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Investigating the energy efficiency determinants in EU countries by using multi-criteria decision analysis and the Tobit regression model

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ABSTRACT

This study investigates the effects of several contextual variables, including renewable energy intensity, capital stock per labor, natural resource rent, the share of imported energy in total energy consumption, the ratio of carbon emissions to GDP, population, and energy production on energy efficiency in EU countries. While Tobit regression is used to examine the effects of contextual variables on energy efficiency, Data Envelopment Analysis (DEA), Slack-Based Data Envelopment Analysis (SBM-DEA), and Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) are used to calculate energy efficiency values of countries. Four different Tobit regression models are estimated as a function of the censored value for the energy efficiency series. The results show that renewable energy intensity, the ratio of carbon emissions to GDP, and population size have negative effects on energy efficiency. In contrast, regardless of the efficiency level, the share of imported energy in total energy consumption, total energy production, capital stock per labor, and technological progress have positive effects on energy efficiency.

KEYWORDS

SBM-DEA; TOPSIS; energy efficiency; Tobit panel regression; energy in EU

1. Introduction

Energy efficiency has recently become an important goal on the political agenda of most countries (El Montasser and Ben-Salha 2022). The importance of energy efficiency as a policy goal is associated with environmental benefits, such as the reduction of greenhouse gas emissions and other pollutants, as well as commercial and industrial competitiveness and energy security, which is defined as unimpeded access to energy resources (Akdag and Yıldırım 2020; Lu 2017; Yusuf, Abubakar, and Mamman 2020). The issue has become increasingly essential in terms of economic sustainability and environmental concerns such as climate change, global warming, and air pollution, as environmental problems caused by fossil fuels have reached alarming levels. Therefore, policy makers in developed countries, as well as international organizations (e.g., the United Nations) and civil society, are increasingly concerned with protecting the environment in the context of sustainable development (Cifuentes-Faura 2022; Skjærseth 2021). The increasing destructive effects of fossil fuels, which are the main source of carbon emissions, combined with globalization and concerns about sustainability, have forced governments and international organizations to take a step. As a result, many international treaties, such as the Kyoto Protocol and the Paris Climate Agreement, have come into force with the aim of reducing carbon emissions.

The EU has also adopted several climate and sustainable growth measures closely linked to energy efficiency, including the Green Deal and the Sustainable Development Goals (SDGs) (Ayres, Turton, and Casten 2007; Oyedepo 2012; Zakari et al. 2022; Ziolo et al. 2020). In addition to environmental

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concerns, energy dependence, defined as the ratio of imported energy to total energy consumption, poses a serious threat to the energy security of EU countries. The fewer suppliers energy importing countries have, the less energy security they have. In 2020, almost 75% of the EU's crude oil imports came from Russia (29%), the United States (9%), Norway (8%), Saudi Arabia and the United Kingdom (both 7%), and Kazakhstan and Nigeria (both 6%). Similarly, more than three-quarters of the EU's natural gas imports came from Russia (43%), Norway (21%), Algeria (8%), and Qatar (5%), while more than half of solid fossil fuel imports, mainly coal, came from Russia (54%), followed by the United States (16%) and Australia (14%). Based on these figures, Russia alone supplies almost a third of the EU's crude oil needs, more than two-fifths of its natural gas needs, and more than half of its solid fossil fuel needs (Eurostat 2022).

The amount of carbon emitted into the atmosphere has reached alarming levels over the past century. Global carbon emissions from fossil fuel combustion and industrial processes totaled 34.81 billion tons in 2022, from 0.01 billion tons in 1750 and 1.3 billion tons at the beginning of the 20th century (Statista 2022). Therefore, countries are striving to reduce the impact of fossil fuels on nature while meeting their energy needs. Transitioning to clean energy, using energy more efficiently, and solving environmental problems are existential challenges for Europe and the world. To overcome these challenges, the European Commission has launched the European Green Deal to eliminate the harmful effects of carbon emissions by 2050 (European Commission 2022). In this context, improving energy efficiency in EU countries would help to reduce the undesirable effects of carbon emissions while reducing energy dependence and thus increasing energy security.

Sustainable economic growth combined with environmental concerns has highlighted the importance of a diversified, clean, and secure energy supply, and thus energy efficiency. In this context, research on the determinants of energy efficiency is crucial. This paper aims to determine the impact of some contextual variables, such as renewable energy intensity on total energy consumption, capital stock per labor, total population, the share of imported energy in total energy consumption, etc., on energy efficiency and to propose measures to improve energy efficiency in EU member states. Data Envelopment Analysis (DEA), Slack-Based Data Envelopment Analysis (SBM-DEA), and Technique of Preference by Similarity to the Ideal Solution (TOPSIS) were used to calculate the energy efficiency of EU countries. The Tobit regression model, one of the limited dependent variable models, was used to determine the impact of the contextual variables on energy efficiency. TOPSIS, SBM-DEA, and DEA are multi-criteria decision methods used to choose between alternatives. However, we used these models to create time series by treating each year as an alternative in this study. The use of three approaches to calculate energy efficiency allowed for robustness checks in the study of energy efficiency. In addition, the combination of multi-criteria decision-making with the Tobit regression model and the application of different censoring limits to the energy efficiency series allowed for a comprehensive analysis of energy efficiency and its determinants in EU countries.

2. Literature review

Energy is defined as the working capacity of a system. It is the general term for all forms that are used or converted into mechanical, temperature, light, electrical, and magnetic forms in all physical and chemical events and reactions in the universe. According to physics, energy can be neither created nor depleted. Nonetheless, it can be consumed more efficiently. Although the concept of energy efficiency is not clearly defined, it essentially refers to consuming less energy for a given level of desired output (Lovins 2017). The main problem in measuring energy efficiency is how to define the desired output accurately, which leads to some important methodological considerations that have yet to be largely ignored in the existing literature. Even though it is a sophisticated topic, the calculation of energy efficiency has always been an essential and riveting topic. In the last twenty years, the multi-criteria decision-making (MCDM) methods have become widely used to calculate energy efficiency. DEA, SBM-DEA, and TOPSIS are some of these methods commonly used in energy-related

studies (Çam, Karataş, and Lopcu 2022; Djordjević and Krmac 2019; Liu et al. 2013). In particular, DEA and its derivatives, as well as all methods of multi-criteria decision making, have been used in many areas of research, such as farm eco-efficiency (Picazo-Tadeo, Gómez-Limón, and Reig-Martínez 2011; Rybaczewska-Błażejowska and Gierulski 2018), healthcare systems and their efficiencies (Ahmed et al. 2019; Asandului, Roman, and Fatulescu 2014), effectiveness and performance of online banking systems (Faccia and Cavaliere 2021; Ho and Wu 2009), measuring innovation and its effectiveness (Bresciani et al. 2021; Zhong, Li, and Wang 2021), calculating airline efficiency (Law 2022; Ngo and Tsui 2021), calculating health and hospital efficiency (Kohl et al. 2019; Yaya et al. 2020), air pollution studies (Lin et al. 2021; Moutinho, Madaleno, and Macedo 2020), etc., and energy efficiency (Alp, Sözen, and Kazancıoğlu 2013; Chien and Hu 2007; Honma and Hu 2008; Hu and Kao 2007; Hu and Wang 2006; Wu, Cao, and Liu 2014). Energy efficiency studies cover a wide range of countries, from China to Japan and from Korea to the G-20 countries (Amowine et al. 2019; Cui et al. 2014; Dogan and Tugcu 2015; Fidanoski, Simeonovski, and Cvetkoska 2021; Kim et al. 2015; Lee, Hu, and Kao 2011; Liu and Sun 2022; Moon and Min 2020; Mukherjee 2008; Tachega et al. 2021; Wang, Le, and Nguyen 2019; Zalaghi et al. 2021; Zhang and Chen 2022; Zheng 2021; Zhou and Xu 2022). Besides, the EU countries have been analyzed by many researchers in terms of efficiency, economic growth, and climate change due to their pioneering role and long-term climate goals (Bampatsou, Papadopoulos, and Zervas 2013; Chang 2014; Chiu et al. 2015; Gökgöz and Güvercin 2018; Gómez-Calvet et al. 2014; Gong, Zhao, and Ge 2014; Lábaj, Luptáčik, and Nežinský 2014; Makridou et al. 2016; Menegaki 2013). In addition, many studies on EU countries have discussed the relationship between energy efficiency and some contextual variables (Khoshnevisan et al. 2013; Mehmood et al. 2020), but they usually focused on the impact of energy on the environment (Borozan 2018; Simeonovski, Kaftandzieva, and Brock 2021).

In this paper, we examined the energy efficiency of 21 EU member states in two stages. In the first stage, energy efficiency values were calculated using the DEA, SBM-DEA, and TOPSIS methods. In the second stage, the influence of some variables on efficiency, such as capital per labor, renewable energy intensity in total energy consumption, share of imported energy in total energy consumption, carbon emission intensity of GDP, etc. were analyzed. We combined multi-criteria decision-making with a time series (or panel) regression model. The analysis allowed us to calculate energy efficiency and determine the direction of the influence of the explanatory variables on efficiency. To determine the relationship between the variables, Tobit panel regressions were run in four different models, depending on the censored value of the energy efficiency series. The methodology used in this work has provided robust and reliable results. Moreover, the effect of each variable on energy efficiency at all levels of efficiency was analyzed by the estimation procedure performed. The methodology used in this study is believed to open new perspectives for future studies.

3. Calculating energy efficiency

There is no unique method to measure energy efficiency, which is essentially defined as the ratio of output to input (Ang 2006; Filippini and Zhang 2016; Hu and Wang 2006; Hu et al. 2012). Nevertheless, it is possible to calculate representative efficiency from different aspects using thermodynamics or some economic indicators such as GDP, capital stock, labor force, and energy consumption, which have been used as indicators of energy efficiency in many studies (Aye, Gupta, and Wanke 2018; Shah et al. 2022). However, the need to value capital stock, labor, and energy efficiency together requires a new definition of efficiency including physical units. In economic terms, GDP is the numerator of energy efficiency in (1), but the denominator must be defined appropriately to include the capital stock and the labor employed in an economy. Thus, the logical calculation of energy efficiency would be as follows:

$$EE = \frac{Y}{f(Energy, Labor, Capital)} \tag{1}$$

where EE is the energy efficiency of an economy, Y is GDP, and f (*) is a function of national energy consumption, labor force, and capital stock representing inputs used in the GDP process. This ratio alone cannot express efficiency, and it should be converted into efficiency values using a mathematical transformation. Many methods such as DEA, SBM-DEA, and TOPSIS can be used to convert the above ratio into an efficiency value.

3.1. Data envelopment analysis

DEA is a non-parametric, linear programming-based method for calculating the efficiency of decision-making units (DMUs) in cases where there are complex relationships between inputs and outputs. DEA constructs an efficient frontier over the data and computes the efficiency of each DMU relative to the frontier. DEA efficiency indicates how far a DMU is from the frontier compared to its peers and represents its ability to convert multiple inputs into multiple outputs (Charnes, Cooper, and Rhodes 1978; Farrell 1957; Mehra et al. 2014). The initial mathematical form of DEA was proposed by Farrell (1957) with one input and one output. Charnes, Cooper, and Rhodes (1978) improved a multivariable model known as CCR based on Farrell's model, while Banker, Charnes, and Cooper (1984) introduced an alternative model known as BCC (Banker, Charnes, and Cooper) to measure overall efficiency under the variable returns to scale (VRS) assumption. The CCR and BCC models can be set up as input or output-oriented in two different mathematical formulations (Ji and Lee 2010). In the following, we present a general input-oriented CCR model that assumes constant returns to scale:

$$EE = Z_{max} = \frac{\sum_{m=1}^{M} u_m y_{jm}^*}{\sum_{n=1}^{N} v_n x_{jn}^*} \tag{2}$$

$$\frac{\sum_{m=1}^{M} u_m y_{km}^*}{\sum_{n=1}^{N} v_n x_{kn}^*} \leq 1$$

$$u_m, v_n \geq 0$$

$k = 1, 2, \ldots, K$; $m = 1, 2, \ldots, M$; $n = 1, 2, \ldots, N$; $j = 1, 2, \ldots, K$

Here, v_n and u_m are the weights of inputs and outputs assigned by linear programming for each DMU,[1] and k is the subscript of DMUs ($DMU_1, DMU_2, DMU_3, \ldots, DMU_K$) and represents the 21 countries of the European Union included in the analysis. Each DMU, i.e., 21 EU countries, has N inputs, namely total energy consumption, labor force, and capital stock, and M outputs, namely GDP, in the analysis. The calculated efficiency values range from zero to one. Here, one corresponds to the most efficient score of a DMU.

3.2. Slack-based data envelopment analysis

The SBM-DEA model can deal directly with surpluses in inputs and shortages in outputs. In the model SBM-DEA, the data unit is invariant, and the slack variables decrease monotonically regarding input surpluses and output deficits. The main advantage of the SBM-DEA model is that it can adequately calculate the efficiency of the less efficient DMUs. To construct the organization of SBM-DEA, we assume that n is the number of DMUs with $X = x_{ij} \in R^{mxn}$ input matrix and $Y = y_{ij} \in R^{sxn}$ output

[1]Matrices are indicated in this paper by bold capital letters.

matrix. No observations in the output and input matrices are negative. The expected output of the SBM-DEA based efficiency generated by using m units of inputs can be represented as follows:

$$EE_0 = \frac{1-(1/m)\sum_{i-1}^{m} s_i^-/x_{io}}{1+(1/s)\sum_{r-1}^{s} s_r^+/y_{ro}}$$

$$\text{s.t.} x_o = X\lambda + s^- \tag{3}$$

$$y_o = Y\lambda - s^+$$

$$\lambda \geq 0, s^- \geq 0, s^+ \geq 0$$

Here, $s^- \in \mathbb{R}^m$ and $s^+ \in \mathbb{R}^s$ are the input surplus and output deficiency variables and called slacks. The target of SMB-DEA would take a value between zero and one as minimum and maximum efficiencies, respectively (Tone 2001). Here, a DMUs is SBM efficient if $EE = 1$ and both slack variables s^- and s^+ are zero in the optimal solution.

3.3. Technique for order of preference by similarity to the ideal solution method

The TOPSIS method developed by Hwang and Yoon (1981) is based on the alternatives that simultaneously consider the shortest distance to the ideal solution, called the best solution, and the farthest distance to the negative solution, called the worst solution (Shih, Shyur, and Lee 2007). The ideal solution is created by considering the best values of all criteria, while the negative solution is created by considering the worst values of all criteria. When calculating TOPSIS scores, all variables in the data set are firstly normalized to eliminate unit effects and obtain more reliable results. TOPSIS treats some variables as undesired inputs (inputs or cost variables in the DEA) and some as desired inputs (outputs or benefit variables in the DEA). In other words, variables in the denominator of efficiency are undesired inputs, while variables in the numerator of efficiency are desired inputs. To gain TOPSIS-based efficiency, several steps should be performed. Assume that $\tilde{D}$ is the matrix of raw variables (decision matrix) and $\tilde{V}$ is the weighted normalized decision matrix transformed by the formula $\tilde{r}_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i-1}^{n} x_{ij}^2}}$. After the weighted normalized decision matrix is constructed, $\tilde{D}$ and $\tilde{V}$ are organized as follows:

$$\tilde{D} = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1j} & \cdots & \tilde{x}_{1m} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ \tilde{x}_{i1} & \cdots & \tilde{x}_{ij} & \cdots & \tilde{x}_{im} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{n1} & \cdots & \tilde{x}_{nj} & \cdots & \tilde{x}_{nm} \end{bmatrix}; \tilde{V} = \begin{bmatrix} \tilde{v}_{11} & \cdots & \tilde{v}_{1j} & \cdots & \tilde{v}_{1m} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ \tilde{v}_{i1} & \cdots & \tilde{v}_{ij} & \cdots & \tilde{v}_{im} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{v}_{n1} & \cdots & \tilde{v}_{nj} & \cdots & \tilde{v}_{nm} \end{bmatrix}$$

Here $\tilde{v}_{ij} = \tilde{r}_{ij} * \tilde{w}_j$ is the weighted observation for the i-th alternative and $\tilde{w}_j$is the weight for the j-th criterion.[2] In practice, there are several weighting methods, but most of them overweight the variables with a wider range, such as GDP, and the calculated efficiency values may be biased. Therefore, to avoid biased efficiency, we preferred to use the formula below, which does not include subjective judgment.

$$\sigma_k = \sqrt{\frac{\sum_{i=1}^{n} (\tilde{v}_{ik} - \bar{v}_k)^2}{n-1}} \tag{4}$$

[2]Here the weighting of the individual criteria is calculated as.$\tilde{w}_j = \frac{\sigma_j}{\sum_{k=1}^{m} \sigma_k}$

Here k represents the criteria, so $k \in (1, 2, \ldots, m)$. The next step is to compute the positive and negative ideal solution vectors.

$$A^+ = \left\{\tilde{v}_1^+, \ldots, \tilde{v}_m^+\right\}, \text{where } \tilde{v}_j^+ = \left\{max\left(\tilde{v}_{ij}\right) \text{if} j \in J; min\left(\tilde{v}_{ij}\right) \text{if } j \in J'\right\} \tag{5}$$

$$A^- = \left\{\tilde{v}_1^-, \ldots, \tilde{v}_m^-\right\}, \text{where } \tilde{v}_i^- = \left\{min\left(\tilde{v}_{ij}\right) \text{if} j \in J; max\left(\tilde{v}_{ij}\right) \text{if } j \in J'\right\}$$

where$J$ and J' symbolize the benefit and cost criteria, respectively. The benefit criteria in the denominator of the energy efficiency in formula (1) are represented by a desired output, such as GDP. In contrast, the cost criteria in the nominator of the energy efficiency formula are represented by undesired outputs, such as energy consumption, labor, and capital stock. The final and intermediate calculations of the efficiency series are as follows:

$$S_i^+ = \left[\sum_{j-1}^m \left(\tilde{v}_i^+ - \tilde{v}_{ij}\right)^2\right]^{1/2} \text{and } S_i^- = \left[\sum_{j-1}^m \left(\tilde{v}_i^- - \tilde{v}_{ij}\right)^2\right]^{1/2} \tag{6}$$

Here, S_i^+ and S_i^- are the measure of the distance to the positive ideal solution vector A^+ and to the negative ideal solution vector A^-, respectively. Consequently, the TOPSIS-based efficiency values are $EE_i = S_i^- / \left(S_i^+ + S_i^-\right)$ and can take a value between zero and one. Zero is the worst value for efficiency, while one is the best value.

4. A fixed effect Tobit regression model

The Tobit regression model proposed by Tobin (1958) is estimated using the maximum likelihood method and is one of the most appropriate estimation models for censored data, such as the efficiency values, which range from zero to one. Therefore, we used a panel Tobit model to investigate the factors underlying the energy efficiency of countries, which can be expressed as follows:

$$y_{it}^* = x_{it}^{'}\beta + \mu_i + v_{it}$$

$$y_{it}^* = y_{it} \ if \ y_{it} < \gamma \tag{7}$$

$$y_{it}^* = 0 \ otherwise$$

where $v_{it} : \text{INN}\left(0, \sigma_v^2\right), i = 1, 2, \ldots, N, \ t = 1, 2, \ldots, T$, and i represents the number of units (countries in the analysis); t denotes the time dimension of the data for each unit; y_{it}^* represents the latent dependent variable censored by values equal to, greater than, or less than γ; x_{it} denotes the independent variable for all units and time; *Accessisdenied* represents a time-invariant individual fixed effects; *AccessisdeniedAccessisdenied* indicates the estimated coefficients; and v_{it} indicates error terms (Baltagi 2005, 224). Four different models are estimated in the analysis depending on the censored value of the energy efficiency series. The details of the estimated models in terms of censored energy efficiency values can be found in the following sections.

5. Analysis and findings

In the energy efficiency calculation phase, we used total energy consumption (in BTU), labor force (in millions), and capital stock (USD) as inputs and GDP (2010 = 100) as outputs in the DEA, SMB-DEA, and TOPSIS models.[3] The Czech Republic, Estonia, Cyprus, Lithuania, Malta, and Poland were not

[3]Renewable energy consumption (2023) and total energy consumption are from the Energy Information Administration (EIA 2022); capital stock and labor force are from Penn World Table 10 (Groningen Growth and Development Centre 2021); total natural resource rents, gross domestic production (GDP), CO2 emissions, total population, and share of imported energy in total energy consumption are from the World Bank (2022) Development Indicators Database.



Figure 1. The energy efficiency scores of TOPSIS, DEA and SBM-DEA models.

included in the analysis because observations were not available for some variables, particularly renewable energy consumption and energy production. Thus, 21 EU countries from 1995 to 2019 were included in the analysis. The energy efficiency of each country was calculated separately using the DEA, SBM-DEA and TOPSIS methods. The number of DMUs is thus 25, corresponding to the years of each country in the analysis period. Due to the nature of the methods, the calculated efficiency values ranged from 0 to 1. Thus, the calculated efficiency values alone do not tell the whole story. We used the efficiency series as dependent variables in Tobit regression models to determine the relationship between efficiency and contextual variables listed in Table 1. When the method for calculating efficiency was changed, country efficiency scores naturally differed from one method to another. Figures 1 and Figure 2 show the combined and individual boxplots and line plots of the energy efficiency series obtained using the DEA, SBM-DEA, and TOPSIS methods. The range of energy efficiency based on TOPSIS was wider than those of based on DEA and SBM-DEA, while the range of energy efficiency based on SBM-DEA was wider than that was based on DEA. The names of the countries in Figure 2 are shown as numbers from 1 to 21 in Figure 1. For example, Austria was the first country labeled 1 in Figure 1, while Sweden was labeled 21.

We preferred to utilize the Tobit regression model, which is an appropriate estimation procedure for models with limited dependent variables, to estimate the effects of the explanatory variables on higher and lower efficiency levels. The mean and maximum values of the individual energy efficiency series were capitalized as censoring values of the Tobit regression models, while RI, CL, RE, IM, COI, POP, and TPR were used as explanatory variables. Four different Tobit regression models were estimated based on the censored values of the energy efficiency series. Here, we intend to analyze how the explanatory variables affect energy efficiency when we exclude below-average, above-average, or unit efficiencies and what happens when all observations (unit and non-efficiencies) are included. In this way, it became clear which factors we would rely on in the case of a less efficient or fully efficient one.

We censored the upper bound of the dependent variable in M1 to the mean of the efficiency series and treated efficiency values equal to or greater than the mean as zero in model estimation. In M2 we censored the lower bound of the dependent variable to the mean of the efficiency series, while in M3

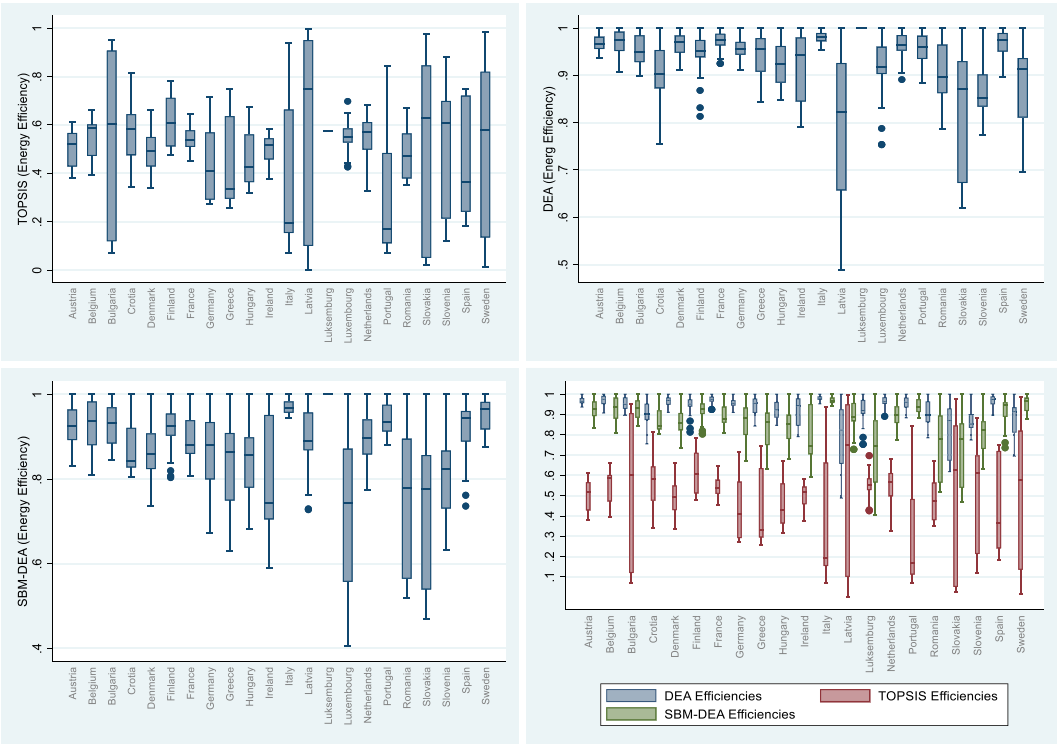


Figure 2. The energy efficiency scores of TOPSIS, DEA and SBM-DEA models.

the dependent variables are censored to the most efficient values, i.e., one. In M4, no censoring was performed for the dependent variables. The purpose of estimating four regression models was to test whether the effects of the variables on energy efficiency change when the efficiency level changes. These are the robustness checks of the coefficients in addition to the three methods used to calculate the energy efficiency series.

Table 2 shows the descriptive statistics of the variables used in the multi-criteria decision-making and Tobit regression models. The logarithms of the variables were harnessed in the estimation process of the Tobit regression models. Whenever panel data series are used in a regression model, especially when the number of observations is 25 or more, cross-sectional dependence and the unit root test performed become essential details in the estimation process. Depending on the cross-sectional dependence, the unit root test to be performed may change, thus the homogeneity of the variables. Therefore, the analysis should begin with the investigation of cross-sectional dependence and continue

Table 1. The notation and description of variables.

Notation	Description
RI	Renewable energy intensity of GDP
CL	Capital stock per labor
RE	Total natural resource rent
IM	Imported energy in total energy consumption
COI	Ratio of carbon emissions to GDP
POP	Total population of the country
TPR	Total energy production
Trend	Deterministic trend
Trend2	The square of deterministic trend
$EE_{(DEA)}$	DEA based energy efficiency scores
$EE_{(TOPSIS)}$	TOPSIS based energy efficiency scores
$EE_{(SBM)}$	SBM-DEA based energy efficiency scores

Table 2. Descriptive statistics.

Variables used in DEA	Mean	Median	Maximum	Minimum	Skewness	Kurtosis
Capital Stock	4106744	1528214	20957202	137847	1.7194	4.4274
Labor Force	8614144	4316583	44351163	169317	1.8250	5.2874
Total Energy Consumption	2.7951	1.1780	14.9430	0.1390	1.9292	5.7538
GDP	695.2984	284.6956	4314.0680	22.4991	1.9317	5.6878
Variables used in Tobit Models						
$EE_{(DEA)}$	0.9267	0.9515	1.0000	0.4881	−2.1403	8.7099
$EE_{(TOPSIS)}$	0.4976	0.5202	0.9977	0.0021	−0.0982	2.6286
$EE_{(SBM)}$	0.8694	0.8947	1.0000	0.4051	−1.3446	4.7089
RI	0.1322	0.1045	0.4102	0.0001	0.8269	2.7008
CL	0.3963	0.4616	0.9640	0.0372	−1.6673	6.3515
RE	0.2141	0.2514	3.5128	0.0098	−0.1703	2.2830
IM	0.1418	0.1310	0.4267	0.0394	1.8896	7.9775
COI	0.00023	0.00022	0.00077	0.00007	0.2443	3.3131
POP	16.0428	16.0291	18.2355	12.9206	−0.1434	3.1641
TPR	1.0949	0.4730	5.9942	0.0010	−1.0937	4.7572

EEs represent the energy efficiency score series obtained by DEA, SBM-DEA and TOPSIS, RI is renewable energy intensity in total energy consumption, calculated as the ratio of renewable energy consumption to GDP, and CL is capital stock per worker, i.e. is calculated as capital stock divided by the labor force, RE is total natural resource rent, defined as the difference between the revenue from extracting a natural resource and the cost of extracting the natural resource, IM is the share of imported energy in total energy consumption, COI is calculated as the ratio of carbon emissions to GDP, POP is total population, TPR is total energy production, which includes renewable and nonrenewable energy.

Table 3. Cross-section dependency test results.

Pesaran CD	Statistic	Pesaran CD	Statistic
$EE_{(DEA)}$	35.8986 ***	COI	57.2129 ***
$EE_{(TOPSIS)}$	12.4045 ***	POP	8.5196 ***
$EE_{(SBM)}$	39.7092 ***	RI	47.7085 ***
RE	23.1680 ***	CL	53.6740 ***
IM	17.2129***	TPR	0.3512

Ho: No Cross Section Dependency.

Table 4. Panel data unit root test results.

Unit Root Test	*CIPS*		*Pesaran CADF*		Levin, Lin, and Chu
Variables	Constant/ None	Constant and Trend	Constant	Constant and Trend	None
$EE_{(DEA)}$	**−2.887 ****	0.727	**−2.280** **	−2.163	Null
$EE_{(TOPSIS)}$	**−2.323** *	−1.487	**−2.069** **	−1.694	Null
$EE_{(SBM)}$	**−1.530** **	−0.048	**−2.154** **	−2.235	Null
RI	**−2.894** ***	**−3.509** ***	**−3.256** ***	**−2.663** ***	Null
CL	−0.052	**−2.037** **	−1.740	**−2.610** **	Null
RE	**−3.902** ***	**−3.272** ***	**−2.584** ***	**−2.974** ***	Null
IM	**−2.458** ***	**−3.052** ***	**−3.494** ***	**−4.09** ***	Null
COI	**−1.052**	**−3.085** ***	**−2.410** ***	−2.524	Null
POP	**−3.186** ***	**−2.924** ***	**−2.431** ***	**−2.903** **	Null
TPR					**-2.410** **

(***), (**), and (*) represent the 10%, 5%, and 1% significance levels of the unit root tests, respectively. "Ho: Unit-root" for all tests.

with a unit root test. The Pesaran CD test for cross-sectional dependence indicated that all variables except TPR were cross-sectionally dependent. Therefore, the second generation panel unit root test must be performed for the variables with cross-sectional dependence, while the first generation panel unit root test must be performed to examine the unit root of TPR.

The CADF test of Im, Pesaran, and Shin (2003) and the CIPS test of Pesaran (2007) were employed as second-generation unit root tests, while the one developed by Levin, Lin, and Chu (2002) was used as first-generation unit root tests to examine the unit root of the variables. The unit root test to be performed was determined using the results of the cross-sectional dependence test in Table 3. According to the unit root test results in Table 4, all variables were I (0) and used in a regression

model without taking the difference of variables. The maximum lags were arranged in the unit root procedure as two.

Table 5 shows the coefficients of the Tobit regression models with the dependent variable DEA, SBM-DEA, and TOPSIS. In the first model (M1), the upper bound was censored to the mean of the efficiency series obtained by using DEA. According to the model coefficient, RI had a negative impact on efficiency. A 1% decrease in the RI ratio would result in an average increase in energy efficiency of 0.0831%. The decrease in the share of renewable energy in total energy consumption can occur in two ways: a decrease in renewable energy consumption while total energy consumption remains constant, or an increase in total energy consumption while renewable energy consumption remains constant. Moreover, the COI coefficient was statistically significant, and its sign was consistent with prior expectations. It is well known that carbon emissions to the atmosphere are an undesirable and energy efficiency-reducing phenomenon. Therefore, a negative relationship is expected between CO2 emissions and energy efficiency (Tan et al. 2011; Zheng et al. 2019).

CL and technological progress (trend) are the conventional variables used in energy efficiency studies referring to growth models (Durlauf, Kourtellos, and Minkin 2001; Lee, Mason, and Miller 2003; Solow 1956). CL ratio may decrease if the numerator decreases or the denominator increases, but it is the other way around if CL increases. According to the findings, a 1% increase in CL would result in a 0.5391% increase in energy efficiency. On the other hand, the trend as a representative of technological progress positively impacted energy efficiency. The results of the models indicated that imported energy had a positive and statically significant influence on the energy efficiency in the EU countries. Furthermore, all coefficient signs were consistent across estimated models. In other words, the relationship between the explanatory variables and energy efficiency in the EU countries was independent of the efficiency level.

SBM-DEA, which can provide more reliable efficiency values for inefficient DMUs due to its mathematical formula, was the second efficiency measurement method used in this paper. The coefficients of the Tobit models based on the SBM-DEA are shown in Table 5. We estimated four different regression models based on the censored values of the efficiency series. In M1 and M2, the upper and lower bounds of the dependent variables were censored to the mean of the efficiency series, respectively. In M3, the upper bound of the dependent variables was censored to 1, and in M4 no censoring was applied to the dependent variables. Here, RI had a statistically significant effect on energy efficiency but with inconsistent signs. In the first two regression models, RI had a positive effect on energy efficiency, while this effect became negative in the last two models. In other words, the level of energy efficiency determined the relationship between renewable energy consumption and energy efficiency. COI, POP, and RENT were also estimated to be negative and statistically significant, except in the first and second models. Accordingly, energy efficiency in EU countries decreases if the carbon emission intensity of GDP increases. The increase in COI variable can occur in two ways: an increase in carbon emission with constant GDP, or a decrease in GDP with constant carbon emissions. CL and IM were positive in all estimated models where the dependent variable was SBM-DEA efficiency. Finally, the sign of the deterministic trend was positive. In contrast, the sign of the trend square was negative, indicating an inverted U-shaped relationship between efficiency and technological progress.

The results of the Tobit models based on the TOPSIS method are shown in the last part of Table 5. The estimated coefficients of RI, COI, and POP were negative in all models, indicating a decreasing effect on energy efficiency in EU countries. The RI coefficient was negative as in the previous models and did not vary with the level of energy efficiency. The result suggests that an increase in renewable energy intensity has a decreasing effect on efficiency. As the COI coefficient was negative in all models, increasing the carbon emission intensity of GDP would decrease energy efficiency regardless of the efficiency level. CL, RENT, and IM had a positive and statistically significant impact on energy efficiency. The share of imported energy in total energy consumption is important for the efficiency of EU countries due to their energy dependence, because the higher the share of imported energy is, the greater the energy dependency is. Finally, the population size harmed energy efficiency. As the population grows, energy demand naturally increases, leading to a decrease in energy efficiency. Trend

Table 5. The coefficients of Tobit regression models.

	M1			M2			M3			M4		
Variable	$EE_{(DEA)}$	$EE_{(SBM)}$	$EE_{(TOPSIS)}$	$EE_{(DEA)}$	$EE_{(SBM)}$	$EE_{(TOPSIS)}$	$EE_{(DEA)}$	$EE_{(SBM)}$	$EE_{(TOPSIS)}$	$EE_{(DEA)}$	$EE_{(SBM)}$	$EE_{(TOPSIS)}$
RI	−0.0852***	0.0147**	−0.0815***	−0.0172***	0.0188**	−0.0658*	−0.0636***	−0.0210*	−0.1031***	−0.0607***	−0.0177*	−0.0993***
COI	−0.3605***	−0.0112	−0.5397***	−0.0609***	−0.0475**	−0.5143***	−0.2728***	−0.2206***	−0.6448***	−0.2579***	−0.2125***	−0.6385***
CL	0.5391**	0.4765***	1.6196**	0.3930***	0.6263***	1.2685**	0.5294***	0.9761***	1.3033**	0.3918***	0.8477***	1.2986**
RENT	0.2434***	−0.0053	0.0428**	0.0421***	−0.0045	0.0333**	0.1385***	−0.0321***	0.0381**	0.1352***	−0.0333***	0.0389**
IM	−0.2256***	0.0404***	0.2125***	−0.0270**	0.0857***	0.2416***	−0.1617***	0.1497***	0.2015***	−0.1627***	0.1495***	0.2032***
POP	0.0260	−0.0025	−0.2298***	−0.0039	−0.0486**	−0.1843**	0.0241**	−0.1349***	−0.1892**	0.0257***	−0.1373***	−0.1865***
TPR	0.0036	−0.0156**	−0.0290	0.0025	−0.0062	−0.0701*	0.0078	0.0351**	−0.0544	0.0060	0.0411***	−0.0561
Trend	0.0058*	−0.0007	0.0091	−0.0010	0.0051**	−0.0118*	0.0011	0.0136***	−0.0093	0.0030*	0.0164**	−0.0095
Trend2	−0.0003**	0.0002**	−0.0005*	0.0001**	0.0002	0.0002	−0.0001	−0.0003***	0.0001	−0.0001**	−0.0004***	0.0001
Constant	−1.9722**	−0.5715***	−2.5883*	−0.5937***	−0.6125*	−3.2707**	−1.2475***	−1.4789**	−3.9753***	−1.0764**	−1.3721**	−3.9755***
Sigma_u	0.1779***	0.0211**	0.1694***	0.0219***	0.0489***	0.2177***	0.0969***	0.1185***	0.2056***	0.0953***	0.1205***	0.2052***
Sigma_e	0.0653***	0.0500*	0.1789***	0.0298***	0.0561***	0.1584***	0.0535***	0.0872***	0.1937***	0.0535***	0.0797***	0.1915***

and trend squared as indicators of technological progress were not statistically significant in the TOPSIS-based Tobit regression models. Energy efficiency has many determinants, but RI, COI, and CL are the most critical variables. We generally focused on these variables in this paper. The consistency of the signs of the variables above served as a robustness check and provided us with valuable information about the impact of these variables on energy efficiency in EU countries.

6. Conclusion and discussion

A successful transition to a low-carbon economy, especially in energy-dependent countries, requires the implementation of energy efficiency measures (Labandeira et al. 2020). However, identifying the main factors affecting energy efficiency is quite problematic due to its complex nature. Previous studies have employed numerous relevant factors to establish the relationship between efficiency and its determinants. The existing literature (Aye, Gupta, and Wanke 2018; Lee, Mason, and Miller 2003; Pehlivanoglu et al. 2021; Sineviciene, Sotnyk, and Kubatko 2017) selected a number of indicators for the analysis, including Renewable energy intensity of GDP, the ratio of carbon emission to GDP, imported energy in total energy consumption, population capital stock per labor, and technological progress. Among these variables, many studies have focused on the relationship between energy efficiency and economic growth, carbon emissions, and renewable energy metrics.

Carbon dioxide emissions are responsible for a large part of environmental problems. EU member states, therefore, intend to eliminate the undesirable effects of carbon dioxide emissions. To this end, the EU has adopted the Green Deal, which aims to eliminate emissions by 2050. Consistent with the model estimates, we concluded that an increase in the carbon intensity of GDP had a negative effect on energy efficiency in all models, regardless of the method or level of energy efficiency. Consequently, the results of the estimated regressions indicate that an increase in energy efficiency requires a strict reduction in carbon emissions (Li and Colombier 2009). The goal of reducing carbon emissions leads to the use of renewable energy. Renewable energy sources are vital for two reasons: environmental concerns and energy security. However, renewable energy is not always the best way to reduce carbon emissions (López-Peña, Pérez-Arriaga, and Linares 2012). The model results also showed that increasing the share of renewables in total energy consumption was not conducive to energy efficiency. Current studies report both contradictory results (Pehlivanoglu et al. 2021) and similar results (Aye, Gupta, and Wanke 2018). Even though investments in renewable energy technologies have recently become cheaper than fossil fuels and the gap between fossil and renewable energy costs will continue to widen in the coming years (Energy Post 2022; IRENA 2022), the results of our analysis may be surprising, but they may suggest that renewable energy technologies are still insufficient or too expensive (Ferroukhi et al. 2016). Of course, the impact of improvements in renewable energy costs may not be reflected in the analysis because the considered period is from 1995 to 2019, and it may take some time for the impact of renewable energy developments to be reflected in the analysis.

Capital stock per labor is used in economic studies as an indicator of investment and as part of economic progress along with technological progress (Durlauf, Kourtellos, and Minkin 2001; Solow 1956). An increase in capital stock per labor can be attributed to an increase in the capital stock, which would lead to an improvement in GDP (Osiobe 2020; Santiago et al. 2020) and thus energy efficiency (Kahia, Aïssa, and Lanouar 2017). The capital stock per labor coefficient was statistically significant and positive, as indicated by the results of the model we estimated. The sign of the coefficient capital stock per labor indicates that the need for improvements in the capital stock is greater than the need for improvements in the labor force. Therefore, the capital stock per labor would increase overall and lead to an improvement in energy efficiency. Moreover, technological progress is represented by a linear trend and its square to illustrate the shape of the relationship between technology and efficiency in econometric models. It is assumed that technological progress drives labor productivity and thus energy efficiency (Çam, Karataş, and Lopcu 2022). In the Tobit regression models, the trend and trend squared coefficients were positive and negative, respectively, except in the models in which they were not significant. The signs of the coefficients indicate an inverted U-shaped or concave relationship between technological progress and energy

efficiency. Finally, EU energy production had a positive impact on efficiency. However, the impact of energy imports was larger than that of energy production. The result may suggest that energy production with existing technology is more expensive than energy imports and that new technology is needed to reduce costs. This result supports the findings on renewable energy discussed above. Although fossil fuel energy has become more expensive than renewable energy, we believe that its impact will soon be detectable in empirical studies.

7. Limitations and future recommendations

There is no consensus on how to define and calculate energy efficiency. Therefore, the direction of the relationship between variables and energy efficiency may vary depending on the method used to calculate energy efficiency. The results of the analysis may also vary due to changes in the time period and countries. Although energy efficiency results that cannot be calculated using a precise method provide valuable information, they are not unique and unchanging. Moreover, the available information can only help identify the variables having a positive or negative impact on energy efficiency. More specific policy recommendations require a detailed and collective evaluation of all available evidence on the topic. It is necessary to use all the studies analyzing energy efficiency in EU countries to develop strategies for the long-term goals of the Green Deal and to conduct new studies to overcome the shortcomings of current applications. There is a need to reexamine the subject with new data that will be available in the near future to determine the impact of renewables.

Disclosure statement

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