MEASURING THE ECONOMIC EFFICIENCY OF THE EU ENERGY SECTOR

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ABSTRACT

This article evaluates the efficiency of primary energy production in EU countries using Data Envelopment Analysis. The analysis is based on aggregated macroeconomic and environmental data obtained from publicly available databases, with efficiency assessment explicitly accounting for carbon dioxide (CO_2) emissions as an undesirable output. The empirical results indicate relatively high average efficiency levels across the observed period, with several countries consistently operating on the efficiency frontier. In the second stage, a censored Tobit model is employed to examine the role of the energy mix. The findings suggest that both renewable and nuclear energy shares are positively associated with efficiency, with nuclear energy showing a somewhat stronger and more robust effect.

KEY WORDS

efficiency, energy mix, emissions, EU, primary energy production

JEL CODES

C61, C24, Q41, Q48, Q53

1 INTRODUCTION

The energy sector represents a fundamental pillar of the EU economy, playing a crucial role in ensuring economic stability, industrial competitiveness, and societal well-being. Although its direct contribution to GDP is not dominant, its importance lies primarily in its function as a core infrastructure enabling the operation of industry, transport, and services. As a key input across virtually all sectors, energy availability and pricing significantly influence production costs, inflation dynamics, and overall economic performance. Consequently, the performance and efficiency of the energy sector are of central importance for sustainable economic development within EU Member States.

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Beyond its economic role, the energy sector has gained increasing strategic and political importance. Recent geopolitical developments, particularly the Russia–Ukraine conflict, have exposed the EU's dependence on external energy suppliers and heightened concerns regarding energy security, see, for example, Shoukat et al. (2024). As a result, strengthening supply resilience through diversification, infrastructure development, and deeper integration of the internal energy market has become a central policy priority. At the same time, the energy sector in the EU operates as a highly interconnected system, in which developments in one Member State can significantly affect others.

In parallel, the sector faces growing pressure to reduce greenhouse gas emissions and transition towards sustainable energy sources. Under the European Green Deal (European Commission, 2019), the EU aims to achieve climate neutrality by 2050, placing the energy sector at the core of decarbonization efforts. This transformation, however, entails substantial challenges, including high investment requirements, modernization of transmission networks, and the need to address the intermittency of renewable energy sources. These factors often create tensions between environmental objectives and economic efficiency.

As a result, the modern EU energy sector is undergoing a complex transformation characterized by the need to balance three fundamental dimensions: security of supply, affordability, and environmental sustainability (Kaschny, 2025). This so-called "energy trilemma" provides a key framework for evaluating both policy measures and sectoral performance. Given the increasing complexity and interdependence of energy systems, there is a growing need for analytical approaches focused on measuring efficiency and identifying its key determinants. Moreover, differences in market structures, regulatory environments, and energy mixes across Member States may lead to significant variations in efficiency levels, further underscoring the importance of systematic efficiency assessment.

1.1 Theoretical Background

Research on energy sector efficiency has expanded rapidly in recent years, particularly in response to the increasing importance of sustainability, decarbonisation, and energy security. A substantial body of literature focuses on evaluating efficiency at both the macro (country and regional) and micro (firm and sectoral) levels, with a strong emphasis on advanced quantitative methods such as Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA).

For instance, Kyshakevych et al. (2024) apply DEA models to evaluate the energy efficiency of 38 European economies over the period 2010–2018, demonstrating that substantial differences exist across countries and that less efficient nations can improve performance by adopting best practices from benchmark economies. In particular, the authors emphasize that effective strategies include a transition towards renewable energy sources and a reduction in dependence on fossil fuels, which are associated with improvements in overall energy performance.

The same period was analysed by Simeonovski et al. (2021), with the difference that their study focused exclusively on EU countries. The authors combined the efficiency analysis with an assessment of labour productivity and trends in energy intensity. Their results indicate significant differences between the performance of new and old Member States. Overall, they conclude that efficiency in the sector is relatively low (around 16%), while new Member States achieve, on average, approximately seven times higher efficiency compared to the old Member States. The unfavourable situation is further underlined by the finding that energy efficiency management did not improve over the analysed period. As a possible pathway for improvement, Simeonovski et al. (2021) suggest measures such as market liberalisation and the implementation of policies aimed at increasing overall economic productivity.

Significant differences among EU countries were also identified by Varvařovská and Staňková (2021), who did not measure efficiency directly using DEA or SFA models, but instead estimated production functions for EU countries based on firm-level microdata. Their findings demonstrate how the structure of firms (and, consequently, the composition of different energy sources) influences the productivity of individual countries. The results indicate that, from a productivity perspective, firms (and thus countries) with a high share of renewable energy sources tend to exhibit lower overall productivity levels.

Many studies can be found that do not directly address the economic aspect of efficiency in the energy sector, but instead focus on other dimensions such as environmental issues, technological development, or sustainability. In recent years, examples of such studies include García-Álvarez et al. (2025), Gouveia et al. (2023), Kermeli at al. (2022) and Fidanoski et al. (2021).

Given the complexity of the analysed problem, researchers often adopt comprehensive approaches that require multi-stage analysis. For example, Basílio (2025) first applied a DEA model to estimate the efficiency of 27 EU countries over the period 2015–2022 and subsequently used fractional regression models to identify the factors influencing the obtained efficiency scores. Among the potential regressors, they considered variables such as energy prices, the business cycle, and the share of renewable energy sources.

Sun et al. (2024) employ a DEA model to obtain slack values (i.e. output surpluses and input shortages), which are subsequently decomposed using econometric approaches into three components: environmental, stochastic, and managerial factors. Based on panel data for 15 cities in Southwest China over the period 2010–2018, the authors are able to identify significant differences across individual cities.

Wu et al. (2026), using data for 14 Chinese prefectures and cities over the period 2016–2022, apply a combination of a DEA model to estimate efficiency and a Tobit model to identify the key factors influencing efficiency from a macroeconomic perspective. Among the determinants, tourism is identified as a factor negatively affecting efficiency, whereas human capital exerts a positive influence and should therefore be further developed in future provincial strategies.

Jiang and Xie (2024) employ a dynamic spatial network DEA model to evaluate the environmental efficiency of China's power systems, with a particular emphasis on spatial interactions, captured through Moran's I test. Beyond highlighting spatial dependence, their results identify CO_2 emissions as the most significant factor contributing to inefficiency.

Zhang et al. (2020), in their evaluation of energy sector efficiency, also consider a variable capturing CO_2 emissions. However, unlike Jiang and Xie (2024), they incorporate it directly into the DEA model as an undesirable output, alongside GDP as a desirable output. A similar approach is adopted by Zhong et al. (2021), with the difference that they use value added as the desirable output and SO_2 and soot emissions as undesirable outputs.

1.2 Aim, Motivation and Contribution

This article focuses on analysing the efficiency of the energy sector across EU countries at an aggregated level, where each country represents a decision-making unit. The analysis is designed to capture cross-country differences in energy performance and is structured as a two-stage procedure, allowing both the measurement of efficiency and the identification of its potential determinants.

In the first stage, efficiency scores for individual EU countries are derived using aggregated macroeconomic data obtained from the EU KLEMS database. Economic efficiency is evaluated using the DEA method. To account for environmental aspects of energy production and consumption, CO_2 emissions are explicitly incorporated into the model as an undesirable output. This specification follows the methodological framework proposed by Jiang and Xie (2024), where undesirable outputs or inputs are directly embedded in the DEA model structure rather than being treated in a second-stage analysis. Such an approach allows for a more realistic representation of production processes, especially in sectors with significant environmental externalities.

At the same time, the analysis takes into account differences in the structure of energy sources across countries. In line with Varvařovská and Staňková (2021), particular attention is devoted to the heterogeneity of the energy mix, as countries differ substantially in their reliance on fossil fuels, renewable energy sources, and nuclear power. These structural differences are expected to play an important role in shaping overall efficiency outcomes.

In the second stage, the determinants of efficiency are examined using a Tobit regression model, following Wu et al. (2026). The dependent variable in this stage is the efficiency score obtained in the first stage, while the explanatory variables capture the composition of the energy mix, represented by the shares of different energy sources. The Tobit model makes it possible to analyse how variations in the energy structure influence efficiency while accounting for the censored nature of the dependent variable.

2 DATA AND METHODS

Given that different data and methodological approaches are used in each stage, this section is divided into two parts corresponding to the two stages of the research.

2.1 DEA Model and Data for Efficiency Analysis

As already mentioned, economic data from the EU KLEMS database are used for the purposes of efficiency analysis. The most recent update (release 2025) provides aggregated annual data for individual EU countries up to 2021 (Luiss, 2026). In order to capture potential trends while avoiding substantial changes associated with technological progress, the period from 2018 to 2021 is selected for the analysis.

Similarly to Varvařovská and Staňková (2021), the model incorporates both labour and capital inputs. Specifically, labour is represented by the variable Total hours worked by persons engaged (in thousands of hours), while capital is captured by Gross fixed capital formation in current prices (in millions of national currency). As an output variable, Value added measured in current prices (in millions of national currency) is used. In addition, CO_2 emissions (in tonnes) are included in the DEA model as an undesirable output. This variable is obtained from the Eurostat database (Eurostat, 2026a).

Both databases allow for the selection of variables according to NACE classification; therefore, only values corresponding to sector D (Electricity, gas, steam and air conditioning supply) are included in the analysis. Unfortunately, Cyprus and Malta had to be excluded from the analysis, as data on the capital factor in sector D are not available in the EU KLEMS database for these countries. As a result, the analysis covers the remaining 25 EU countries.

When working with economic data in an international comparative context, an additional issue arises from the fact that databases such as EU KLEMS provide data in national currencies, while not all countries use the euro. For this reason, the values for Bulgaria, Czechia, Denmark, Hungary, Poland, Romania, and Sweden are converted into euros using the average annual exchange rates provided by the European Central Bank (2026).

Descriptive statistics of the variables used in the DEA model by year are reported in Tab. 1.

To incorporate the emissions variable into the model as an undesirable output, the approach proposed by Seiford and Zhu (2002) was adopted, whereby undesirable outputs are incorporated using the translation approach. Let bk denote the undesirable output. It is transformed as follows:

$$b_k^* = M_k - b_k, \qquad (1)$$

where $M_k = \max_j(b_{jk}) + 1$ for each undesirable output k. The DEA model is then formulated as an input-oriented model (similarly to Kyshakevych et al., 2024, and Simeonovski et

Tab. 1: Descriptive statistics of variables used in the DEA model by year

Characteristics		2018	2019	2020	2021
Total hours worked	Min	2,428	2,553	2,609	2,756
	Average	74,252	75,412	76,618	79,617
	Median	41,806	42,288	41,848	44,063
	Max	391,105	394,453	401,120	410,892
Capital formation	Min	254	239	205	329
	Average	3,890	4,149	4,113	4,603
	Median	1,513	1,363	1,652	1,637
	Max	18,122	18,682	18,459	22,418
Value added	Min	408	445	452	478
	Average	7,495	8,185	8,308	8,806
	Median	4,660	4,936	4,780	5,090
	Max	33,611	38,525	37,901	40,357
Emission	Min	258,700	256,700	245,400	246,100
	Average	35,013,967	30,199,848	25,625,421	28,202,177
	Median	14,775,608	10,578,683	10,382,946	9,671,914
	Max	265,117,663	215,553,796	180,339,336	207,468,174

al., 2021), the model is specified under the assumption of variable returns to scale):

$$
\begin{aligned}
& \min \theta, \\
\text{subject to} \quad & \sum_j \lambda_j x_{ij} \leq \theta x_{io}, \\
& \sum_j \lambda_j y_{rj} \geq y_{ro}, \\
& \sum_j \lambda_j b_{kj} \geq b_{ko}, \\
& \sum_j \lambda_j = 1, \\
& \lambda_j \geq 0
\end{aligned} \tag{2}
$$

DEA models are calculated separately for each year, as the analysed period includes, among other things, the COVID-19 pandemic, during which significant shifts in the production possibility frontier can be expected, as has been demonstrated in other economic sectors (see, for example, Staňková et al., 2025).

2.2 Tobit Model and Determinants of Efficiency

In the second stage of the analysis, the factors influencing the efficiency of individual countries are examined based on data on energy production in EU countries. Using data from the Eurostat database (Eurostat, 2026b), three variables are included in the model: fossil fuels (comprising solid fossil fuels, natural gas, and oil and petroleum products excluding the biofuel component), renewables (renewables and biofuels), and nuclear energy. All variables are expressed in thousand tonnes of oil equivalent.

As all data in the first stage of the analysis refer exclusively to domestic energy production, only primary production values are also used in the second stage. Descriptive statistics of primary energy production (in thousand tonnes of oil equivalent) for different types of energy sources are presented in Tab. 2.

Given that efficiency scores are bounded within the interval from 0 to 1, with the value of 1 typically occurring for more than one decision-making unit, the use of a standard linear regression approach is not appropriate. In particular, such models do not account for the censored nature of the dependent variable and may lead to biased and inconsistent estimates.

For this reason, a Tobit regression model is adopted in the second stage of the analysis. The Tobit model is specifically designed for situations in which the dependent variable is limited within a certain range, allowing for consistent

Tab. 2: Descriptive statistics of variables used in the Tobit model by year

Characteristics		2018	2019	2020	2021
Fossil fuels	Min	<1	<1	<1	<1
	Average	7,998	6,997	5,846	5,962
	Median	1,558	1,430	1,203	1,137
	Max	51,512	48,788	44,363	46,294
Renewables	Min	172	197	262	272
	Average	8,828	9,081	9,335	9,793
	Median	3,973	4,183	4,328	4,576
	Max	43464	45,689	46,594	47,204
Nuclear energy	Min	<1	<1	<1	<1
	Average	7,810	7,847	7,007	7,467
	Median	812	910	956	890
	Max	107,629	103,987	92,211	98,864

estimation in the presence of censoring (Greene, 2003; Tobin, 1958). In this study, it enables the examination of how differences in the structure of the energy mix influence the efficiency scores while properly accounting for their bounded nature.

Although DEA models are typically estimated separately for each period to account for potential changes in the production possibility frontier over time, the Tobit model is estimated in a pooled form in order to increase the number of degrees of freedom and improve the robustness of the results:

$$\begin{aligned} y_i^* &= x_i'\beta + \epsilon_i, \\ \epsilon_i &\sim N(0, \sigma^2), \\ y_i &= \max\big(0, \min(y_i^*, 1)\big), \end{aligned} \tag{3}$$

where i denotes the individual country, t denotes the time, y^* is the latent (unobserved) efficiency score, y is the observed efficiency score bounded between 0 and 1, β are unknown parameters to be estimated, ϵ is a random error term. As the Tobit model belongs to the class of regression models, it is necessary to examine potential violations of standard assumptions, particularly heteroskedasticity, autocorrelation, and non-normality of the error term (Greene, 2018). Such issues may affect the reliability of statistical inference and the validity of the estimated results. In the presence of these problems, bootstrap-based estimation can be employed to enhance the robustness of the inference, as it does not rely on strict distributional assumptions and provides empirically derived standard errors and confidence intervals (Cameron and Trivedi, 2005).

3 RESULTS

According to the results of the DEA model, the energy sector performs relatively well in the production of primary energy in the EU. The average efficiency during the observed period ranges between 78% and 83% (see Tab. 3). Median values are even higher, ranging from 78% to 93%. In addition to these aggregated indicators, Tab. 3 also presents efficiency scores for individual countries, including the average score for the entire period 2018–2020, as well as the average ranking derived from these averages.

There are five countries (France, Germany, Luxembourg, Spain, and Sweden) that remain efficient throughout the entire observed period. These countries can therefore be considered the best performers in the production of primary energy in terms of labour and capital inputs.

Tab. 3: Estimated efficiency scores by country for each year

Unit	2018	2019	2020	2021	Average	Average rank
Austria	0.7627	0.7749	1	0.7910	0.8321	11
Belgium	0.5508	0.6396	0.8404	1	0.7577	17
Bulgaria	1	0.9975	0.9066	1	0.9760	7
Croatia	0.5667	0.6128	0.3532	0.7713	0.5760	23
Czechia	0.8472	0.7196	0.9642	0.7788	0.8274	12
Denmark	0.5546	0.6159	0.5515	0.6895	0.6029	22
Estonia	0.7251	0.7584	0.6227	0.9186	0.7562	18
Finland	0.6134	0.7991	0.7847	0.7449	0.7355	19
France	1	1	1	1	1	1
Germany	1	1	1	1	1	1
Greece	1	1	0.9950	1	0.9988	6
Hungary	0.4423	0.4057	0.6042	0.4599	0.4781	25
Ireland	0.5920	0.6674	0.8062	0.8722	0.7345	20
Italy	0.8057	0.8527	0.9287	0.7159	0.8258	13
Latvia	0.9539	1	0.3675	0.8447	0.7915	14
Lithuania	0.6954	0.5415	0.6751	0.6894	0.6504	21
Luxembourg	1	1	1	1	1	1
Netherlands	0.4929	0.6035	0.6063	0.5214	0.5560	24
Poland	0.8836	0.7898	1	1	0.9183	9
Portugal	1	1	1	0.7906	0.9476	8
Romania	0.5226	1	1	1	0.8807	10
Slovakia	0.6467	0.7224	0.9529	0.7377	0.7649	15
Slovenia	0.7799	0.7823	0.7852	0.7042	0.7629	16
Spain	1	1	1	1	1	1
Sweden	1	1	1	1	1	1
Average	0.7774	0.8113	0.8298	0.8412		
Median	0.7799	0.7898	0.9287	0.8447		

According to Tab. 3, Hungary ranks in the worst position, with an average efficiency of 48%, i.e. several tens of percentage points below both the sectoral average and median. It is the only country that does not reach at least 50% efficiency on average over the entire period. Alongside Hungary, other highly inefficient countries include Croatia, Denmark, and the Netherlands.

An alternative way of constructing the ranking is presented in Tab. 4, where the focus is not on the absolute value of efficiency scores; instead, countries are ranked for each year according to their position. These rankings are then averaged, and the final ranking of countries is determined based on this average position. This methodological change in constructing the ranking does not alter the positions of the five best-performing countries (i.e. the efficient countries), nor does it affect the position of the least efficient country, Hungary, followed by the Netherlands. For the remaining countries, only minor changes in rankings can be observed, amounting to at most two positions, which can be considered negligible.

A more detailed examination of both Tab. 3 and Tab. 4 shows that the rankings (as well as the absolute efficiency values) changed in 2020, when the COVID-19 pandemic began in Europe. This challenging period was addressed differently by individual countries through various restrictive measures. The effects on

Tab. 4: Evaluation of countries based on their rankings in individual years

Unit	2018	2019	2020	2021	Average rank	Final rank
Austria	14	15	1	14	11.00	11
Belgium	22	20	15	1	14.50	15
Bulgaria	1	10	14	1	6.50	9
Croatia	20	22	25	17	21.00	22
Czechia	11	18	11	16	14.00	13
Denmark	21	21	23	22	21.75	23
Estonia	15	16	20	11	15.50	16
Finland	18	12	18	18	16.50	19
France	1	1	1	1	1	1
Germany	1	1	1	1	1	1
Greece	1	1	10	1	3.25	6
Hungary	25	25	22	25	24.25	25
Ireland	19	19	16	12	16.50	19
Italy	12	11	13	20	14.00	13
Latvia	9	1	24	13	11.75	12
Lithuania	16	24	19	23	20.50	21
Luxembourg	1	1	1	1	1	1
Netherlands	24	23	21	24	23.00	24
Poland	10	13	1	1	6.25	8
Portugal	1	1	1	15	4.50	7
Romania	23	1	1	1	6.50	9
Slovakia	17	17	12	19	16.25	17
Slovenia	13	14	17	21	16.25	17
Spain	1	1	1	1	1	1
Sweden	1	1	1	1	1	1

Sector D can be observed in these changes in efficiency during this period, which are strongly influenced not only by shifts in the production possibility frontier, but also by changes in its shape, against which individual country efficiency is assessed. Examples of substantial individual changes resulting from these alterations in both the position and shape of the production possibility frontier can be seen, for instance, in Croatia and Latvia.

The second part of the analysis focuses on identifying variables that may influence the obtained efficiency scores. To mitigate the problem of heteroskedasticity, which is likely driven by substantial data heterogeneity, the variables were transformed from their original units (thousand tonnes of oil equivalent) into shares. Tab. 5 presents the key information for the final Tobit model, including variables representing the shares of different types of energy.

During the model specification process, it was found that the time factor is not statistically significant, indicating that no clear trend was identified over the observed period. The final model therefore retains the variables representing the shares of renewable and nuclear energy, both of which are statistically significant at the 10% significance level. The intercept term is positive and highly significant, reflecting a relatively high baseline level of latent efficiency across the sample.

The parameters associated with both renewable and nuclear energy indicate a positive effect. However, the estimated coefficients reported in Tab. 5 relate to the latent efficiency

Tab. 5: Tobit Model Estimates

Coefficients	**Estimates**	**Std. Error**	***Z*-value**	***P*-value**
Intercept	0.71634	0.06095	11.75289	<0.00001
Renewables	0.14129	0.08253	1.71190	0.08691
Nuclear energy	0.18224	0.09781	1.86323	0.06243
Ln(Scale)	−1.60140	0.07785	−20.57062	<0.00001

variable rather than directly to the observed efficiency scores. The uncensored effects can be approximated using the scale parameter. The value of the scale parameter (after exponentiation) is 0.2016. This relatively low value, combined with the high intercept, implies that the value of the standard normal cumulative distribution function is very close to one. As a result, the marginal effects on observed efficiency are very similar to the original Tobit model coefficients.

Specifically, a 10 percentage point increase in the share of renewable energy is associated with an increase in efficiency of approximately 0.014, while a comparable increase in the share of nuclear energy corresponds to an increase of about 0.018. This suggests that the effect of nuclear energy is somewhat stronger.

To enhance the robustness of the results, bootstrap-based standard errors were computed (1000 repetitions). The bootstrap results suggest that the estimated coefficients are stable, as indicated by the negligible bias across all parameters (see Tab. 6). Bootstrap-based inference was further used to assess the statistical significance of the estimated coefficients. The resulting p-values largely confirm the original findings, with renewable energy remaining weakly significant at the 10% level (p-value $= 0.091$). In contrast, the effect of nuclear energy becomes statistically significant at the 5% level (p-value $= 0.049$) when evaluated using bootstrap standard errors, suggesting a somewhat stronger and more robust relationship.

Tab. 6: Bootstrap Statistics

Coefficients	**Original**	**Bias**	**Std. Error**
Intercept	0.71634	0.00014	0.06310
Renewables	0.14129	−0.00055	0.08364
Nuclear energy	0.18224	−0.00283	0.09239

Overall, the results suggest that the energy mix plays a role in shaping efficiency outcomes, with nuclear energy showing a more robust association, while the effect of renewable energy remains less conclusive.

4 DISCUSSION, LIMITATIONS AND FUTURE DIRECTIONS

Based on the DEA model, a total of five countries were identified as being 100% efficient throughout the entire observed period, namely France, Germany, Luxembourg, Spain, and Sweden. These countries clearly share the characteristic of being highly economically developed, which is also associated with a high level of technological advancement (European Commission, 2025). From the perspective of energy production, they have in common a relatively limited domestic fossil fuel base, and they can also be described as countries representing low-carbon energy models (Wojciechowski et al., 2023).

A closer look at the strategies of, for example, France and Germany reveals that it is possible to achieve an efficient state even through fundamentally different approaches. France is undoubtedly a country with a large share of energy generated from nuclear power. In contrast, Germany is well known for its opposition to nuclear energy. Although the complete phase-out was finalized in 2023, a significant reduction in the share of nuclear energy had already taken place during the observed period. Specifically, in 2021, Germany shut down three of its six remaining nuclear power plants (Euronews, 2021). Germany's strategy, which also resulted in efficiency within the DEA model, is based on a strong deployment of renewable energy sources.

The suitability of both strategies is further supported by the results of the Tobit model, which indicate a positive effect on efficiency for countries with a high share of both nuclear energy and renewable energy sources. From this perspective, it is therefore not necessary to direct all countries toward a single common European strategy, as an efficient state can be achieved through fundamentally different approaches.

The mere dominance of either nuclear energy or renewable energy in a given country does not automatically represent a key to success, as demonstrated by the results for Hungary. According to the cluster analysis presented in Varvařovská and Staňková (2021), Hungary belongs to the same cluster as France in terms of its energy mix, due to the strong share of nuclear energy. Nevertheless, these countries are positioned at completely opposite ends of the ranking. Although the DEA model itself does not include any variable explicitly capturing the transformation process, it does reflect production efficiency, which is logically also determined by technological progress. France operates a highly developed system consisting of numerous reactors across nearly two dozen nuclear power plants, allowing it to cover more than half of its energy production from nuclear sources (Euronews, 2020). In contrast, Hungary relies on a single nuclear power plant, Paks, which, although also capable of producing roughly half of the country's required energy, is based on Russian technology (see, for example, Sarlós, 2015). Although both France and Hungary rely heavily on nuclear energy, differences in technology mean that France ranks among the five efficient countries, whereas Hungary is positioned at the bottom of the ranking.

As already mentioned, this study focuses exclusively on the production of primary energy; therefore, all variables (labour, capital, and emissions) are related solely to the activities of sector D, which can be considered a limitation of this research. Countries (not only within the EU) actively trade energy, yet these linkages are not incorporated into the constructed DEA model. Future research could extend the model by including these energy flows, either in the form of a net export variable or by directly accounting for the volumes of exports and imports.

Another limitation of this study lies in the borderline *p*-values obtained in the Tobit model. Future research could address this issue by adopting a less aggregated approach and including variables such as biofuels, wind energy, solar energy, and geothermal energy separately. However, such a model would require a panel dataset with a longer time horizon in order to ensure a sufficient number of degrees of freedom. For longer time periods than the four years considered in this study, it would also be necessary to more thoroughly analyse shifts in the production possibility frontier resulting from technological progress, which can be expected in longitudinal research.

5 CONCLUSIONS

This study examined the efficiency of primary energy production in 2018–2021 across selected EU countries using the DEA and Tobit models, with a particular focus on the role of different energy sources. Efficiency is derived from aggregated economic indicators with respect to the amount of CO_2 emissions produced, which are treated as an undesirable output in the DEA model. Based on the model results, France, Germany, Luxembourg, Spain, and Sweden can be identified as the leading countries. Although these countries do not follow identical strategies in terms of their energy mixes, all of them remained efficient throughout the entire observed period. As evidenced by the results of the Tobit model, high shares of both renewable and nuclear energy have a positive effect on the efficiency of individual countries. Taken together, these findings suggest that a uniform European energy strategy may not be necessary, as countries can achieve efficiency through diverse approaches.

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