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Energy Efficiency Management across EU Countries: A DEA Approach

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Abstract: We examine energy efficiency in the European Union (EU) using an integrated model that connects labor and capital as production factors with energy consumption to produce GDP with a limited amount of environmental emissions. The model is a linear output-oriented BCC data envelopment analysis (DEA) that employs variables with non-negative values to calculate efficiency scores for a sample of 28 EU member states in the period 2010–2018. We assume variable returns to scale (VRS) considering the natural inclination of countries to adopt technologies that allow them to produce higher outputs over extended periods of time, which we observed through the trends of increasing labor productivity and decreasing energy intensity over the analyzed period. The average EU inefficiency margin in the sample period is 16.0%, with old member states being significantly more efficient (4.2%) than new member states (29.5%). Energy efficiency management does not improve over time, especially in new member states that had substantially worse efficiency by 2018 than in 2010. New member states could increase energy efficiency through the liberalization of the energy market, the support of energy-saving and technologically advanced industries, and the introduction of measures aimed at increasing the productivity levels in the economy.

Keywords: energy efficiency; production function; primary energy; electricity; DEA analysis

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1. Introduction

To achieve both economic growth and sustainable development, more focus on explicit energy inputs and green GDP has occurred in the literature. Although the use of clean energy is gradually increasing, about 80% of the energy consumed globally comes from fossil fuels while about 50% of power generation depends on coal causing severe environmental pollution [1]. The evaluation of the energy efficiency of different regions and industry sectors is an essential component of formulating energy and environmental policies aimed at efficiency improvement. One of the major objectives of the EU's economic policy and development strategy is to become a low-carbon and resource-efficient economy. Towards this, the EU set a goal to increase the efficiency of energy use by 20%, decrease CO_2 emissions by the same amount, and have 20% of overall energy consumption coming from renewable energy resources by 2020 [2]. Although primary energy (−2%) and final energy consumption (−1%) in the EU has been gradually decreasing, this progress is not enough to achieve these objectives. The lag is probably due to a lack of political will to cut energy consumption and the failure of non-binding targets, as member states shirk their obligations as they have done in the past with debt/GDP targets [3].

Since the assessment of energy efficiency in diverse regions may pose as a direction for further development, our study is focused on the EU in order to evaluate each of the countries' performances as well as to examine practical implications and shape overall energy policies. Managers will find our results helpful in selecting effective management and investment strategies. Policymakers, on the other hand, can use our results to generate appropriate action plans and strategies. Energy efficiency is potentially one of the most important and cost-effective means by which industries can mitigate their greenhouse gas emissions for sustainable development. Despite the availability of cost-effective energy efficiency measures in industries, their implementation is not always assured due to various barriers and obstacles [4].

Energy efficiency is often measured relatively rather than absolutely. Three common types of indicators are used to measure energy efficiency, namely thermodynamic, physical, and monetary factors [5]. As production involves both energy as an input and pollution as an undesirable output, a total-factor efficiency evaluation model is necessary to measure both energy and environmental efficiency. This paper provides insight and future direction in applying a DEA model to examine energy efficiency in the EU.

Within the sample, we can also compare efficiency results over time and space (e.g., old vs. new members) as well as how the results correlate with other production indicators. Providing our aim is to present the most recent indicators and trends, our study covers the time period between 2010 and 2018, due to the availability of data. Hence, it covers the member states in the given period, excluding more recent events (such as Brexit). The core of the model is the development of a production function with labor, capital, and primary and secondary energy consumption (electricity) as inputs; GDP as a desired output; and CO_2 emissions as an undesired output. The model yields an efficiency score for each country/year in the sample.

Our paper adds to the literature in the following ways. Firstly, it provides a quantitative scoring of the EU's recent macroeconomic energy efficiency. Secondly, our approach in dividing the EU into groups of old member states and new member states allows us to explore if differences in levels of development and the structure of different economic systems have an impact on the results. Third, the DEA methodology contributes to further evidence of the utility of using this approach to measure energy efficiency. Fourth, the panel nature of the results highlights the necessity of conducting a comprehensive approach towards smart, sustainable, and inclusive growth.

The rest of the paper is structured as follows: Section 2 provides a detailed literature review of the DEA studies pertaining to energy and environmental efficiency evaluation in general—both on a macro and micro level. Section 3 provides an overview of the data and variables included in the empirical analysis and Section 4 presents the descriptive statistics. The DEA methodology used in the analyses is introduced in Section 5 while the results are discussed in Section 6. Finally, Section 7 concludes.

2. Literature Review

DEA is the dominant method for measuring environmental efficiency according to a recent literature review [6] of 50 environmental and energy economics journals in the period 2006–2015 covering 144 studies. Within the DEA literature, both parametric and nonparametric models are used with the advantage of the latter being that if the relationship between inputs and outputs is unknown there should be no structure imposed a priori. Therefore, the use of a parametric production function is relatively rare given the unclear relationship between inputs and outputs. Studies of China's energy efficiency dominate the application of the DEA method in the literature. The conclusions of this first review of the literature were supported by a second review covering 145 articles between 2000–2018 [7]. The keywords which come up repeatedly in published papers dealing with the application of DEA in the assessment of energy and environmental economics in the Web of Science database are "energy efficiency", "environmental efficiency", and "efficiency performance". A third review covering 1206 articles published throughout 2018 [8] shows that the literature has grown rapidly since 2011, with China dominating this output in terms of most often being the subject of the analysis and having the most citations and largest number of authors and where they work. The most recent overview of the DEA application in the field of energy efficiency covers the literature published during 2011–2019 [1]. Due to the technical heterogeneity of energy efficiency between different research goals, the existing research adjusts the models to improve the accuracy of the efficiency assessments. Most analysis is at a macroeconomic region level of aggregation or higher due to data availability. A summary of these reviews is shown in Table 1.

Table 1. Summary of literature reviews using the DEA approach to study energy efficiency.

Author(s) and Year	Time Interval	Scope	Results and Outcomes
Mardani et al. (2017)	2006–2015	144 articles	DEA models, especially non-parametric ones are appropriate for evaluation of the energy efficiency. China was shown to have the biggest contribution to the publication of DEA-related papers on this topic.
Mardani et al. (2019)	2000–2018	145 articles	The applications of DEA have increased in the area of environmental and energy economics, especially energy efficiency, environmental efficiency, and efficiency performance.
Yu and He (2020)	2011–2018	1206 documents	The annual volume of publications has grown rapidly since 2011 with China dominating the research in this area.
Xu et al. (2020)	2011–2019	281 articles	Energy efficiency analyses at the regional level prevail. The energy efficiency DEA model has improved, the accuracy has increased, and the model has evolved from static to dynamic and complex.

While early studies treated energy consumption as an input with GDP as a desirable output, ignoring undesirable outputs such as pollution, more recent DEA literature evaluates energy and environmental efficiency with an integrated method using many inputs and explicitly modelling undesirable outputs reflecting growing concerns over climate change. Including additional inputs, such as capital and labor, acknowledges that energy must be complimented with other inputs and not stand alone [9–11]. Carbon emissions, wastewater, and the overuse of natural gas are examples of undesirable outputs. The integrated approach measures both the operational efficiency of producing desirable outputs and the environmental efficiency regarding the production of undesirable outputs within a single model. Therefore, DEA examinations of energy efficiency have evolved from a single factor index to a total-factor framework, from radial to non-radial and slack-based models, and from simple static models to dynamic panel models. The rationale for this is that the non-radial DEA model has higher discriminatory power compared to the traditional DEA model [12]; the inputs and outputs are not restricted to improve uniformly [13] and the efficiency indicator for each variable in the process can be identified in order to increase the efficiency of the DMU being studied [14]. The DMUs in most studies are entire countries or regions, as firm-level microeconomic studies are fewer in number (e.g., [15–18]) and are not the focus of this paper.

Our approach towards measuring energy efficiency implies the categorization of energy as primary and secondary, as proposed in one study [19] which focuses on energy usage trends in the world. Primary energy consists of fossil-fuel energy (oil, natural gas, and coal) and non-fossil energy (renewable and nuclear), while secondary energy refers to electricity. DEA can be seen as a holistic methodology, recognizing the balance between economic development and environmental protection by combining desirable outputs (e.g., electricity) and undesirable outputs (e.g., GHG emission) in performance assessment.

As there are many studies that use the DEA method in China, and bearing in mind that China's CO_2 emissions not declining fast enough [20], taking a closer look at some of these studies constitutes an essential part of addressing global climate change and is important in understanding our approach [20]. One recent study utilizes improved DEA models to measure the total-factor energy and environmental efficiency of 29 administrative regions of China during the period of 2000–2008, taking into account both desirable outputs (GDP) and undesirable outputs (CO_2 and SO_2) while including both an energy input (total energy consumption) and non-energy inputs (labor and capital stock) [21]. The dynamic panel results show that the eastern coastal provinces maintain a higher energy efficiency and advanced production technology in comparison to the central and the western areas, despite a general increase in environmental efficiency across all three areas. The efficiency differences of the three areas may arise from the imbalance of economic development and a technology gap [21–23]. An independent study [24] using the same sample in a similar time frame (2000–2007) confirmed the results, indicating that China has a real problem with energy inefficiency as one moves away from the coast. One paper [25] uses a non-radial DEA approach that combines energy structure adjustment and DEA-based target setting together to measure energy saving and energy-related carbon dioxide emission reduction in China. Importantly, since non-fossil energy incorporated as a fixed factor cannot be decreased in the efficiency optimization process [25], regional technological heterogeneity and carbon emissions must be addressed when developing solutions for energy efficiency improvement [26].

In a sample of 25 countries during the period 2010–2017, the use of the non-energy and energy inputs revealed that developed countries (Australia, Canada, France, Germany, Italy, Japan, South Korea, Spain, the United Kingdom, and the United States) are more effective in promoting GDP growth and reducing CO_2 emissions than developing countries (Brazil, China, Egypt, India, Indonesia, Iran, Kazakhstan, Malaysia, Mexico, Poland, Russia, Saudi Arabia, South Africa, Thailand, and Turkey) [20]. Two studies [27,28] that consider many factors and pollutant emissions evaluate the environmental efficiency of 26 OECD countries in the period 1995–1997 [27] and 21 OECD countries in the period 1997–2002 [28]. The first incorporates pollutants into the traditional DEA framework but uses a non-radial DEA-based model for multilateral environmental performance comparisons. The labor force and primary energy consumption are employed as two inputs, whereas GDP is the only desirable output and carbon dioxide, sulfur oxides, nitrogen oxides, and carbon monoxide are undesirable outputs. The second includes the capital stock and labor force as non-energy inputs, GDP as the desirable output, and carbon dioxide emissions as the undesirable output. Overall, both papers show that OECD countries have the potential to reduce their energy consumption, but in fact did not. Using a longer time period and more recent data for 30 OECD states in the period 2001–2018 demonstrated that those with higher nominal GDP per capita use primary energy and electricity (secondary energy) more efficiently [29]. Extending the time period even further (1995–2016), a very recent DEA study [30] with 32 OECD countries found that measuring energy efficiency levels without considering undesired outputs tends to lead to an overestimation of the energy efficiency level of environmentally friendly countries and an underestimation of the energy efficiency level of countries that value environmental protection.

Looking at just the EU, a study [31] assessing general energy inefficiency in the period 2001–2008 showed that countries such as Germany, Sweden, or Austria, who have strong environmental protection standards, appear to be less energy and environmentally efficient relative to Denmark, Belgium, Spain, France, or Ireland. Eastern European countries have low efficiency scores as expected given their lower level of energy saving technology. Yet [32] shows a wide range of environmental performance scores in the EU over the period 2001–2012, illustrating that differences in emissions persist and may be explained with the share of renewable and non-renewable energy sources. They found that Ireland, Latvia, Sweden, Hungary, and the United Kingdom are the five relatively efficient countries, while Estonia, the Czech Republic, Poland, Bulgaria, and Germany are the five least efficient countries. Further, the EU's environmental taxes imposed on top of national tax regimes cause distorting effects in eco-efficient countries. In general, efficiency scores tend to be quite low across the EU [33] based on a sample of 28 EU member states for the years 2008, 2010, 2012, 2014, and 2016, with little improvement. A two-stage DEA model is used in yet another study [34] in evaluating the evolution of eco-efficiency in the EU-27 over the period 2008–2018, taking into account the dichotomy between economic growth and environmental protection. In the first stage, through the use of a non-parametric DEA model, eco-efficiency scores were computed for all the member states considering the ratio of GDP per capita and greenhouse gas emissions (GHG) as outputs, whereas in the second stage the obtained scores were used as a dependent variable in the proposed fractional regression model (FRM) with three greenhouse gases and five atmospheric pollutants as explanatory variables. The outcomes of the present analysis pointed to different stages of the eco-efficiency process in EU countries, with Ireland being the country that most mitigated its emissions, whereas the lowest reductions in emissions are noted in Greece and Spain. Following the adoption of the Energy Efficiency Directive by the EU member states, the findings from the study assessing the annual reports submitted from 2013 to 2018 [35] show that although significant progress has been achieved in declining the absolute values of primary and final energy consumption at national levels since 2005, only 11 member states significantly reduced their total final energy consumption over the period 2011–2016. Therefore, the results indicate that further commitment towards meeting the Directive's requirements is necessary, mainly with introduction of new national policy actions and the straightening of the existing ones, as well as the regular monitoring of the progress made towards the targets. Based on these EU efficiency studies, a move towards alternative energy sources must be made in order to ensure reliable energy supplies at rational prices and with the least environmental impacts. The conclusions of the studies point to the importance of a heterogeneous approach of policy application on a country level. Furthermore, the authors of [36] confirm the results that an increase in energy efficiency can be achieved by a joint effort on the macro and micro level, the latter indicating the necessity of implementing an energy management system with specific leadership skills and top management support. When establishing energy management, the authors of [37] propose that energy efficiency should be measured through the adoption of specific energy consumption (SEC) as a key energy performance indicator, calculated as a ratio of the energy used for producing a product and especially useful when undertaking longitudinal benchmarking, i.e., the same company, sector, or country, over time.

In this section we have integrated the contributions of many authors to energy efficiency measurement, whilst further enriching the literature by presenting the recent progress towards the achievement of the goals set out at the EU level. Compared to the reviewed studies, our analysis differs from the others in dividing the EU into groups of old member states and new member states, which allows us to study if differences in the levels of economic development and the different structures of economic systems have an impact on a country's energy efficiency. This also helps us to determine if energy efficiency is related to the time evolution of the modelled variables and if countries from the two groups need to pursue different strategies towards improving energy efficiency.

3. Sample and Variables

We constructed a sample of 28 EU member states with annual data for the period 2010–2018 and divided it in old member states (OMSs) and new member states (NMSs). The former group includes all countries that have acceded to the EU before 1996, while the latter consists of all countries that have joined the EU since 2004 (Table A1, Appendix A). Croatia is the only country that joined during the analyzed period and it was decided that we should include it in the study.

Given that we developed a DEA framework, the variables in the model are divided into inputs and outputs. Regarding inputs, we use the production function as a starting point and employed the labor force and capital stock as non-energy inputs, and primary energy consumption and electricity consumption as energy inputs that make up the total-factor energy in the model. We note that primary energy encompasses all forms of energy found in nature that are not subject to any conversion process (e.g., fossil fuels, mineral fuels, solar energy, wind energy, etc.), while electricity is an example of secondary energy produced from primary energy sources. Regarding outputs, we choose the nominal GDP as a desired output and CO_2 emissions as an undesired output. We assumed that countries seek to maximize GDP and minimize CO_2 emissions. Using the raw data, we constructed additional derived variables: GDP per worker, GDP per capital stock, primary energy intensity, electricity intensity, and CO_2 per GDP. Table A2 (Appendix B) gives a detailed overview of the variables employed and the derived indicators.

The data for the selected variables were collected from the US Energy Information Administration (EIA) and World Bank's World Development Indicators (WDI) databases.

4. Descriptive Statistics

The descriptive statistics are reported in Appendix C, where Table A3 (raw data) and Table A4 (derived variables) present the summary statistics for the variables used in the model for each sample year and over the entire sample period ("All" at the bottom). Individual country means plus OMS and NMS groups during the sample period are reported in Table A5.

The average size of the labor force increased from around 8.69 million in 2010 to around 8.96 million workers in 2018, while there is no clear trend on the movement of the average capital stock with ups and downs from year to year. Primary energy consumption decreased from around 792 billion kWh in 2010 to 732 billion kWh on average in 2014, but then started to gradually increase though not up to the 2010 mean. Similar movement can be noticed for electricity consumption, which fell from 105.8 billion kWh in 2010 to 101.2 billion kWh in 2014 and then increased to 104.4 billion kWh in 2017. Finally, the amount of CO_2 emissions follows the same trend as for energy consumption, with downward movement from 146.7 MM tones in 2010 to 131.5 MM tones on average in 2014, followed by a rise to 134.7 MM tones in 2017. The downward movement of these variables in the early 2010s reflects the decline in production during the economic recession amidst the European debt crisis during that period. While the pattern of these raw data reflects the economic circumstances throughout the analyzed period, our derived variables better explain the differences across countries and over time.

Labor productivity (GDP/L) averages at US$ 67,178 over the entire period. Luxembourg records the highest mean GDP per worker of US$ 226,611, with Ireland, Denmark, Sweden, and Belgium also having a value above US$ 100,000. The lowest mean GDP per worker is recorded in Bulgaria at US$ 16,747. Old member states have a GDP per worker of US$ 96,113 on average, which is almost three times the mean ratio of US$ 33,791 for the new member states. A comparison of the mean GDP per worker in 2010 and 2018 shows an increase from US$ 65,043 to US$ 72,213 on average, although this increase was not steady.

The ratio of GDP per capital stock (GDP/K) shows that, on average, EU countries use US$ 1 of capital to produce US$ 5.029 of GDP, ranging from a mean of US$ 3.990 for Estonia to a mean of US$ 7.864 for Greece. Unlike labor productivity, there are no significant differences across countries and country groups in terms of capital productivity, however the group of old member states still has a somewhat higher mean of 5.203 compared to the 4.829 mean for NMS. There is no significant difference between the mean GDP-to-capital ratio in 2010 and 2018, though there was an upward movement until 2013, followed by a decline in the years until 2017.

Energy intensity indicators show how much energy countries consume to make their GDP. The primary energy intensity for all countries over the entire period is 1.596 or, in other words, a consumption of 1.596 kWh per US$ 1 of GDP. In a similar manner, the mean electricity intensity of 0.221 shows that EU states consume 0.221 kWh of electricity per US$ 1 of GDP. The new member states have a markedly higher energy intensity than the old member states, which is more noticeable with regards to primary energy consumption. For instance, Bulgaria has both the highest primary energy intensity with a mean value of 3.551 and electricity intensity with a mean value of 0.514, whereas Ireland records the lowest mean values of 0.658 for primary energy intensity and 0.093 for electricity intensity. No general trend can be tracked over time, though it is evident that the mean intensities in 2010 were somewhat higher than those in 2018. Overall, this trend reflects some success in increasing returns to scale from energy as a production input, which is subject to factors such as the development and application of new technologies and the reducing of energy waste.

The mean value of 0.302 for CO_2 emissions per GDP indicates an emission of 0.302 MM tones of CO_2 per US$ 1 of GDP. Countries with a higher energy intensity also have higher

CO_2 emissions, hence, the new member states average higher values than those of the old member states. Bulgaria, Malta, and Poland all have an average CO_2-to-GDP ratio above 0.6, while Sweden (0.095) is the only country with CO_2 emissions below 0.1 MM tones per US$ 1 of GDP. Fortunately, the general trend over time is decreasing.

From the results of the two-group mean comparison test (Table A6 of Appendix C), it can be inferred that the differences between the OMS and NMS groups are statistically significant at a significance level of 1% for all derived indicators.

5. Methodology

Our approach is to apply an output-oriented DEA model to calculate efficiency scores for each country in each period. DEA is a linear programming method that was popularized for measuring efficiency starting in the late 1970s [38,39], though linear programming has been around even longer than that. Each decision-making unit (DMU) is compared over time and space. A key advantage of the DEA methodology compared to other methods that use econometrics is that it does not necessarily require functional assumptions for efficiency assessment [40], and thus one can impose a functional form (parametric) or not (non-parametric) depending on what the underlying technology is believed to be.

There are two variations of the DEA models used in empirical studies: CCR (or Charnes, Cooper, and Rhodes; see [38]) and BCC (or Banker, Charnes, and Cooper; see [39]). The main difference between the two is that the CCR DEA model assumes constant returns to scale (CRS), while the BCC DEA model analyzes variable returns to scale (VRS). In reality, it is hard to believe that production relies on CRS over an extended period of time given the natural inclination of countries to adopt technologies that allow them to produce higher outputs, thus implying increasing returns to scale (IRS), and the impact of some factors that adversely affect productivity, thus leading to decreasing returns to scale (DRS). One sign that the latter stands to reason in our analysis is the observation that countries have had some success in increasing labor productivity and decreasing energy intensities over time. Logically, when higher GDP can be produced with less labor employed and less energy consumed, the IRS and thereby the VRS assumption practically holds. Given that the assumption of variable returns to scale is the mean difference between the BCC DEA and the CCR DEA, we opt for the former and utilize this as a technique for measuring pure technical efficiency.

Yet, before moving on to the optimization problem, it is necessary to set a couple of assumptions regarding the optimization problem and we consulted [41] to introduce necessary conditions for achieving relative DEA-efficiency. The assumptions and the necessary conditions for efficiency are summarized in the following three definitions.

Definition 1. *The following assumptions hold for the optimization problem.*

- *A1 (linearity): The objective function in the optimization using DEA is linear.*
- *A2 (non-negativity): The values of the inputs $x_{i,n}$ and outputs y_i^D and y_i^U as well as the weights λ_i are non-negative, i.e., $x_{i,n}, y_i^D, y_i^U, \lambda_i \geq 0$.*
- *A3 (convexity constraint): The weights λ_i sum up to 1, i.e., $\sum_{i=1}^{C} \lambda_i = 1$.*

The linearity assumption implies that the optimization is done using a linear programming technique, requiring the optimization problem to be formulated in a linear form. Non-negativity requires that the values of the variables in the model cannot be negative. The convexity constraint is a standard assumption added in a BCC DEA model. In fact, it is a restriction on the production possibility set, which allows the projection of an inefficient DMU to be represented as a linear combination of efficient DMUs.

Definition 2. *If the optimal program satisfies $f(x, y) = max\ \theta_i$, then DMU_i is weakly DEA-efficient.*

The definition states that $\theta_i = 1$ is the efficient score that one can obtain from solving the optimisation problem. In fact, this indicates that a weak DEA-efficient DMU_i when

$\theta_i = 1$ lies on the DEA frontier. In the case of $\theta_i > 1$, then the $1 - \theta_i$ is an inefficiency margin, which reveals the degree to which the output level could be improved while keeping the inputs unchanged to reach efficiency.

Definition 3. *If the optimal program satisfies Definition 2 and A2 of Definition 1 holds, then DMU_i is relatively DEA-efficient.*

This definition is important because it gives necessary conditions that should be satisfied in order to reach a stronger form of DEA-efficiency.

We suppose that there are DMUs denoted by DMU_i ($i = 1, \ldots, C$) that represent the EU member states. The DMUs use the set of N inputs $x = (x_1, \ldots, x_n) \in R_+^N$ to produce a desired output $y^D \in R_+$ and an undesired output $y^U \in R_+$. Given that the DMUs have opposite preferences towards the desired and undesired outputs—that is, they intend to maximize the desired output and minimize the undesired output—it is necessary to find a way to deal with this within the DEA-BCC model. Some possible ways to treat the undesired outputs include: using reciprocals of the undesired output [42], treating the undesired output as an input [43], and translating the undesired output to a desired output using classification invariance [44]. Nevertheless, the use of reciprocals violates the linear property and treating the undesired output as an input does not reflect the production process as it is, so we therefore resort to a linear monotone decreasing transformation with the classification invariance method proposed by [44]. The idea is to use a translation vector v in order to convert the undesired output y^U to a desired one y^*, such that $y^* = -y^U + v > 0$ where $v = \max\left(y_i^U\right) + \min\left(y_i^U\right)$. The latter implies that the DMU with the highest value of the undesired output will have the lowest value after the transformation. In essence, adding the maximum value of the undesired output guarantees the non-negativity of the transformed values, and additionally adding the minimum value sets it as the lowest value.

After dealing with the undesired output, the objective function that we aim to maximize is:

$$f(x, y) = \max \theta_i \tag{1}$$

s. t.

$$\sum_{i=1}^{C} \lambda_i x_{i,n} \leq x_{0,n},\ n = 1, \ldots, N \tag{2}$$

$$\sum_{i=1}^{C} \lambda_i y_i^D \geq \theta_i y_0^D \tag{3}$$

$$\sum_{i=1}^{C} \lambda_i y_i^* \geq y_0^* \tag{4}$$

$$\sum_{i=1}^{C} \lambda_i = 1 \tag{5}$$

$$x_{i,n}, y_i^D, y_i^* \geq 0 \tag{6}$$

$$\lambda_i \geq 0 \tag{7}$$

where λ_i are the intensity weights for the linear combination of the sampled countries and $\theta_i = \left(\sum_{i=1}^{C} \lambda_i y_i^D + \sum_{i=1}^{C} \lambda_i y_i^*\right) / \sum_{i=1}^{C} \lambda_i x_{i,n}$ denotes the efficiency score. The constraint in (4) results directly from Assumption 3, while the constraints in (5) and (6) illustrate Assumption 2.

6. Results and Discussion

The optimized efficiency scores are shown in Table A7 (Appendix D). The aggregate average efficiency score for all EU member states is 1.160, indicating an inefficiency of 0.160 or 16.0%. Holding inputs constant, EU members can improve their output—that is, increase GDP or/and reduce the CO_2 emissions—by 16.0%. However, the DEA model does not allow the score to be decomposed between the two outputs, and so exactly how much GDP could be raised and/or CO_2 emissions be decreased is unknown. The NMS group clearly has higher scores on average, with a mean inefficiency core of 29.5%, while the

OMS group has only 4.2% (see Figures 1, A1 and A2 of Appendix E). Consequently, new member states could benefit more from efficiency-enhancing policies. Across individual countries, nine are DEA-efficient in each year, with six belonging to the OMS group and three to the NMS group. These countries are: Cyprus, Denmark, Estonia, France, Germany, Luxembourg, Malta, Sweden, and the United Kingdom. Outside this consistently more efficient group, there are countries which temporarily had high relative efficiency in some years but not all: Greece (2011–2018), Ireland (2010–2011, 2015–2018), Italy (2010–2011, 2013), the Netherlands (2010–2013, 2017), Lithuania (2010), and Latvia (2017). The most inefficient countries—the Czech Republic (70.3%), Romania (61.9%), and Bulgaria (54.7%)—are all in the NMS group. Across all countries and years, Romania has the highest single inefficiency score of 87.4% in 2012.

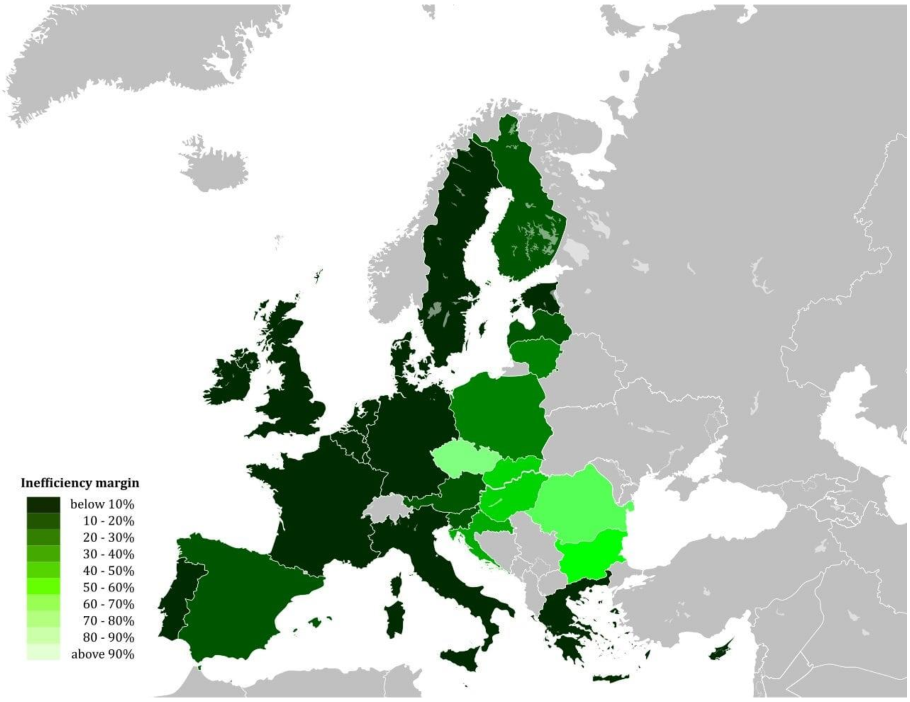

Figure 1. Average efficiency scores across countries on a map of Europe.

There is no clear yearly trend in scores (Figure 2). Energy inefficiency is slightly higher in 2018 (17.3%) than in 2010 (14.0%), and thus there is more work to be done. With a starting score of 5.6%, the OMS group has improved energy efficiency during the decade. However, results within the OMS group are quite mixed, with four countries improving efficiency, five developing more inefficiency, and another six with constantly high efficiency levels. Overall, energy efficiency within the NMS group displayed the opposite pattern, with growing inefficiency. Only four countries had improved efficiency, three constant efficiency, while all the rest deteriorated. This suggests that a different approach to improving energy efficiency in the EU is necessary between OMSs and NMSs. An example of a country that has done well is Portugal from the OMS group. After starting with an inefficiency score of 21.1%, the country experienced a sharp drop in its inefficiency levels that dipped to 0.4% in 2013 and it maintained an inefficiency level below 10% until 2018 when it jumped up to 14.1%. On the contrary, Lithuania from the NMS group, started from a level of full efficiency in 2010, however inefficiency soared to above 10% in 2011 and continued to increase to 30.4% in 2015, finishing with a country record high of 32.1% in 2018.

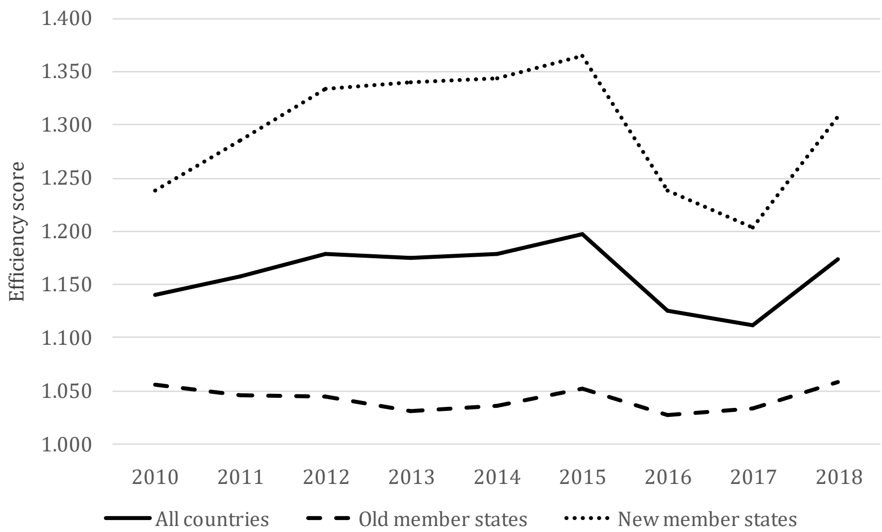

Figure 2. Time evolution of the average efficiency scores for the country groups.

Over time, energy efficiency in the OMS group is quite stable despite the recession included in the sample period. The NMS group and overall efficiency improved in the period 2016–2017 but then reverted to more inefficiency in 2018 with NMS driving the overall trend-line variation. Looking at year-by-year score differences (Table A8 of Appendix D), two years exhibit especially worsening levels of inefficiency (2012: 14 countries with worsening efficiency of the 17 that had a score change; 2015: 12 countries with worsening efficiency of the 18 that had a score change). Particularly poor performers in 2012 were Bulgaria (28.7%) and Romania (10.3%), while in 2015 they were Slovakia (17.3%) and the Netherlands (11.7%). Across the sample, the improvement in efficiency in 2016 (0.072) off-set the cumulative inefficiency in 2010–2015 to yield a record low overall score of 1.112. Both the OMS and NMS groups improved efficiency in 2016–2017 as all 17 countries that had score changes moved in the right direction. Nine countries—Bulgaria, the Czech Republic, Hungary, Latvia, the Netherlands, Poland, Romania, Slovakia, and Slovenia—managed to increase their efficiency by more than 10% in a single year. Unfortunately, the average efficiency in the final sample year (2018) declined by 0.062 and all 17 countries that recorded significant improvements fell back to their 2015 efficiency level.

7. Conclusions

Given there is no single widely accepted measure of energy efficiency, the DEA method provides an opportunity for a more comprehensive analysis of inefficiency which is of great importance for policymakers. Production factors are integrated with energy-related variables on the input side to enable GDP to be a desired output and less CO_2 emissions an undesired output.

We find that average inefficiency in the EU for the period 2010–2018 is 16.0% with old member states having markedly better energy efficiency management as illustrated by a mean inefficiency of 4.2% against that of 29.5% on average in the new member states. Nine countries (Cyprus, Denmark, Estonia, France, Germany, Luxembourg, Malta, Sweden, and the United Kingdom) are DEA-efficient in each year, a list made of six old member states and three new member states. On the other hand, the Czech Republic (70.3%), Romania (61.9%), and Bulgaria (54.7%) are farthest from the efficiency line on average and are all new member states. The gap between the two country groups expands over the decade as inefficiency of the new member states worsens. There are many reasons that may explain the differences across countries from the two country groups, such as uneven productivity levels, different GDP sector composition, unfavorable energy structures, excessive energy consumption, and the existence of technological gaps. Comparing the results from the descriptive statistics for the modelled variables and the efficiency scores reveals that higher energy efficiency is, in general, associated with higher labor productivity and lower energy intensity. This implies that the GDP sector composition of the new member states is heavily reliant on labor and energy-intensive industries whose contribution is of high importance to securing sustainable economic growth.

Our results indicate that the EU strategy towards energy efficiency could achieve better results if member states are compared relative to other members within specific regions and if specific national conditions are controlled for. An important aspect in promoting more efficient energy management is improved communication between countries to benefit from more extensive mutual cooperation. There are several methods that new member states could transform into policies targeting energy efficiency. Firstly, one effective method in increasing energy efficiency is the liberalization of the energy market, which would facilitate adjustment in the energy structure by increasing alternative energy supplies (e.g., non-fossil energy) with a particular emphasis on energy from renewable sources. In this regard, regulatory frameworks should be formulated and adopted to gradually mitigate energy dependency and lower CO_2 emissions, while another viable solution could be the adoption of a carbon tax and the increase of investment in technological advances for producing alternative energy sources. Secondly, energy efficiency could be increased through targeting changes in the composition of the GDP sector that would increase the contribution of energy-saving and technologically advanced industries in place of labor and energy-intensive industries. This would enable the production of similar levels of economic output with significantly lower energy intensity and lower CO_2 emissions. Policies aimed in this direction should encourage the growth of such industries through subsidies or tax incentives for investment, increased R&D expenditure, and industrial digitization. Third, it is necessary to target the improvement of energy management needs through an increase of the productivity levels in the economy. Policy frameworks should include measures aimed at reducing technological gaps by promoting innovations. Increased productivity levels would allow higher production at lower energy intensities.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Sampled Countries

Table A1 contains all countries included in the sample along with their ISO 3166-2 alpha-3 codes, as well as information regarding their accession to the European Union and consequently the group which they belong to.

Table A1. List of countries included in the sample.

Country	Code	Year of Accession	Group
Austria	AT	1995	Old member states
Belgium	BE	1957 (founder)	Old member states
Bulgaria	BG	2007	New member states
Croatia	HR	2013	New member states
Cyprus	CY	2004	New member states
Czech Republic	CZ	2004	New member states
Denmark	DK	1973	Old member states
Estonia	EE	2004	New member states
Finland	FI	1995	Old member states
France	FR	1957 (founder)	Old member states
Germany	DE	1957 (founder)	Old member states
Greece	GR	1981	Old member states
Hungary	HU	2004	New member states
Ireland	IE	1973	Old member states
Italy	IT	1957 (founder)	Old member states
Latvia	LV	2004	New member states
Lithuania	LT	2004	New member states
Luxembourg	LU	1957 (founder)	Old member states
Malta	MT	2004	New member states
Netherlands	NL	1957 (founder)	Old member states
Poland	PL	2004	New member states
Portugal	PT	1986	Old member states
Romania	RO	2007	New member states
Slovakia	SK	2004	New member states
Slovenia	SI	2004	New member states
Spain	ES	1986	Old member states
Sweden	SE	1995	Old member states
United Kingdom	UK	1973	Old member states

Appendix B. Definition of Variables

Table A2 contains details about the variables used in the empirical analysis, including both the variables used in the DEA model and the derived indicators. Variables are classified into three groups—input, output, and derived indicators—in order to indicate their purpose in the analysis.

Table A2. Definition of variables.

Variable	Abb.	Unit	Source
Input variables			
Labor force	L	million workers	WDI
Capital stock	K	US$	WDI
Primary energy consumption	PEI	kWh	EIA
Electricity consumption	ELC	kWh	EIA
Output variables			
Nominal GDP	GDP	GK$	WDI
CO_2 emissions	CO_2	MMt	EIA
Derived indicators			
Nominal GDP/Labor force	GDP/L	US$/worker	WDI *
Nominal GDP/Capital stock	GDP/K	US$-to-US$ indicator	WDI *
Primary energy intensity	PEI	kWh/US$	EIA/WDI *
Electricity intensity	ELI	kWh/US$	EIA/WDI *
CO_2 emissions/Nominal GDP	CO_2/GDP	MMkg/US$	EIA/WDI *

Notes: The US$ is, in fact, the Geary–Khamis dollar, also known as international dollar, which measures the US$ adjusted to purchasing power parity (PPP). The symbol * denotes own calculations based on data from the given sources.

Appendix C. Descriptive Statistics

Table A3 presents the summary statistics from the raw data, with Table A4 showing the derived indicators and Table A5 reporting the country means for the derived indicators. Table A6 shows the results from the two-group mean comparison test.

Table A3. Summary statistics for the variables used in the DEA model over time.

Year	Measure	Variables					
		Inputs				Outputs	
		L	K	PEC	ELC	GDP	CO_2
		Million Workers	Billion US$	Billion kWh	Billion kWh	Billion US$	Million Tones
2010	Mean	8.69	121.7	792.3	105.8	607.8	146.7
	Min	0.18	1.9	23.9	1.8	9.0	5.4
	Max	42.01	663.7	4150.1	554.5	3396.4	863.0
	St. Dev.	11.26	181.2	1073.5	145.2	921.4	203.6
2011	Mean	8.68	131.8	765.1	104.1	657.3	141.9
	Min	0.18	1.8	23.0	1.9	9.6	5.2
	Max	41.66	762.8	3974.3	547.6	3744.4	833.4
	St. Dev.	11.24	199.5	1033.3	141.7	1000.7	195.9
2012	Mean	8.73	121.4	758.7	104.2	619.3	140.0
	Min	0.19	1.7	27.5	1.9	9.5	6.1
	Max	41.73	716.8	4018.7	545.9	3527.3	847.0
	St. Dev.	11.33	186.2	1034.6	142.3	951.6	197.8
2013	Mean	8.77	123.7	754.5	103.2	645.7	137.2
	Min	0.19	1.7	26.1	1.9	10.6	6.0
	Max	42.10	742.9	4090.3	545.0	3732.7	862.9
	St. Dev.	11.40	191.0	1040.7	141.8	993.9	197.6
2014	Mean	8.80	128.5	732.0	101.2	667.7	131.5
	Min	0.20	1.9	25.4	2.0	11.6	5.4
	Max	42.32	778.3	3955.9	533.7	3883.9	826.9
	St. Dev.	11.45	199.2	1001.1	137.3	1037.7	187.7
2015	Mean	8.82	115.6	738.7	102.7	588.3	132.7
	Min	0.21	2.6	26.6	2.1	11.1	5.3
	Max	42.59	671.9	4003.2	538.2	3356.2	829.1
	St. Dev.	11.50	175.4	1010.4	139.1	917.6	187.8
2016	Mean	8.87	118.0	743.2	103.6	592.2	132.2
	Min	0.22	2.8	25.9	2.1	11.7	5.4
	Max	43.06	703.8	4028.2	538.5	3467.5	827.7
	St. Dev.	11.59	178.3	1009.2	139.5	913.6	186.3
2017	Mean	8.92	125.8	756.3	104.4	622.3	134.7
	Min	0.22	2.9	26.6	2.3	13.1	5.4
	Max	43.29	752.3	4165.8	538.8	3682.6	844.3
	St. Dev.	11.64	188.6	1026.7	139.5	949.5	188.9
2018	Mean	8.96	137.2	752.5	104.3	672.3	132.0
	Min	0.24	3.1	27.8	2.3	14.8	5.5
	Max	43.56	837.6	4060.3	533.2	3963.8	810.8
	St. Dev.	11.70	207.0	1014.7	138.5	1019.0	182.9
All	Mean	8.80	124.9	754.8	103.7	630.3	136.5
	Min	0.18	1.7	23.0	1.8	9.0	5.2
	Max	43.56	837.6	4165.8	554.5	3963.8	863.0
	St. Dev.	11.27	186.9	1011.0	138.3	953.1	189.1

Notes: Variables are labelled using the abbreviations introduced in Appendix B.

Table A4. Summary statistics for the derived variables over time.

Year	Measure	Indicator				
		GDP/L	GDP/K	PEI	ELI	CO_2/GDP
2010	Mean	65,043	4.907	1.750	0.232	0.339
	Min	14,748	3.683	0.751	0.104	0.118
	Max	223,681	6.327	4.186	0.599	0.849
	St. Dev.	43,499	0.594	0.794	0.104	0.187
2011	Mean	70,735	4.933	1.559	0.210	0.306
	Min	17,219	3.671	0.669	0.096	0.094
	Max	246,525	6.550	3.944	0.552	0.839
	St. Dev.	47,620	0.716	0.736	0.093	0.180
2012	Mean	65,796	5.079	1.641	0.225	0.317
	Min	16,167	3.509	0.668	0.100	0.093
	Max	222,119	7.921	4.068	0.576	0.823
	St. Dev.	43,696	0.954	0.746	0.099	0.178
2013	Mean	68,708	5.212	1.528	0.211	0.288
	Min	16,515	3.607	0.648	0.096	0.086
	Max	234,611	8.225	3.699	0.546	0.711
	St. Dev.	46,008	1.010	0.666	0.093	0.153
2014	Mean	70,382	5.210	1.471	0.206	0.274
	Min	16,933	3.910	0.610	0.091	0.085
	Max	241,507	8.662	3.855	0.542	0.750
	St. Dev.	47,369	1.067	0.687	0.093	0.156
2015	Mean	61,876	5.051	1.697	0.240	0.318
	Min	15,192	3.768	0.603	0.087	0.098
	Max	204,231	8.651	4.572	0.630	0.892
	St. Dev.	41,551	1.105	0.808	0.110	0.182
2016	Mean	63,142	5.025	1.674	0.237	0.311
	Min	16,483	2.807	0.615	0.086	0.099
	Max	214,020	8.292	4.107	0.599	0.776
	St. Dev.	42,705	0.986	0.754	0.106	0.170
2017	Mean	66,706	4.908	1.598	0.224	0.299
	Min	17,564	3.186	0.558	0.078	0.094
	Max	218,556	7.754	3.778	0.569	0.748
	St. Dev.	43,968	0.854	0.710	0.100	0.167
2018	Mean	72,213	4.937	1.451	0.204	0.269
	Min	19,904	3.801	0.505	0.071	0.086
	Max	234,247	9.031	3.356	0.504	0.627
	St. Dev.	46,882	1.004	0.631	0.088	0.146
All	Mean	67,178	5.029	1.596	0.221	0.302
	Min	14,748	2.807	0.505	0.071	0.085
	Max	246,525	9.031	4.572	0.630	0.892
	St. Dev.	44,267	0.927	0.723	0.098	0.168

Notes: Variables are labelled using the abbreviations introduced in Appendix B.

Table A5. Country means for the indicator variables over the entire period.

Country	Indicator				
	GDP/L	GDP/K	PEI	ELI	CO_2/GDP
Austria	94,104	4.455	1.136	0.164	0.182
Belgium	101,510	4.549	1.431	0.157	0.257
Bulgaria	16,747	4.962	3.551	0.514	0.699
Croatia	30,731	4.947	1.936	0.272	0.337
Cyprus	39,687	5.737	1.430	0.184	0.329
Czech Republic	40,013	4.018	2.215	0.265	0.467
Denmark	114,634	5.148	0.920	0.109	0.193
Estonia	35,955	3.990	1.061	0.339	0.226
Finland	96,160	4.441	1.392	0.319	0.187
France	89,206	4.511	1.158	0.171	0.140

Table A5. *Cont.*

Country	Indicator				
	GDP/L	GDP/K	PEI	ELI	CO_2/GDP
Germany	85,676	4.946	1.116	0.149	0.231
Greece	48,188	7.864	1.490	0.238	0.337
Hungary	30,389	4.756	2.120	0.280	0.363
Ireland	120,379	4.609	0.658	0.093	0.133
Italy	81,571	5.597	0.999	0.146	0.182
Latvia	28,654	4.623	1.695	0.234	0.282
Lithuania	30,369	5.303	1.784	0.225	0.320
Luxembourg	226,611	5.363	0.897	0.103	0.182
Malta	55,051	5.071	2.769	0.184	0.679
Netherlands	94,493	5.099	1.364	0.129	0.289
Poland	28,161	5.207	2.364	0.281	0.608
Portugal	42,345	6.067	1.380	0.211	0.243
Romania	21,014	4.099	2.167	0.259	0.392
Slovakia	35,180	4.692	2.232	0.274	0.371
Slovenia	47,332	5.235	1.745	0.273	0.294
Spain	57,769	5.331	1.266	0.180	0.219
Sweden	105,863	4.252	1.173	0.242	0.095
United Kingdom	83,185	6.131	0.910	0.115	0.173
Old member states	96,113	5.203	1.135	0.168	0.198
New member states	33,791	4.829	2.129	0.283	0.423
All	67,178	5.029	1.596	0.221	0.302

Notes: Variables are labelled using the abbreviations introduced in Appendix B.

Table A6. Results from the two-group mean comparison test.

Country Group	Indicator				
	GDP/L	GDP/K	PEI	ELI	CO_2/GDP
OMSs mean	96,113	5.203	1.135	0.168	0.198
	(3,613)	(0.089)	(0.024)	(0.005)	(0.016)
NMSs mean	33,791	4.829	2.129	0.283	0.423
	(953)	(0.069)	(0.066)	(0.009)	(0.006)
p-value	0.000	0.001	0.000	0.000	0.000

Notes: Standard errors are reported in parentheses. The hypotheses of the two-mean comparison test are $H_0 : \mu_{OMS} = \mu_{NMS}$ and $H_1 : \mu_{OMS} \neq \mu_{NMS}$.

Appendix D. Efficiency Scores from the DEA Model

Table A7 shows the annual efficiency scores calculated as θ_i per Definition 1 for all countries and country groups. Table A8 reports the differences between efficiency scores in two successive years where positive differences are coloured in red and negative differences are coloured in green.

Table A7. Efficiency scores across countries.

Country	Year									
	2010	2011	2012	2013	2014	2015	2016	2017	2018	Mean
AT	1.126	1.115	1.123	1.133	1.125	1.176	1.114	1.118	1.169	1.133
BE	1.036	1.035	1.036	1.045	1.035	1.123	1.024	1.031	1.108	1.053
BG	1.364	1.348	1.635	1.706	1.790	1.782	1.395	1.323	1.585	1.547
HR	1.266	1.257	1.321	1.355	1.342	1.373	1.323	1.253	1.413	1.323
CY	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
CZ	1.707	1.734	1.770	1.734	1.750	1.772	1.633	1.567	1.664	1.703
DK	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
EE	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table A7. *Cont.*

Country	Year									
	2010	2011	2012	2013	2014	2015	2016	2017	2018	Mean
FI	1.206	1.175	1.198	1.171	1.157	1.170	1.146	1.147	1.200	1.174
FR	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DE	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
GR	1.103	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.011
HU	1.255	1.270	1.355	1.436	1.508	1.528	1.371	1.427	1.627	1.420
IE	1.000	1.000	1.049	1.002	1.038	1.000	1.000	1.000	1.000	1.010
IT	1.000	1.000	1.024	1.000	1.027	1.013	1.007	1.020	1.048	1.015
LV	1.039	1.105	1.177	1.224	1.199	1.228	1.037	1.000	1.117	1.125
LT	1.000	1.156	1.182	1.268	1.264	1.304	1.206	1.148	1.321	1.205
LU	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
MT	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
NL	1.000	1.000	1.000	1.000	1.010	1.127	1.014	1.000	1.022	1.019
PL	1.278	1.348	1.357	1.293	1.319	1.296	1.150	1.099	1.182	1.258
PT	1.211	1.172	1.059	1.004	1.030	1.075	1.035	1.076	1.141	1.089
RO	1.636	1.770	1.874	1.673	1.649	1.656	1.485	1.410	1.417	1.619
SK	1.309	1.500	1.411	1.441	1.412	1.586	1.418	1.370	1.458	1.434
SI	1.235	1.221	1.249	1.290	1.237	1.226	1.077	1.042	1.210	1.199
ES	1.160	1.183	1.179	1.109	1.114	1.095	1.069	1.103	1.174	1.132
SE	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
UK	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Means										
OMS	1.056	1.045	1.044	1.031	1.036	1.052	1.027	1.033	1.058	1.042
NMS	1.238	1.285	1.333	1.340	1.344	1.365	1.238	1.203	1.307	1.295
All	1.140	1.157	1.178	1.174	1.179	1.197	1.125	1.112	1.173	1.160

Notes: Countries are labelled using the ISO codes introduced in Appendix A.

Table A8. Differences between successive efficiency scores across countries (ne).

Country	Year							
	2011	2012	2013	2014	2015	2016	2017	2018
AT	−0.011	+0.007	+0.011	−0.008	+0.051	−0.062	+0.004	+0.051
BE	−0.002	+0.001	+0.009	−0.011	+0.088	−0.099	+0.008	+0.076
BG	−0.016	+0.287	+0.070	+0.084	−0.008	−0.387	−0.072	+0.262
HR	−0.009	+0.064	+0.033	−0.013	+0.031	−0.050	−0.070	+0.161
CY	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
CZ	+0.027	+0.036	−0.036	+0.016	+0.022	−0.139	−0.066	+0.097
DK	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
EE	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
FI	−0.031	+0.023	−0.027	−0.014	+0.013	−0.024	+0.001	+0.053
FR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DE	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GR	−0.103	0.000	0.000	0.000	0.000	0.000	0.000	0.000
HU	+0.016	+0.084	+0.081	+0.072	+0.020	−0.157	+0.057	+0.200
IE	0.000	+0.049	−0.047	+0.036	−0.038	0.000	0.000	0.000
IT	0.000	+0.024	−0.024	+0.027	−0.013	−0.006	+0.013	+0.029
LV	+0.066	+0.071	+0.048	−0.026	+0.029	−0.191	−0.037	+0.117
LT	+0.156	+0.026	+0.086	−0.004	+0.040	−0.098	−0.058	+0.173
LU	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
MT	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NL	0.000	0.000	0.000	+0.010	+0.117	−0.113	−0.014	+0.022
PL	+0.069	+0.009	−0.064	+0.026	−0.023	−0.145	−0.051	+0.083
PT	−0.039	−0.113	−0.055	+0.026	+0.045	−0.039	+0.040	+0.065
RO	+0.134	+0.103	−0.201	−0.024	+0.007	−0.171	−0.075	+0.007
SK	+0.191	−0.089	+0.030	−0.029	+0.173	−0.168	−0.048	+0.088
SI	−0.014	+0.028	+0.041	−0.053	−0.011	−0.149	−0.035	+0.169
ES	+0.023	−0.004	−0.070	+0.005	−0.019	−0.026	+0.034	+0.072
SE	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
UK	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Means								
OMS	−0.011	−0.001	−0.014	+0.005	+0.016	−0.025	+0.006	+0.025
NMS	+0.048	+0.048	+0.007	+0.004	+0.022	−0.127	−0.035	+0.104
All	+0.016	+0.022	−0.004	+0.004	+0.019	−0.072	−0.013	+0.062

Notes: Countries are labelled using the ISO codes introduced in Appendix A.

Appendix E. Heat Maps of Efficiency Across Countries

Figures A1 and A2 depict the distribution of efficiency scores across countries in the year with highest average score (2015) and the year with lowest average score (2017) on a heat map of Europe.

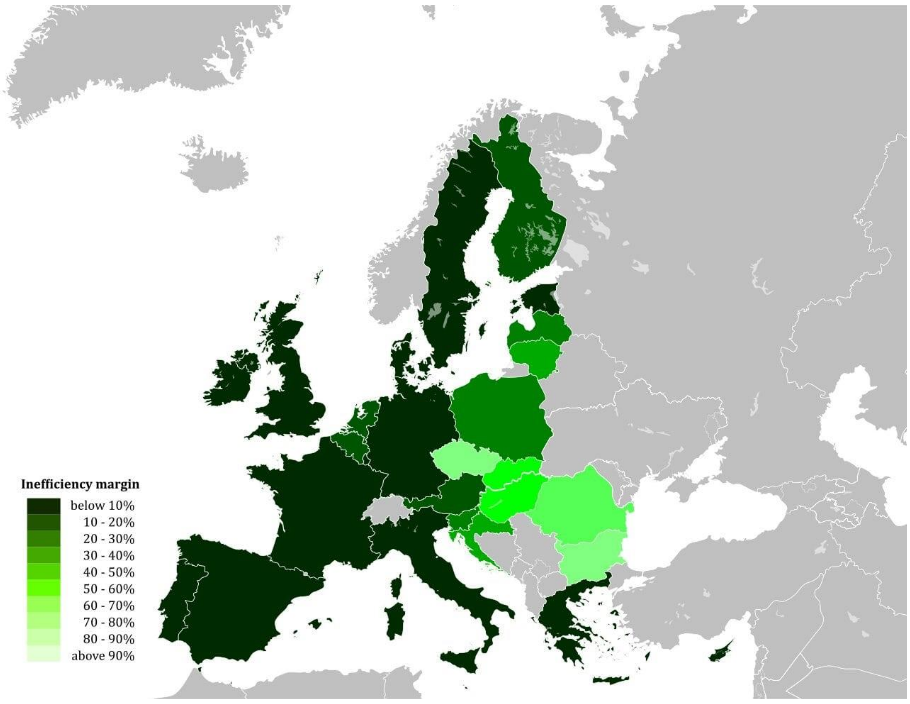

Figure A1. Efficiency scores across countries in 2015 on a map of Europe.

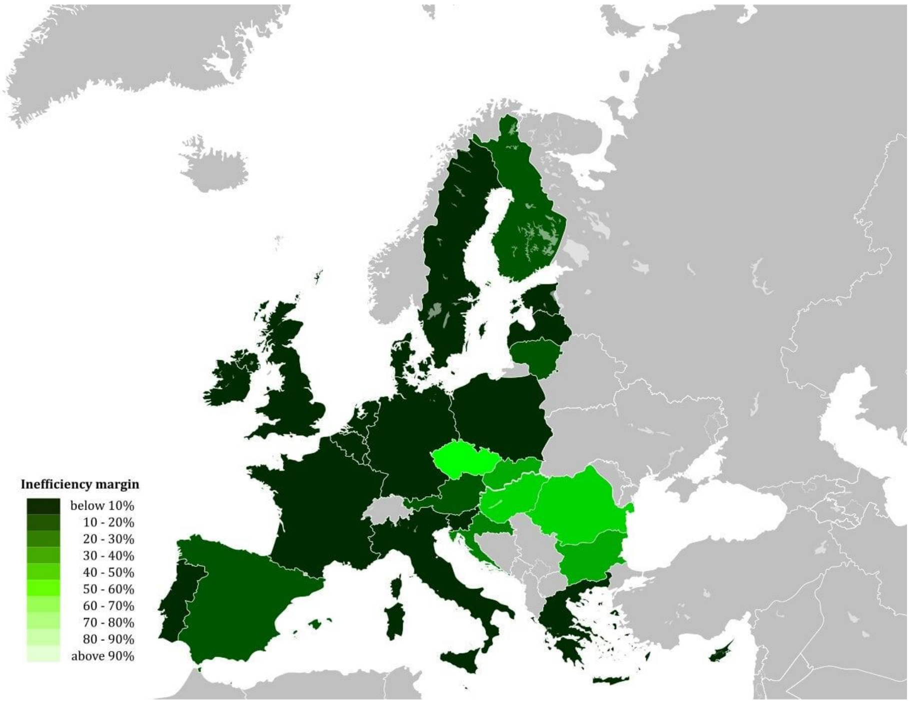

Figure A2. Efficiency scores across countries in 2017 on a map of Europe.

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