The industries with the greatest direct influence on the decrease in emissions in the E&G sector were D35–Electricity, gas, steam, and air conditioning supply; B—Mining and quarrying; E37–E39–Sewerage; waste collection, treatment, and disposal activities; materials recovery; remediation activities, and other waste; C19–Manufacture of coke and refined petroleum products; and C20–Manufacture of chemicals and chemical products [6,36]. In this regard, the UK, followed by France and Germany (which is the biggest producer of emissions since it is the biggest energy consumer in the EU), were the countries that considerably cut their pollution impacts on the E&G sector. France continued to show major emission reductions in the remaining sectors (occupying fourth place in terms of TFP gains from an environmental perspective) due to its power production structure, which uses 77% nuclear energy and 18% renewable energy, and a 51% reduction in fossil fuel usage [38]. Germany was the country that showed the largest reduction in sector B emissions (showing the biggest frontier shift in either perspective). The UK followed (the second country with the biggest TFP gains from an environmental viewpoint), sharing the top spot for direct emissions from this sector with Poland. While the former country is one of Europe's top producers of natural gas, the latter is a major player in coal production [39].

Another fact about Germany is that it leads the world in the emission contributions from industries C23, which produces other non-metallic products, and C24, which produces basic metals (iron and steel), both of which are used to make parts for wind turbines. These results are influenced by the fact that Germany dominates the EU in terms of wind power [38].

Also, in this regard, the emissions from sectors E37–E39 are primarily produced by Italy, which decreased its emissions in 2014 (but not enough to reach eco-efficiency gains) and was ranked third in the EU28 for power generated from biogas, primarily from anaerobic digesters [40].

As the largest electricity producer in the EU using petroleum products, Spain also leads sector C19 emissions, which have increased in 2014 (resulting in a negative TFP from an environmental perspective), along with Italy, which displayed a loss in eco-efficiency, while France leads sector C20 emissions because of its dominant position in the chemical industry (thus showing eco-efficiency losses during the time horizon under evaluation).

All in all, it is curious to see that the only countries that can be considered "innovators" from an environmental perspective in the direct supply chain were Cyprus, which increased the use of renewable energy in 2014 by 334% and reduced the use of fossil fuels by 23% [38], robustly showing gains in TC, EC, and TFP for both tolerances; Germany, robustly showing gains in TC for a tolerance of 5%; Denmark, despite its TFP losses; Ireland and the UK, with positive gains across all TFP components; and Luxembourg, with TFP gains. Finally, the fact that countries from Eastern Europe, like Bulgaria, Estonia, Hungary, Latvia, Romania, and Slovakia, show robust TFP gains from an environmental perspective for at least a tolerance of 5%, highlights the effort of these countries to shift their paradigm of resistance to renewable energy sources. In the case of Romania, this country has heavily invested in solar, wind and hydro after 2010, significantly reducing its dependency on fossil fuels, particularly on natural gas [37]. In the case of Hungary and Slovakia, nuclear power remained the main source of electricity production [37].

The industries with the highest indirect contribution to raising the emissions of the E&G sector were A01, H51, A03, C26 (manufacture of computer, electronic, and optical products), and U (activities of extra-territorial organizations and bodies) [6,36]. In this context, Italy shows the largest increase in emissions in sectors A01 (for the same reasons mentioned for the direct supply chain) and H51, thus showing a negative TFP and an eco-efficiency loss. Despite being at the top in terms of emissions in sector A03 [6,36], Slovakia managed to reach eco-efficiency gains across both components of TFP.

The sectors that contributed the most to the decrease of emissions in the indirect supply chain of the power sector were D35, B, C23, E37-E39, and C20 [6,36]. France has the largest decrease in emissions across all industries in this circumstance. Other countries that reduced emissions the most were Italy in sector C23 (but not enough to avoid TFP losses), Spain in sector B (but not enough to avoid a negative TFP), the UK in sector D35 (with gains across all TFP components), Cyprus in sectors

[3] The codes of the activity sectors are given in Appendix C, see Supplementary Material.

E37-E39 (with gains in eco-efficiency and TFP), and Germany in sector C20 (not enough to avoid the worst values for TFP). It is also worth noting that Germany (which shows a robust loss of eco-efficiency for a tolerance of 5%), the UK, Italy, and France (with a gain on TFP but with a loss on TC) rank at the top in indirect emission contributions from sectors D35 and C23, B, E37-E39, and C20, in that order.

Once more, countries from Eastern Europe, usually regarded as policy laggards that resisted the ambitious EU decarbonization targets [41], like Bulgaria, Estonia, Hungary, Lithuania, Latvia, Poland, Romania, and Slovakia show TFP gains.

Czechia is the only country that shows TFP losses across all chains. A potential explanation for this fact might be related to the importance of coal-fired electricity generation in the years assessed [42].

8. Conclusions

This paper assesses the factors behind the relative eco-efficiency changes in the production and supply chains of the E&G sector in 28 European countries, also identifying which countries were true “innovators".

A VBDEA productivity index was used, and robustness analysis formulations were proposed for this indicator, allowing one to determine if a DMU is surely, potentially, or not robust in terms of its TFP, EC, and TC for a given tolerance.

We compare the outcomes generated by linear value functions (which we refer to as neutral preferences) with those obtained from a model utilizing non-linear value functions that allow to value differently the same performance differences depending on the starting point (known as the demanding environmental perspective). This model employs convex functions, which have a decreasing and convex shape, meaning that the same absolute improvement in emissions is more valuable to a DMU (a country) with lower emissions than one with higher emissions. As a result, countries with higher emissions must make a more significant reduction in their emissions to achieve the same increase in value. Thus, these assume that high-polluting countries should be more environmentally demanding than low- and middle-polluting countries to achieve their eco-efficiency targets. Therefore, for example, requiring a reduction of 1000-ton of CO2 eq. emissions may be considered more equitable and feasible for a high-polluting country than a low-polluting country.

Our findings show that most countries attained productivity gains in the direct production chain of the E&G sector according to a neutral perspective, while the opposite occurs when we follow an environmentally demanding stance (only nine countries show TFP gains). Furthermore, TFP gains are primarily driven by the catch-up effect across all chains of the E&G sector. These outcomes are related to the stringent conditions imposed by the configuration of nonlinear value functions representing a more environmentally demanding preference.

The results obtained highlight the importance of using value functions in the context of productivity analysis, indicating the existence of different productivity gains if the DMs’ preferences are expressed through nonlinear value functions. In the direct supply chain, except for Denmark, Spain, and Germany, almost all countries show productivity gains following a neutral perspective, while under an environmentally demanding stance, the number of countries showing TFP losses increases to seven. Nevertheless, according to both types of value functions, most countries manage to obtain productivity gains for the activity sectors that directly supply the E&G sector, which is mainly supported by technological progress. In the indirect supply chain, most of the countries had positive total factor productivity (23 and 19 for the neutral and environmental perspectives, respectively), and most of the countries underwent technological progress. Either way, the biggest frontier shift belongs to Germany across all chains of the E&G sector. Many of these conclusions are robust to perturbations of the DMU’s performance up to 5%, and a few are still robust up to 10%.

Germany, Luxembourg, and Belgium were consistently considered “innovators” across all chains of the E&G sector and according to both perspectives.

Since the number of countries facing TFP losses from an environmentally demanding perspective always increases across all chains, our findings suggest that a restructuring of the EU E&G sector should be fostered to enhance the eco-efficiency of this sector.

It is worth mentioning in this context, that these findings reflect the impacts of the reduction of natural gas consumption in the E&G sector from 2010 to 2014 due to the increase of RES penetration in electricity generation. However, as of 2016, the consumption of natural gas in the European electricity sector increased as a result of the systematic phase-out of coal-fired power plants across Europe and the decommissioning of nuclear power plants specifically in Germany. This transition, however, has rendered the EU’s energy balance much more reliant on world trade dynamics and geopolitical alliances. Although coal may be produced in the EU, natural gas is mostly imported.

Currently, the geopolitical tensions between Russia and Europe have serious consequences for Europe’s carbon neutrality goals. In the medium term, it appears that Europe will need to raise its GHG emissions to keep providing inexpensive energy to its consumers and businesses. In effect, the carbon emissions of the EU’s power sector have risen dramatically, indicating a partial return to coal as a source of electricity. In the meantime, as efforts to speed the adoption of renewable energy and clean technology are implemented, net zero emissions for Europe appear to be still within reach. Nevertheless, a few major obstacles lie ahead, as supply disruptions of crucial raw materials to build the infrastructure needed to produce solar and wind power might undermine the EU’s ability to meet its green ambitions.

Examining the eco-efficiency through the proposed productivity analysis of the E&G sector in Europe shows different insights gained from different perspectives, by considering linear vs. convex value functions, contrasting the results obtained with a more neutral vs. environmentally demanding perspective. Yet, certain limitations should be acknowledged. First, the value functions may not necessarily reflect the preferences of policymakers since they were not consulted for this study. Additionally, our findings may not be comparable with those of other studies because of the use of value functions. Furthermore, we only conducted an analysis for the initial and final years, but it may be interesting to conduct studies with shorter or longer time lengths, either in this or other geographical locations. Moreover, it is worth mentioning that with regards to returns to scale, VBDEA, like other non-radial additive models, does not assume anything about returns to scale. However, VBDEA is not ratio-based, and the variables undergo a transformation that allows for easily handling null or negative data.

Finally, future work should be conducted, once more current and comparable data becomes available, to evaluate the impacts of recent events on the eco-efficiency productivity progress of the E&G sectors across Europe.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.seps.2023.101609.

References

[1] Sueyoshi T, Goto M. Environmental assessment on energy and sustainability by data envelopment analysis. In: The wiley series in operations research and management science features. John Wiley & Sons Ltd All; 2018.
[2] Bigerna S, D'Errico MC, Polinori P. Heterogeneous impacts of regulatory policy stringency on the EU electricity Industry: a Bayesian shrinkage dynamic analysis. Energy Pol 2020;142:111522. https://doi.org/10.1016/j.enpol.2020.111522.
[3] Bigerna S, D'Errico MC, Polinori P. Sustainable power generation in Europe: a panel data analysis of the effects of market and environmental regulations. Environ Resour Econ 2022:1–35. https://doi.org/10.1007/s10640-021-00631-4.
[4] Ehrenfeld JR. Eco-efficiency: philosophy, theory, and tools. J Ind Ecol 2005;9(4): 6–8. https://doi.org/10.1162/108819805775248070.
[5] Zurano-Cervelló P, Pozo C, Mateo-Sanz JM, Jiménez L, Guillén-Gosálbez G. Sustainability efficiency assessment of the electricity mix of the 28 EU member countries combining data envelopment analysis and optimized projections. Energy Pol 2019;134:110921. https://doi.org/10.1016/j.enpol.2019.110921.
[6] Tenente M, Henriques C, da Silva PP. Eco-efficiency assessment of the electricity sector: evidence from 28 European Union countries. Econ Anal Pol 2020. https://doi.org/10.1016/j.eap.2020.05.003.
[7] Henriques CO, Gouveia CM, Tenente M, da Silva PP. Employing Value-Based DEA in the eco-efficiency assessment of the electricity sector. Econ Anal Pol 2022;73: 826–44. https://doi.org/10.1016/j.eap.2022.01.010.
[8] Kahneman D, Tversky A. Prospect theory: an analysis of decision under risk. Econometrica 1979;47(2):263–92.
[9] Gouveia MC, Dias LC, Antunes CH. Additive DEA based on MCDA with imprecise information. J Oper Res Soc 2008;59(1):54–63. https://doi.org/10.1057/palgrave.jors.2602317.
[10] Almeida PN, Dias LC. Value-based DEA models: application-driven developments. J Oper Res Soc 2012;63(1):16–27. https://doi.org/10.1057/jors.2011.15.
[11] Gouveia MC, Dias LC, Antunes CH, Boucinha J, Inácio CF. Benchmarking of maintenance and outage repair in an electricity distribution company using the value-based DEA method. Omega 2015;53:104–14. https://doi.org/10.1016/j.omega.2014.12.003.
[12] Gouveia MC, Dias LC, Antunes CH, Mota MA, Duarte EM, Tenreiro EM. An application of value-based DEA to identify the best practices in primary health care. Spectrum 2016;38(3):743–67. https://doi.org/10.1007/s00291-015-0407-x.
[13] Gouveia MC, Henriques CO, Costa P. Evaluating the efficiency of Structural Funds: an application in the competitiveness of SMEs across different EU beneficiary regions. Omega 2021;101:102265. https://doi.org/10.1016/j.omega.2020.102265.
[14] Henriques CO, Gouveia MC. Assessing the impact of COVID-19 on the efficiency of Portuguese state-owned enterprise hospitals. Socio-Economic Planning Sciences; 2022, 101387. https://doi.org/10.1016/j.seps.2022.101387.
[15] Labijak-Kowalskaa A, Kadzinskia M, Spychałaa I, Dias LC, Fiallosd J, Jonathan Patricke J, Michalowskie W, Farionf K. Performance evaluation of emergency department physicians using robust value-based additive efficiency model. Int Trans Oper Res 2021;0:1–42. https://doi.org/10.1111/itor.13099.
[16] Chambers R, Chung Y, Färe R. Profit, directional distance functions, and Nerlovian efficiency. J Optim Theor Appl 1998;98(2):351–64. https://doi.org/10.1023/A:1022637501082.
[17] Färe R, Grosskopf S, Norris M, Zhang Z. Productivity growth, technical progress, and efficiency change in industrialized countries. Am Econ Rev 1994:66–83.
[18] Färe R, Grosskopf S, Yaisawarng S, Li SK, Wang Z. Productivity growth in Illinois electric utilities. Resour Energy 1990;12(4):383–98. https://doi.org/10.1016/0165-0572(90)90030-M.
[19] Nakano M, Managi S. Regulatory reforms and productivity: an empirical analysis of the Japanese electricity industry. Energy Pol 2008;36(1):201–9. https://doi.org/10.1016/j.enpol.2007.09.003.
[20] Aghdam RF. Dynamics of productivity change in the Australian electricity industry: assessing the impacts of electricity reform. Energy Pol 2011;39(6):3281–95. https://doi.org/10.1016/j.enpol.2011.03.019.
[21] Munisamy S, Arabi B. Eco-efficiency change in power plants: using a slacks-based measure for the meta-frontier Malmquist–Luenberger productivity index. J Clean Prod 2015;105:218–32. https://doi.org/10.1016/j.jclepro.2014.12.081.
[22] Arabi B, Doraisamy SM, Emrouznejad A, Khoshroo A. Eco-efficiency measurement and material balance principle: an application in power plants Malmquist Luenberger Index. Ann Oper Res 2017;255(1–2):221–39. https://doi.org/10.1007/s10479-015-1970-x.
[23] Balk BM, Färe R, Grosskopf S, Margaritis D. Exact relations between Luenberger productivity indicators and Malmquist productivity indexes. Econ Theor 2008: 187–90. https://doi.org/10.1007/s00199-007-0228-5.
[24] Fujii H, Managi S, Matousek R. Indian bank efficiency and productivity changes with undesirable outputs: a disaggregated approach. J Bank Finance 2014;38: 41–50. https://doi.org/10.1016/j.jbankfin.2013.09.022.
[25] Aparicio J, Pastor JT, Zofio JL. On the inconsistency of the Malmquist–Luenberger index. Eur J Oper Res 2013;229(3):738–42. https://doi.org/10.1016/j.ejor.2013.03.031.
[26] Gouveia MC, Dias LC, Antunes CH. Super-efficiency and stability intervals in additive DEA. J Oper Res Soc 2013;64(1):86–96. https://doi.org/10.1057/jors.2012.19.
[27] Ali AI, Lerme CS, Seiford LM. Components of efficiency evaluation in data envelopment analysis. Eur J Oper Res 1995;80(3):462–73. https://doi.org/10.1007/0-387-24138-8_1.
[28] Keeney RL, Raiffa H. Decisions with multiple objectives: preferences and value trade-offs. Cambridge university press; 1993.
[29] Bell DE. Regret in decision making under uncertainty. Oper Res 1982;30(2): 961–81. https://doi.org/10.1287/opre.30.5.961.
[30] Sueyoshi T, Sekitani K. Measurement of returns to scale using a non-radial DEA model: A range-adjusted measure approach. Eur. J. Oper. Res. 2007;176(3): 1918–46. https://doi.org/10.1016/j.ejor.2005.10.043.
[31] Epure M, Kerstens K, Prior D. Bank productivity and performance groups: a decomposition approach based upon the Luenberger productivity indicator. Eur J Oper Res 2011;211:630–41. https://doi.org/10.1016/j.ejor.2011.01.041.
[32] Shaocheng T. Interval number and fuzzy number linear programmings. Fuzzy Set Syst 1994;66(3):301–6. https://doi.org/10.1016/0165-0114(94)90097-3.
[33] Chinneck JW, Ramadan K. Linear programming with interval coefficients. J Oper Res Soc 2000;51(2):209–20. https://doi.org/10.1057/palgrave.jors.2600891.
[34] Luptacik M, Mahlberg B. Eco-Efficiency and Eco-Productivity change over time in a multisectoral economic system. Department of Economic Policy - WP No 2013;4 (2):1–18. https://doi.org/10.1007/s10663-014-9262-2.
[35] Zurano-Cervelló P, Pozo C, Mateo-Sanz JM, Jiménez L, Guillén-Gosálbez G. Eco-efficiency assessment of EU manufacturing sectors combining input-output tables and data envelopment analysis following production and consumption-based accounting approaches. J Clean Prod 2018;174:1161–89. https://doi.org/10.1016/j.jclepro.2017.10.178.
[36] Henriques C, Tenente M, Silva PP. Data for: eco-efficiency assessment of the electricity sector: evidence from 28 European Union countries. Mendeley Data 2020. https://doi.org/10.17632/2pc36hgz7d.1.
[37] Gökgöz F, Güvercin MT. Energy security and renewable energy efficiency in EU. Renew Sustain Energy Rev 2018;96:226–39. https://doi.org/10.1016/j.rser.2018.07.046.
[38] European Commission. Energy statistical datasheets for the EU countries. Retrieved March 30, 2019. Retrieved from: https://ec.europa.eu/energy/sites/ener/files/documents/countrydatasheets_august2018.xlsx; 2018.
[39] Brown TJ, Hobbs SF, Idoine NE, Mills AJ, Wrighton CE, Raycraft ER. European mineral statistics 2010-14: a product of the world mineral statistics database. 2016.
[40] Scarlat N, Dallemand JF, Fahl F. Biogas: developments and perspectives in Europe. Renew Energy 2018;129:457–72. https://doi.org/10.1016/j.renene.2018.03.006.
[41] Skjærseth JB. Towards a European Green Deal: the evolution of EU climate and energy policy mixes. Int Environ Agreements Polit Law Econ 2021;21(1):25–41. https://doi.org/10.1007/s10784-021-09529-4.
[42] Kochanek E. The energy transition in the Visegrad group countries. Energies 2021; 14(8):2212. https://doi.org/10.3390/en14082212.

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