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Technical Efficiency and Productivity Change in the European Union with Undesirable Output Considered

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Abstract: Global competition and climate change are changing the nature of economic activity and impose the urgent need to have environmentally sensitive productivity growth. The paper addresses both desirable and undesirable output to assess technical efficiency and productivity changes, as well as evaluate the importance of an energy input in the production function and productivity change differentials in the European Union (EU) over the period 2000–2018. To that end, it uses output-oriented data envelopment analysis and Malmquist productivity analysis. The results reveal that the EU is facing significant challenges due to a decreasing trend in technical efficiency and slow productivity growth. The absence of major improvements in human resource performance has reduced the benefits of technological innovations which are the main source of productivity growth. Additionally, the results show that energy use did not critically influence efficiency and productivity.

Keywords: technical efficiency; productivity; environmental adjustment; data envelopment analysis; Malmquist productivity index

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1. Introduction

Recent economic crises along with global environmental changes have motivated many scientists to investigate how to make the optimal economic use of resources in the production process, while minimizing harmful effects on the environment. Many scholars have responded to this challenge by conducting a number of studies that address environmental impacts on technical efficiency and productivity (for a review of empirical studies, see Ancev et al. [1]). They concluded that environmentally undesirable transformation processes such as air pollution or hazardous waste should not be ignored in the field of efficiency and productivity analysis.

As European Union (EU) countries, which are the focus of this paper, are no exception in this regard, much emphasis should be placed on effective utilization of resources so as to enhance efficiency and productivity as well as to achieve the goals set in their energy and environmental strategic documents. The EU is strongly committed to participating in the global efforts to cut greenhouse gas (GHG) emissions, aiming for a 40% reduction by 2030 and an 80–95% reduction by 2050 [2,3]. Although it is a world leader in reducing emissions, it has been the third largest emitter after China and the United States for years [4]. The energy sector is the most important source of GHG emissions responsible for about 80% of GHG emissions [4]. The European Environment Agency (EEA, [5]) demonstrated that renewables have become the major contributor to reducing GHG emissions from this source and that improving innovation capabilities and monitoring changes are of crucial importance to accelerate this trend.

There is an urgent need to consider both outputs, desirable and undesirable, when assessing efficiency and productivity changes over time. Recently, as already mentioned, research on this subject has started to grow and some of them were focused on how to treat undesirable output in technical efficiency analyses, usually within the framework of data envelopment analysis (DEA, [6]) or stochastic frontier analysis (SFA, [7]). Nevertheless, only a few studies have addressed undesirable output in cross-country technical efficiency (e.g., Gokgoz and Turkoglu [8] for Organization for Economic Cooperation and Development (OECD) countries) or productivity change analysis (e.g., Shen et al. [9] for OECD countries).

Surprisingly, there is quite limited evidence on efficiency and productivity growth in the EU, even when only desirable output is addressed [10,11]. This is particularly true when studies of productivity changes with desirable and undesirable output come into question [12–15]. However, neglecting undesirable output and energy as a factor of production in efficiency and productivity analyses may lead to misleading results and policy implications.

The paper aims to reveal the behavioral pattern of technical efficiency and productivity changes accounting for both kinds of output—desirable and undesirable—in the EU as a whole over the period 2001–2018. It also aims to unveil the drivers of productivity changes as well as assess the importance of an energy input in the production function and productivity change differentials, distinguishing also between the period of expansion (2000–2006) and turbulent economic times (2007–2018). The first sub-period refers to the period before the Great Recession, while the second sub-period covers the period during and after the recession. Since the latter is characterized by crisis situations, including financial, economic and energy crises, it is referred to as 'turbulent economic times'. The analysis proceeds through two steps; in the first one, the technical efficiency scores for 28 EU countries were calculated for each of the investigated 19 years. In the second step, the productivity changes were decomposed, and their sources assessed and discussed. The variable returns to scale output-oriented DEA model with desirable and undesirable output is applied to measure technical efficiency, while the Malmquist productivity index (MPI) is used to measure productivity change. The latter, proposed by Caves et al. [16], has become extensively popular in recent years, especially after Färe et al. [17] demonstrated that it can be assessed within the DEA framework.

Focusing on the EU, the paper provides an analysis of technical efficiency and productivity growth paths with desirable and undesirable output, showing thereby that improvements in the latter were achieved partially at the expense of the environment in the turbulent economic times. In addition, it shows that it is essential for productivity growth to ensure that human resource improvements keep pace with innovations. Besides, by decomposing the MPI into different components and addressing different economic times, it fills the gap in the existing literature on productivity analysis in the EU and provides policy implications to support productivity growth which is, at the same time, environmentally friendly.

The reminder of this paper is structured as follows. The next section describes the conceptual background and provides a literature review. Section 3 depicts the data and methods used in the analysis, while Section 4 gives and discusses the results obtained. Section 5 draws conclusions and policy implications.

2. Conceptual Background with Literature Review

The present paper deals with technical efficiency and productivity, which are strongly related to economic theory of production (see Kurz and Salvatori [18] for historical origins of the concept and analytical treatment). There is a difference between these two economic concepts. The former is the quotient of actual aggregated input and maximum aggregated output obtained by operating at the efficiency frontier, i.e., employing the best production techniques with a given set of aggregated inputs [19]. The latter is the quotient of aggregated outputs and aggregated inputs. Hence, the concepts are related and efficiency is a part of productivity. Deterioration in productivity may result in particular from inefficiency and technical regress or a combination of both; as such, it is of serious concern for policymakers.

To assess the changes in technical efficiency and productivity, the paper addresses two issues related to the production function. The first issue refers to a selection of inputs in the production function. Although there can be a number of inputs, the mainstream theories of economic growth, which consider capital, labor and technology as the critical ones, pay little or no attention to the role of energy in production and economic growth in general. However, this paper follows Stern [20], who, together with ecological and resource economists, underlined that energy is its own special input to the production function and is non-substitutable. As such, it may have enormous implications for future economic growth, what policy authorities must not ignore. Indeed, Stern [20] demonstrated that when effective energy is scarce, economic growth will be strongly constrained. In contrast, when it becomes more abundant, the mainstream models explain economic growth fairly well. Hence, two practical reasons are commonly delineated to justify the incorporation of energy in the production function: first, energy is irreplaceable in the production process and energy shortages have the power of an adverse supply shock. Second, energy consumption is a critical generator of GHG emissions which seriously threaten climate and sustainable life on the Earth. Both reasons give new impetus to improve energy efficiency together with improving efficient use of other inputs and to mitigate harmful pollution and other undesirable outputs. Recently, numerous papers have incorporated energy as a factor of production in assessing technical efficiency [11,21,22]. Most of them used DEA to that end [1].

The second issue addresses the role of undesirable inputs and outputs in the production function. Traditionally, technical efficiency is assessed ignoring joint production of desirable and undesirable output. It assumes that inputs have to be minimized and outputs maximized. This is true when the production process does not generate undesirable outputs or when undesirable inputs are used in the production process. However, the production process is not free from the creation of adverse environmental side effects. Recently, their synergic environmental effects have become particularly observable in the form of climate change that may, in turn, negatively affect economic growth of all countries. The existence of undesirable (bad) outputs and inputs imposes the urgent need to incorporate them in the production function (for a review of approaches to this issue, see [23]). Consequently, a growing literature has emerged, especially in the last two decades, that studies technical efficiency and productivity in the presence of desirable and undesirable outputs at the cross-country, national, sectoral or micro levels [1]. A brief analysis of previous studies revealed a lack of consensus on the term used to describe technical efficiency and productivity considering desirable and undesirable output. Thus, for example, the terms 'environmental', 'environmentally sensitive', 'ecological' or 'environmentally adjusted' efficiency and productivity appeared in the literature. Individual attempts (e.g., [24]) to establish a clear demarcation between these and similar terms have not led to a consensus. This paper uses the term environmentally sensitive technical efficiency and productivity as an alternative, generic term for technical efficiency and productivity with desirable and undesirable output.

Previous studies pointed to positive shifts towards more environmentally friendly production processes in many countries and sectors (e.g., Gu et al. [25] for the Canadian manufacturing sector; Jahan and Ancev [26] for shrimp farming in Bangladesh). The same conclusion about the improvement in environmentally sensitive performance is drawn, for example, by Rodriguez et al. [27], who evaluated productivity in OECD and G20 countries over the period 1990–2013, and Beltran-Esteve et al. [28] for the sample of EU countries over the period 2001–2016. Wang et al. [29] also documented environmentally sensitive productivity growth in Chinese regions. Using the Malmquist–Luenberger productivity index, Sun et al. [30] calculated that this process averaged 1.3% over the last four decades (1980–2016). Their sample included seven world regions, i.e., 104 countries, and revealed large disparities between developing and developed countries in this regard. However, both groups of countries showed a turbulent development path. The findings on geographical differences and sensitivity of environmental performance to specific situations were confirmed by Woo et al. [31] for the sample consisting of OECD countries.

Decomposing the causes of poor environmental performance is especially important for policy authorities to design proper policies. Human resources coupled with environmentally friendly policy and public sector interventions and supportive sources of finance play a crucial role in ensuring environmentally sensitive efficiency and productivity growth, as clearly highlighted by Prokop et al. [32]. Although they confirmed their importance on the sample of developed countries for the period 2009–2013, many other studies found just technological innovation as the main contributor to productivity growth. For example, Wang et al. [29] estimated that technological progress contributes to 90% of productivity growth on average. Sun et al. [30] identified it as the main driver of environmentally sensitive efficiency and productivity in all seven world regions considered (East Asia and Pacific, Europe and Central Asia, Latin America and Caribbean, Middle East and North Africa, North America, South Asia and Sub-Saharan Africa).

As already mentioned, when it comes to the EU, the literature on technical efficiency and productivity is quite limited. It can be categorized into four groups based on output selection. The first group includes the studies that address only technical efficiency with a single output, a commonly desirable one [33–35]. The second group includes the studies that address only technical efficiency but with a desirable and undesirable output or with their combination [21,36,37]. The third group considers the studies that analyze efficiency and productivity change over time but without considering undesirable output [11]. Finally, the last group includes studies that address desirable and undesirable output in analyzing efficiency and productivity changes [12,14,15,28]. Their findings will be integrated into the results and discussion section.

The analysis in these papers was typically performed by using a nonparametric production frontier approach. All of them observed that there is still much room for improving technical efficiency in the EU. However, only few of them included desirable and undesirable output into their analysis and evaluated the development path of productivity. It is of critical importance for the economic, energy and environmental policy of the EU to have a deeper insight into the underlying sources of environmentally sensitive efficiency and productivity changes. The main aim of this paper is to provide such insight in different economic times.

3. Methods and Data

3.1. Methods

DEA was applied to estimate technical efficiency and total factor productivity change of decision making units (DMUs) in this paper. It does not demand a prior known behavioral functional form and price information, but allows multiple inputs and outputs to be simultaneously assessed. Since it was developed by Charnes et al. (CCR, [38]) under the assumption of the constant returns to scale (CRS), it has been used in many studies (for a review, see [39]). It has also become the most commonly used method in efficiency and productivity analysis [1]. Banker, Charnes and Cooper (BCC, [40]) extended the CCR model by allowing the variable returns to scale (VRS), which assumes that a change in inputs or outputs will not result in a proportional change in the outputs or inputs. Both methods combine multiple input and output data of DMUs to develop a discrete piecewise linear surface or the best-practice frontier for given data. They can be used in either an input- or an output-oriented form, depending on the purpose of the study. Assuming that policy authorities are more oriented to outputs, an output-oriented DEA model with VRS is used in this paper. If there are an I number of inputs, an M number of outputs and if $N = I + M$, it may be presented by model (1).

Max η, subject to

$$\sum_{j=1}^{I} z_j x_j + s^- = x_0, \sum_{j=1}^{M} z_{j+K} y_j - s^+ = \eta y_0, \sum_{j=1}^{N} z_j = 1, \quad (1)$$
$$z_j \geq 0,\ j = 1, \ldots, n,$$

where for the i-th country (i = 1, . . . , 28), x represents a $I \times 1$ vector of inputs and y_i represents an $M \times 1$ vector of outputs. An index zero denotes the input and output vectors of DMU_0 to be evaluated, while $s-$ and $s+$ refer to the input slacks and the output slacks, respectively. The efficiency scores of the i-th DMU, η, are computed for each DMU and for each year. Additionally, z is an $N \times 1$ vector of parameters to be calculated. In our case, the vector of inputs is $x = [K, L, E]$ ($I = 3$), where K refers to capital, L to labor and E to energy. The vector of outputs is $y = [GDP, GHG]$ ($M = 2$), where GDP and GHG denote gross domestic product and GHG emissions, respectively. The latter variable is transformed by using Seiford and Zhu [41] linear transformation, which will be explained below. The main difference between the CCR and the BCR model lies in the convexity constraint ($\sum_{j=1}^{N} z_j = 1$), that BCC [40] added to account for VRS. A DMU is considered efficient only if both $\eta = 1$ and all accompanying slack variables are equal to zero. For more details, see BCC [40].

The classical BCC model does not treat properly the existence of desirable and undesirable output since it assumes that relatively inefficient DMUs cannot simultaneously increase desirable output and decrease the undesirable one. This issue was addressed by Seiford and Zhu [41], who separated output into desirable (y^d) and undesirable output (y^u). They suggested transforming undesirable output to y^U. To that end, after putting a minus sign on an undesirable output, a transaction vector ω should be added thereto. That is, $y^U = max\ (y^u) + 1 - y^u > 0$. Now, it is possible to maximize the desirable output and simultaneously minimize the undesirable one to upgrade the performance of inefficient DMUs by setting $y = [y^d; y^U]$.

Productivity indicates performance of DMUs at a point in time. Thereby, the movements in productivity of DMUs over two periods of time refer to productivity change. An assessment of productivity change between two periods is based on the Shephard distance function, which is related to the production frontier, and can have input or output orientation as well. The concept connects multiple inputs and outputs within a parametric or a non-parametric approach. The latter is applied in this paper due to an unknown behavioral assumption underlying the distance function. The paper focuses on the output distance function which assesses the maximal expansion of the output vector given an input vector and production technology.

The MPI (*MPIo*) is a geometric mean of two Malmquist indices, i.e., the product of two mutually exclusive and exhaustive components, technical efficiency change (TEC) and technological change (TC), over two periods [17]:

$$MPI_0\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \left(\frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}\right)\left[\left(\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})}\right)\left(\frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^t, y^t)}\right)\right]^{1/2}, \tag{2}$$

where MPI_0 refers to productivity of the $(t+1)$-th production period (x^{t+1}, y^{t+1}) relative to the previous production period (x^t, y^t) with their respective technologies. D_0 is an output distance function. The component in the round brackets, TEC, measures whether a DMU is getting closer to the efficiency frontier. Hence, it is commonly named the catch-up effect. It is usually decomposed into pure technical efficiency (PTE) and scale efficiency (SE). While the former refers to the ability of human resources to use given resources efficiently, the latter refers to their ability to utilize scale economies by operating at the efficiency frontier. The component in the square brackets, TC, measures whether the frontier is shifting out over time. Hence, it is known under the name the frontier-shift or innovation effect.

Values of the MPI_0 greater than one indicate performance improvement, whereas values less than one reflect performance deterioration. If the index equals one, there is no change in productivity. Likewise, if TEC > 1, a DMU has converged to the period $t + 1$ efficiency frontier compared to its position against the period t frontier. If TEC < 1, the opposite case occurs. If TEC = 1, a DMU has kept its position with respect to the efficiency frontier in two considered periods. Likewise, a value of TC > 1 (or TC < 1) suggests technological progress (technological regress), while a value of TC = 1 indicates no change in technology best practice. For more technical details, see Färe et al. [17]. R packages “rDEA” and “Productivity” were used to conduct analyses.

3.2. Data

The set of variables includes input and output variables selected for calculation and assessment of technical efficiency and productivity changes in the EU-28 over the period 2000–2018. The same selection of relevant variables had followed many scholars [21,34,37], who enriched the traditional production function that relates output to capital and labor with energy. Table 1 provides information on the data whose source is Eurostat [42].

Table 1. Descriptive statistics of the data.

Variable	Variable Description	Symbol	Obs	Mean	Std. Dev.	Min.	Max.
Output	Real GDP (in billions of euros at 2015 constant prices), calculation based on nominal GDP [TEC00001]	*GDP*	532	501.83	769.74	6.08	3215.74
	GHG emissions (in million tons) [env_air_gge]	*GHG*	532	176.82	235.88	2.27	1079.27
Input	Capital stock (in billions of euros at 2015 constant prices), calculation based on gross fixed capital formation [TEC00011]	*K*	532	107.59	159.09	1.08	707.64
	Total number of employed workers (in million persons) [TEC00112]	*L*	532	8.04	10.43	0.15	44.85
	Total final energy consumption (in million TOE) [TEN00124]	*E*	532	40.75	53.95	0.37	223.81

Note: Obs. = observations. The Eurostat code of variables is given in square brackets. The missing data for the energy (*E*) and *GHG* variables in 2018 was filled in by using linear interpolation.

Capital is proxied by capital stock which was calculated by employing the perceptual inventory method to the data on real gross fixed capital formation. Thereby, the depreciation rate of 6% was used and the year 2000 was set as the base year. The data on gross fixed capital formation and GDP was deflated by using harmonized indices of consumer prices (2015 = 100) whose source is Eurostat [42]. Labor is represented by the number of employed workers. It is expressed in thousands of persons. Energy refers to total final energy consumption. It includes end user consumption (industry, transport, households, services and agriculture) expressed in million tons of oil equivalents (TOE).

Two kinds of outputs are included in the analysis, desirable and undesirable ones, i.e., real GDP and GHG emissions, respectively. GDP is the total value of all final goods and services produced in a country and a commonly used measure of desirable output. GHG emissions, resulting from the transformation processes, represent undesirable output. They are considered to be a major threat to global warming and climate change. GHG emissions are expressed in units of CO_2 equivalents and represent total national emissions of the 'Kyoto basket' of GHGs.

4. Results with Discussion

4.1. Preliminary Analysis

Efficiency and productivity analysis within the DEA framework requires the data to exhibit certain characteristics. Firstly, to adjust technical efficiency of countries with an environmental issue and conduct the selected analyses, undesirable output has to be transformed. To that end, the procedure developed by Seiford and Zhu [41] was employed. The new variable is named *GHG*.

The good discriminatory power among the DMUs in our empirical DEA models is corroborated by meeting the Boussofiane rule. Furthermore, since the results in the presence of outliers may be misleading, the Tukey box-plot method is used to check for their existence. It unveiled five countries (France, Germany, Italy, Spain and the UK) as outliers, probably due to their scope of economic activities. However, since there were no statistically significant differences in the means of the calculated technical efficiency indices between the full (the EU-28; 0.871) and the reduced sample (the EU-23, 0.858), according to the independent samples *t*-test at the 5% significance level, the analysis of the former continued.

The isotonicity requirement is not violated since there are positive associations between each input and output (Table A1 in the Appendix A). Finally, following Sarkins [43], the mean normalization process was performed to ensure comparability of the data. Descriptive statistics are given in Table 1.

4.2. Measuring Efficiency and Productivity Change

Efficiency development in the EU. The VRS BCC-DEA model was used to calculate the efficiency scores for each DMU, i.e., EU country in our case. In so doing, three models were created, and their results are presented in Table 2. Model 1 is the initial, environmentally insensitive model of the form *Y (GDP) = f(K, L)*. All other models are environmentally sensitive; in addition to GDP, they include GHG emissions as outputs. They differ with respect to inputs (all models include capital and labor, but total final energy consumption is included in Models 2 and 3) and the period covered (Models 1 and 2 cover the period 2000–2018, while Model 3 covers the period 2007–2018). Several other models were also tested, but their results are not presented separately in Table 2 since they do not exhibit statistically significant differences. A DMU with efficiency scores less than 1 is seen as inefficient, and the lower the value, the more inefficient the DMU.

Table 2. Average efficiency scores for Models 1–3.

	2000–2018							
	Model 1: *Y(GDP) = f(K, L)*				**Model 2: *Y(GDP, GHG) = f(K, L, E)***			
	Min	**Max**	**Aver**	**SD**	**Min**	**Max**	**Aver**	**SD**
Min	0.467	0.605	0.550	0.037	0.478	0.631	0.572	0.040
Max	1.000	1.000	1.000	0.000	1.000	1.000	1.000	0.000
Aver	0.781	0.866	0.826	0.024	0.811	0.914	0.871	0.026
SD	0.126	0.189	0.152	0.020	0.114	0.180	0.145	0.020
	2007–2018							
	Model 3: *Y(GDP, GHG) = f(K, L, E)*							
Min	0.478	0.631	0.560	0.044				
Max	1.000	1.000	1.000	0.000				
Aver	0.811	0.914	0.867	0.030				
SD	0.114	0.180	0.153	0.021				

Note: Min = minimum; Max = maximum, Aver = average; SD = standard deviation.

The average efficiency scores calculated for Models 1–3 are given in Table 2. All of them indicate inefficiency in producing output, whereby the largest average inefficiency is recorded in Model 1. Undesirable output is an integral part of the production process; hence, it must not be ignored. An important role that it plays within the production function framework is supported by the fact that there is a statistically significant difference in terms of efficiency estimation with and without GHG emissions and energy.

The average efficiency score of 0.826 for Model 1 (environmentally insensitive) is statistically lower than the one of 0.871 calculated for Model 2 (environmentally sensitive technical efficiency) ($p < 0.01$). This indicates that the latter has significantly improved compared to the former in the period of interest. Energy is an important input in the production process and the largest contributor to adverse emissions. The EU has invested a lot of effort to use energy more efficiently, decouple it from economic growth and reduce GHG emissions in particular. Positive gains of this effort in terms of smaller inefficiency are observed through the estimated production function. Interestingly, an extension of the initial model just with energy (*Y(GDP) = f(K, L, E)*) did not result in a statistically significant difference in technical efficiency than calculated for Model 1. Likewise, there is no statistically significant difference between Model 2 and the model of the form *Y(GDP, GHG) = f(K, L)*. Their results are therefore not reported separately in Table 2. Still, one should note that the former indicates better technical performance (0.871 vs. 0.867). It seems that energy use did not critically impact environmentally sensitive technical efficiency despite the large energy dependence of the EU and occasional energy crises. This could be a sign that the EU has benefited from the implemented programs and measures. Certainly, further research should explore this more deeply.

To give more insight into environmentally sensitive technical efficiency, we focus on Model 2. The development of its average scores together with the average minimum and maximum scores for the period under consideration is graphically illustrated in Figure 1. The calculated average scores indicate that the EU as a whole still failed to achieve environmentally sensitive technical efficiency in the period considered. Efficiency even exhibits a decreasing trend compared to the efficiency frontier over the period considered (with the average annual drop of 0.41%). This indicates that there is plenty of room for its improvement. The average efficiency score of 0.871 (Table 2, Model 2) suggests that there is capacity of the EU (of 12.9%) to generate a higher level of outputs for a given level of inputs. The EU experienced the largest decline in efficiency in the years 2007 and 2008 with the outbreak of the Great Recession. A big drop in economic activities and uncertain outlook forced European countries to improve their efficiency. However, it seems that many of them did not take the need to tackle inefficiency more seriously since it started to decline again after 2011. The average environmentally sensitive efficiency score for the period 2000–2006, when the EU experienced stronger economic growth, is even greater than the one obtained for the period 2007–2018 (0.878 vs. 0.867), suggesting its further worsening.

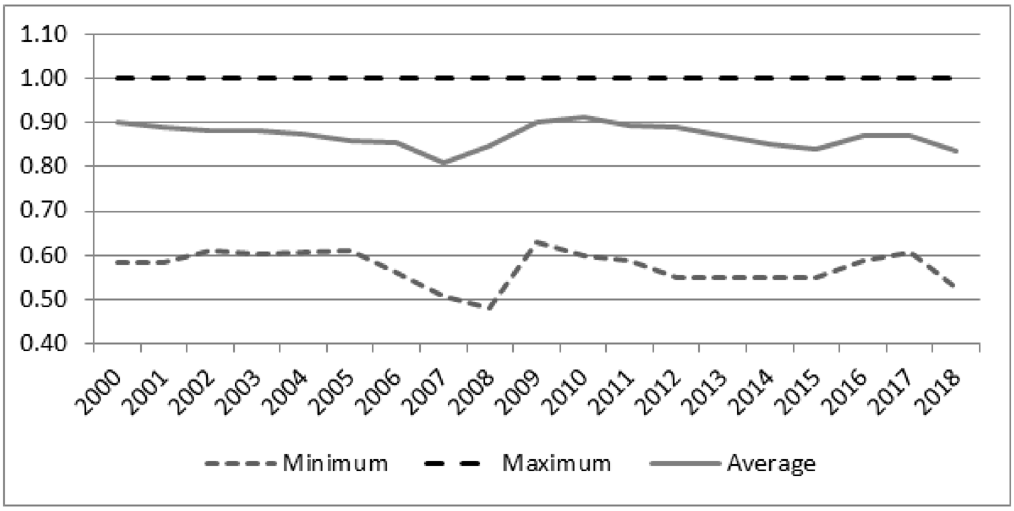

Figure 1. Development of the average BCC-DEA environmentally sensitive efficiency scores for Model 2 in the period 2000–2018.

The results are in line with Wang and Le [15], who revealed the loss in technical efficiency and calculated the average efficiency score of 0.835 for 17 EU countries in the period 2013–2017. Technical inefficiency existing in most EU countries is also observed by Desli [33], Vlahinic and Segota [34] and other scholars in the period before 2010. Some of them, such as Makridou et al. [21] highlighted deterioration in efficiency performance especially during the economic crisis as we did. By contrast, although Hsieh et al. [37] observed poor energy ecological efficiency in the EU-28 in the period 2006–2013, they pointed out its improvement in the period 2009–2012. This implies, together with our results, that technical efficiency improvements in these years were partially at the expense of ecology. Specifically and in contrast to environmentally sensitive technical efficiency, for the production function of the form $Y(GDP) = f(K, L)$, i.e., environmentally insensitive efficiency, we observed a mild increase in scores (from 0.819 in 2000–2006 to 0.831 in 2007–2018). Certainly, this demands further research.

To explore the sources of this inefficiency, we conducted MPI analysis, focusing thereby on Model 2. Given the turbulent fluctuations in economic activity in the period considered, two sub-periods were also separately investigated: the first one, 2000–2006, when the EU exhibited stronger growth, and the second one, 2007–2018, when it faced the economic, energy and debt crisis.

Changes in EU productivity. Although the BCC-DEA model enabled us to unveil environmentally sensitive technical efficiency of the EU-28, it does not indicate the factor enhancing its performance. To that end, MPI analysis was applied. Figure 2 graphically illustrates the changes in average environmentally sensitive technical efficiency and productivity for Model 2 in the EU-28 including its particular sources, while Table 3 provides the average values for the period of interest.

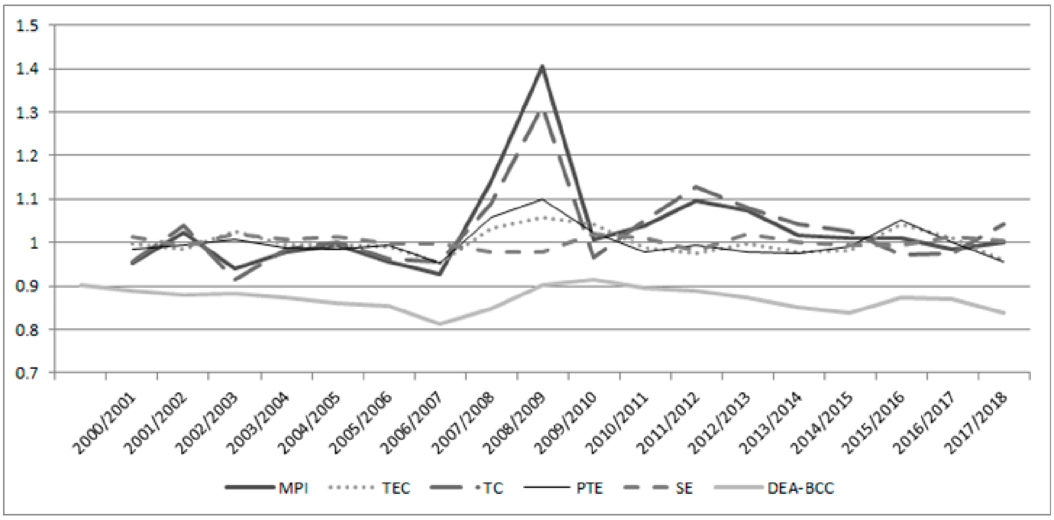

Figure 2. Development of average environmentally sensitive efficiency and productivity changes.

Table 3. Malmquist productivity index and its components, average values (2000/2001–2017/2018).

Index	Model 2: *Y(GDP, GHG) = f(K, L, E)*				
	Minimum	**Maximum**	**Average**	**Standard Deviation**	**Compound Growth Rate, %**
MPI	0.926	1.406	1.031	0.108	0.280
TC	0.916	1.314	1.028	0.091	0.513
TEC	0.953	1.060	1.000	0.029	−0.224
PTE	0.954	1.100	1.001	0.037	−0.176
SE	0.977	1.021	1.002	0.014	−0.048

On average, the MPIs show a mild improvement in environmentally sensitive productivity of European countries, indicating thereby an expansion in the average efficiency frontier. From 2000/2001 to 2017/2018, European countries recorded the average productivity gain of 3.1%, i.e., 0.28% on a period basis (Table 3). This is a huge slow-down in productivity growth compared to Krūger's study [44] for the period 1960–1990. Krūger [44] assessed the MPI of 47.85% for old 15 EU countries based on GDP as an output and the number of workers and capital stock as inputs. However, his analysis clearly detected a slow-down in productivity in the considered period (from 108.44% in the period 1960–1973 to 1.9% in the period 1973–1990), which has evidently continued in the 21st century. This can be confirmed in the present study, where productivity deteriorated (MPI = 0.975) in the first sub-period (2000–2006). It was only in the second sub-period (2007–2018) that it showed a statistically significant improvement (MPI = 1.066) at the 5% significance level. As can be observed in Figure 2, the largest changes in MPIs occurred during the period of greatest turbulence, when the EU was suffering from the pressures of the financial and economic crisis. This is to be expected; Woo et al. [31] already detected high sensitivity of environmental performance to this crisis situation in OECD countries. Draghi [45] also observed a sharp slow-down in Euro area productivity, which was positive but below 0.5% in 2016.

The main contributor to environmentally sensitive productivity change is technological innovation. The results show that an average but mild increase in technology change was 2.8% or about 0.5% per period. In several periods, as shown in Figure 2, the EU as a whole experienced even mild technological regression. Namely, the average growth rate of innovation (TC) ranged between 0.916 and 1.314 within the period of interest, suggesting that there are significant disparities in technological development between the best-frontier countries and the non-frontier ones. The existence of geographical disparities, already observed in cross-country studies [31,46], implies the need to implement specifically tailored environmental and economic policies to promote productivity growth. In addition, unlike the first sub-period (2000–2006) when technological innovations stagnated (TC = 1.001), they have become a powerful driving force in the second sub-period (2007–2018; TC = 1.063).

Obviously, innovation is a dynamic process, moving beyond the existing ideas, concepts, and ways of production or organizational boundaries. Since desirable shifts in behavior towards sustainable innovation which takes care of desirable and undesirable output are unlikely to happen on a sufficiently large scale, effective and consistent policies together with collective action are necessary to promote and govern this process. The EU bears a heavy responsibility in this regard, particularly bearing in mind that some researchers, e.g., Morley [47] or Borozan [48] discovered that a reduction in GHG emissions was more a consequence of using cleaner technologies than environmental policies. Likewise, Beltan-Esteve and Picazo-Tadeo [14], who also detected enhancement in ecological performance in the period 2001–2013, explained this by environmental technological progress, i.e., eco-innovation. There does not appear to be a significant shift in the importance of the components that influence environmentally sensitive productivity growth. Indeed, the crucial importance of technology for productivity growth can be supported by Kortelainen [49], who showed that the improvement in environmental performance of 20 EU countries over the period 1990–2003 can be attributed primarily to technology.

By contrast, the average technical efficiency change, which is the product of pure technical efficiency and scale efficiency, shows no average change in the period considered (TEC = 1.000). Thereby, no significant difference was found between two sub-periods. Although the average pure technical efficiency and scale efficiency values do not indicate efficiency regress, their negative average period growth rates imply a mild deterioration in efficiency over the considered period and a divergence trend from the best-practice frontier. This could be a continuation of the trend observed by Mahlberg et al. [12] for most of old EU countries for the period 1995–2004. Similarly, the efficiency loss (TEC = 0.995) for 17 EU countries was also detected by Wang and Le [15], who employed a DEA slacks-based measure (SBM) and MPI analysis in the period 2013–2017 (see also Beltan-Esteve and Picazo-Tadeo [14]). Their TEC is very close to one, which is consistent with the results obtained in the present study. However, their average total productivity change (MPI = 0.988) and technological change (TC = 0.993) suggest a marginal decrease in productivity and no change in technology during the considered period.

The average annual deterioration in technical efficiency is a direct consequence of an average annual decrease in both PTE (by 0.18%) and SE (by 0.05%). The former indicates insufficient investments in human resources and a worsening balance between inputs and outputs as well as in quality improvements. The latter indicates that the EU slightly moved away from the best practice, i.e., it could clearly augment its outputs given its capacity of inputs. This is consistent with the previous analysis of technical efficiency obtained within the BCC-DEA framework. Beltran-Esteve et al. [28] pointed out that efficiency change is losing the race with technological innovation and there is an urgent need for effective policy measures. Chertow et al. [50] suggested that economic performance can be improved without degrading environmental performance if agglomeration economies are augmented with environmental benefits that can be generated through industrial symbioses. The important role of agglomeration in environmentally sensitive economic performance is supported in Han et al. [51]. However, supportive policies are needed for this.

In Figure 2, one can notice a sharp jump in the environmentally sensitive MPI at the beginning of the Great Recession. It indicates that the EU struggled with the recession using both innovations and improvements in technical efficiency, but failing at the same time to maintain the optimum level of production. Chang and Yu [11] also observed a decrease in efficiency (the average efficiency change was 0.990) and a rise in productivity in the EU-27 in the period 1995–2010. They explained productivity growth by technological changes. However, an increase in productivity by 29.8% is considerably higher than noticed in this paper, which could be a consequence of not only a different time period under consideration, but also the fact that they took into consideration only desirable output. Evidently, undesirable output should not be ignored in efficiency and productivity analysis. Mahlberg et al. [12] delineated that a trade-off between the economy and ecology is possible and that the performance of an economy can be sustainable with an efficient ecological system. They revealed average eco-productivity growth of 22% in 14 old EU countries, which was driven by technological progress, i.e., environmental savings, in spite of eco-efficiency regression in the period 1995–2004. Likewise, Lozano and Gutierrez [52] demonstrated that even higher GDP growth may be achievable despite GHG emission reduction. Clean tech and energy and utilities sectors took second and third place in terms of the potential to drive economic growth across Europe [53]. In addition, the EEA's finding [5] on the importance of renewable energy in reducing GHG emissions has not been ignored as well as that of Pan et al. [54], who delineated the need to formulate place-specific nature-based strategies to better link ecosystem services and development planning.

Further research should reveal how much technological innovation in energy (renewable and non-renewable) and how much in other factors of production is responsible for productivity gains.

5. Conclusions

The present paper applied the non-parametric output-oriented VRS BCC-DEA method to evaluate technical efficiency and MPI analysis to assess productivity changes in the EU-28 over the period 2000–2018. Both methods were applied to different model specifications, aiming at revealing not only the behavioral pattern in technical efficiency, but also whether an inclusion of energy as an input influences desirable (GDP) and transformed undesirable (GHG emissions) output. The paper also distinguished between two sub-periods, i.e., the period of expansion (2000–2006) and turbulent economic times (2007–2018).

Regardless of model specification and the period considered, the calculated average efficiency scores clearly indicate that there is plenty of room for efficiency improvement. Interestingly, the results show that energy use did not critically impact technical efficiency signaling that the EU has benefited from the implemented programs and measures. The results also show that undesirable output is an integral part of the production process and hence must not be ignored. Furthermore, MPIs suggest an improvement in productivity by an average of 3.1% in the period 2000–2018. However, on a yearly basis, EU productivity grew by only 0.3% on average, indicating that the EU will face a significant productivity challenge in the coming decades.

Technological innovation was the main source of average EU productivity growth and consequently an expansion of the average efficiency frontier. However, its values show that it stagnated in the first sub-period, while it became a strong driver in the second sub-period. In contrast to innovation, the calculated average values of technical efficiency scores indicate insufficient investment in human resources and deterioration in scale operation, regardless of the sub-periods considered. Improving innovation and reversing the negative trends in technical efficiency and therefore increasing productivity require a creation of a competitive but fair and environmentally sensitive business environment. To that end, the EU economic, energy and environmental policies are of critical importance. They should provide directives but also support and space for national governments to carry out necessary structural reforms. Overall, the essential policy implication for the EU is that it needs not only to foster innovations but also to ensure that technology diffusion and knowledge spillover keep pace with them. Specifically, there are five policy implications arising from this paper, which can meet the productivity and efficiency challenge.

First, innovation drives technological progress and consequently productivity changes in the EU. However, an increase in productivity was mild in the period considered and hence should be fostered. This can be done not only by boosting innovations by providing capital or research and development (R&D) subsidies at the European or national level, but also by stimulating venture capital or R&D subsidies to energy technologically innovative companies. Climate change does not recognize national borders; hence, networking without borders in R&D activities has to be boosted in the long run. Different actors, including governments, industry, academia and research organizations have to collaborate sharing common goals—strong and environmentally sensitive economic growth. The EU policy is particularly important in spurring basic research which industry and business are less interested in. It also has to prevent any attempt to increase efficiency at the expense of ecology. The EU experienced this case in the second sub-period.

Second, this paper suggests that EU's slow environmentally sensitive productivity growth appears to be generally a result of insufficient knowledge needed to transform the European economy towards a competitive and climate neutral economy. Indeed, average technical efficiency, including its both components, pure technical efficiency and scale efficiency, exhibited a decrease on a period basis. Unfavorable movements therein generally indicate the need for new business and industrial models based on competitive but environmentally friendly production. This paper implicitly shows that human capital, equipped with new knowledge and the will to innovate, is an important factor in combining necessary improvement in economic performance with the environmental one; technological innovation alone cannot do that. Adequate policy that supports cross-country networking as well as an efficient and effective institutional system that ensures fair competition is of critical importance in this regard. Further research should detect which countries shape the best-practice frontier and how to increase returns to human capital as well as simulate innovation and technology diffusion, technology transfer, knowledge spillover and development of an innovative mindset.

Third, energy is an important factor of production, but it seems yet not a critical one with respect to GDP growth regardless of the period considered. However, EU's high import dependence on energy, a large portion of non-renewable energy in final energy consumption and the observed deterioration in technical efficiency indicate energy as a future potentially constrained factor of production. The issues of energy security, energy efficiency and a contribution of energy to GHG emissions open the question about sustainability of the still prevailing economic paradigm which relativizes the role of energy towards a new eco-economic paradigm which integrates sustainability requirements with the economic ones into national policies and programs.

Fourth, there are disparities in environmentally sensitive performance across European countries. To reduce these, not only innovative and effective technology should be adapted, but a diffusion of new production knowledge and good management and organizational practices from the best-frontier countries to the non-frontier ones should also be encouraged and supported by policy.

Finally, the paper shows that environmentally sensitive technical efficiency and productivity are sensitive to turbulent economic times. The largest changes in MPIs occurred during the period of the greatest turbulence, when the EU suffered particularly from the pressures of the economic crisis. It is therefore plausible to expect that the newest crisis, caused by the COVID-19 pandemic, is affecting European productivity. Indeed, crisis situations are definitely situations that require new policy responses aimed at boosting viable sectors, i.e., companies, always taking into account the long term and the need for the gains obtained to spill over into other countries.

Further research should compare and evaluate the results obtained in this paper with novel methods and alternative environmental variables to gain a deeper understanding of the technical efficiency and productivity development path. The paper emphasizes the importance of proper policy and institutional frameworks for improving environmentally sensitive technical efficiency and productivity. However, it does not answer how a particular policy and/or institutional variable influence it in the European context. This should be analyzed in further research through a two-stage regression analysis.

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Appendix A

Table A1. Pearson correlation coefficients.

Variable	*GDP*	*GHG*	*K*	*L*	*E*
GDP	1				
GHG	0.9464 *	1			
K	0.9893 *	0.9403 *	1		
L	0.9663 *	0.9806 *	0.9594 *	1	
E	0.9812 *	0.9800 *	0.9815 *	0.9845 *	1

* denotes statistically significant correlation coefficients at the level of 0.05.

References

1. Ancev, T.; Azad, M.A.S.; Akter, M. Environmentally adjusted productivity and efficiency: A review of concepts, methods and empirical work. In *New Direction in Productivity Measurement and Efficiency Analysis, Counting the Environment and Natural Resources*; Ancev, T., Azad, M.A.S., Hernandez-Sancho, F., Eds.; Edward Elgar: Cheltenham, UK, 2017; pp. 9–58.
2. European Commission. *A Roadmap for Moving to a Competitive Low Carbon Economy in 2050, COM/2011/0112 Final*; European Commission: Brussels, Belgium, 2011.
3. European Commission. *A Policy Framework for Climate and Energy in the Period from 2020 to 2030, COM/2014/015 Final*; European Commission: Brussels, Belgium, 2014.
4. European Parliament. Greenhouse Gas Emissions by Country and Sector (Infographic), News, 17 October 2019. Available online: https://www.europarl.europa.eu/news/en/headlines/society/20180301STO98928/greenhouse-gas-emissions-by-country-and-sector-infographic (accessed on 20 May 2020).
5. European Environment Agency (EEA). Renewables Helping to Reduce Greenhouse Gas Emissions across the EU, 24 April 2017. Available online: https://www.connect4climate.org/article/renewables-eu-energy-helping-reduce-greenhouse-gas-emissions (accessed on 20 May 2020).
6. Hua, Z.; Bian, Y. DEA with undesirable factors. In *Modeling Data Irregularities and Structural Complexities in Data Envelopment Analysis*; Zhu, J., Cook, W.D., Eds.; Springer: Boston, MA, USA, 2007; pp. 103–121.
7. Parmeter, C.F.; Kumbhakar, S.C. Efficiency analysis: A primer on recent advances. *Found. Trends Econom.* **2014**, *7*, 191–385. [CrossRef]
8. Gokgoz, F.; Turkoglu, S.P. Investigating the energy efficiencies of OECD countries via a slack-based undesirable output model. *Econ. Policy Energy Environ.* **2018**, 73–94. [CrossRef]
9. Shen, Z.; Boussemart, J.-P.; Leleu, H. Aggregate green productivity growth in OECD's countries. *Int. J. Prod. Econ.* **2017**, *189*, 30–39. [CrossRef]
10. Gehringer, A.; Martinez-Zarzoso, I.; Nowak, N.; Danziger, L. The determinants of total factor productivity in the EU: Insights from sectoral data and common dynamic processes. *Econ. Model.* **2013**, 5343. Available online: https://econpapers.repec.org/paper/ekd004912/5343.htm (accessed on 20 May 2020).
11. Chang, M.-C.; Yu, C.-H. Estimation of energy productivity change in Baltic Sea and EU non-Baltic Sea states. *Balt. J. Econ.* **2016**, *17*, 78–102. [CrossRef]
12. Mahlberg, B.; Luptacik, M.; Sahoo, B. Examining the drivers of total factor productivity change with an illustrative example of 14 EU countries. *Ecol. Econ.* **2011**, *72*, 60–69. [CrossRef]
13. Picazo-Tadeo, A.J.; Castillo-Giménez, J.; Beltrán-Esteve, M. An intertemporal approach to measuring environmental per-formance with directional distance functions: Greenhouse gas emissions in the European Union. *Ecol. Econ.* **2014**, *100*, 173–182. [CrossRef]

14. Beltran-Esteve, M.; Picazo-Tadeo, A.J. Assessing environmental performance in the European Union: Eco-innovation versus catching-up. *Energy Policy* **2017**, *104*, 240–252. [CrossRef]
15. Wang, L.-W.; Le, K.-D. Energy Efficiency and Improvement European countries: Data Envelopment Analysis approach. *Int. J. Sci. Res. Publ. (IJSRP)* **2019**, *9*. [CrossRef]
16. Caves, R.; Christensen, I.; Diewert, W.E. The economic theory of index numbers and the measurement of input, output and productivity. *Econometrica* **1982**, *50*, 1414. [CrossRef]
17. Färe, R.; Grosskopf, S.; Norris, M.; Zhang, Z. Productivity growth, technical progress, and efficiency change in industrialized countries. *Am. Econ. Rev.* **1994**, *84*, 66–83.
18. Kurz, H.D.; Salvatori, N. *Theory of Production—A Long Period Analysis*; Cambridge University Press: Cambridge, MA, USA, 1995.
19. Farrell, M.J. The measurement of productive efficiency. *J. R. Stat. Soc.* **1957**, *120*, 253–290. [CrossRef]
20. Stern, D.I. *The Role of Energy in Economic Growth*; Taylor & Francis: Oxfordshire, UK, 2011; pp. 35–47.
21. Makridou, G.; Andriosopoulos, K.; Doumpos, M.; Zopounidis, C. A two-stage approach for energy efficiency analysis in Eu-ropean Union countries. *Energy* **2015**, *36*, 47–69.
22. Duman, Y.S.; Kasman, A. Environmental technical efficiency in EU member and candidate countries: A parametric hyperbolic distance function approach. *Energy* **2018**, *147*, 297–307. [CrossRef]
23. Halkos, G.; Petrou, K.N. Testing undesirable output in DEA: A critical review. *Econ. Anal. Policy* **2019**, *62*, 97–104. [CrossRef]
24. Huppes, G.; Ishikawa, M. Eco-efficiency and Its Terminology. *J. Ind. Ecol.* **2005**, *9*, 43–46. [CrossRef]
25. Gu, W.; Hussain, J.; Willox, M. *Environmentally Adjusted Multifactor Productivity Growth for the Canadian Manufacturing Sector*; Analytical Studies Branch Research Paper Series; Research Gate: Berlin, Germany, 2019.
26. Jahan, H.; Ancev, T. Environmentally adjusted efficiency of shrimp farming in Bangladesh. In *New Direction in Productivity Measurement and Efficiency Analysis, Counting the Environment and Natural Resources*; Ancev, T., Azad, M.A.S., Hernandez-Sancho, F., Eds.; Edward Elgar: Cheltenham, UK, 2017; pp. 249–274.
27. Rodríguez, M.C.; Haščič, I.; Souchier, M. Environmentally Adjusted Multifactor Productivity: Methodology and Empirical Results for OECD and G20 Countries. *Ecol. Econ.* **2018**, *153*, 147–160. [CrossRef]
28. Beltran-Esteve, M.; Gimenez, V.; Picazo-Tadeo, A. Environmental productivity in the European Union: A global Luen-berger-metafrontier approach. *Sci. Total Environ.* **2019**, *692*, 136–146. [CrossRef] [PubMed]
29. Wang, J.; Wang, K.; Shi, X.; Wei, Y.M. Spatial heterogeneity and driving forces of environmental productivity growth in China: Would it help to switch pollutant discharges fee to environmental taxes? *J. Clean. Prod.* **2019**, *223*, 36–44. [CrossRef]
30. Sun, H.; Kporsu, A.K.; Taghizadeh-Hesary, F.; Edziah, B.K. Estimating environmental efficiency and convergence: 1980 to 2016. *Energy* **2020**, *208*, 118224. [CrossRef]
31. Woo, C.; Chung, Y.; Chun, D.; Seo, H.; Hong, S. The static and dynamic environmental efficiency of renewable energy: A Malmquist index analysis of OECD countries. *Renew. Sustain. Energy Rev.* **2015**, *47*, 367–376. [CrossRef]
32. Prokop, V.; Stejskal, J.; Kuba, O. Effective financing of environmentally adjusted productivity growth in sustainable development framework: An international comparative study. *Eur. J. Sustain. Dev.* **2012**, *8*, 172. [CrossRef]
33. Desli, E. Convergence and efficiency: Evidence from the EU-15. *J. Post Keynes. Econ.* **2009**, *31*, 403–430. [CrossRef]
34. Vlahinic-Dizdarevic, N.; Segota, A. Total-factor energy efficiency in the EU countries. *Zb. Rad. Ekon. Fak. Rij.* **2012**, *30*, 247–265.
35. Lacko, R.; Hajduová, Z. Determinants of Environmental Efficiency of the EU Countries Using Two-Step DEA Approach. *Sustainability* **2018**, *10*, 3525. [CrossRef]
36. Vlahnic Lenz, N.; Segota, A.; Maradin, D. Total-factor energy efficiency in EU: Do environmental impacts matter? *Int. J. Energy Policy* **2018**, *8*, 92–96.
37. Hsieh, J.-C.; Lu, C.-C.; Li, Y.; Chiu, Y.-H.; Xu, Y.-S. Environmental Assessment of European Union Countries. *Energies* **2019**, *12*, 295. [CrossRef]
38. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
39. Emrouznejad, A.; Yang, G.-L. A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio-Econ. Plan. Sci.* **2018**, *61*, 4–8. [CrossRef]
40. Banker, R.D.; Charnes, A.; Cooper, W.W. Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Manag. Sci.* **1984**, *30*, 1078–1092. [CrossRef]
41. Seiford, L.M.; Zhu, J. Modeling undesirable factors in efficiency evaluation. *Eur. J. Oper. Res.* **2002**, *142*, 16–20. [CrossRef]
42. Eurostat. Database on Energy, Luxembourg. 2020. Available online: http://ec.europa.eu/eurostat/web/energy/data/main-tables (accessed on 16 January 2020).
43. Sarkins, J. Preparing Your Data in DEA. In *Modeling Data Irregularities and Structural Complexities in DEA*; Zhu, J., Cook, W.D., Eds.; Springer: Boston, MA, USA, 2007; pp. 305–320.
44. Krüger, J.J. The global trends of total factor productivity: Evidence from the nonparametric Malmquist index approach. *Oxf. Econ. Pap.* **2003**, *55*, 265–286. [CrossRef]
45. Draghi, M. The Productivity Challenge for Europe, Speeches, European Central Bank 2016. 30 November 2016. Available online: https://www.ecb.europa.eu/press/key/date/2016/html/sp161130_1.en.html (accessed on 20 October 2018).
46. Montinho, V.; Madaleno, M.; Robaina, M. The economic and environmentally efficiency assessment in EU cross-country: Evidence from DEA and quantile regression approach. *Ecol. Indic.* **2017**, *78*, 85–97. [CrossRef]

47. Morley, B. Empirical evidence on the effectiveness of environmental taxes. *Appl. Econ. Lett.* **2012**, *19*, 1817–1820. [CrossRef]
48. Borozan, D. Efficiency of energy taxes and the validity of the residential electricity environmental Kuznets curve in the European Union. *Sustainability* **2018**, *10*, 2464. [CrossRef]
49. Kortelainen, M. Dynamic environmental performance analysis: A Malmquist index approach. *Ecol. Econ.* **2008**, *64*, 701–715. [CrossRef]
50. Chertow, M.R.; Ashton, W.S.; Espinosa, J.C. Industrial Symbiosis in Puerto Rico: Environmentally related agglomeration economies. *Reg. Stud.* **2008**, *42*, 1299–1312. [CrossRef]
51. Han, F.; Xie, R.; Lu, Y.; Fang, J.; Liu, Y. The effects of urban agglomeration economies on carbon emissions: Evidence from Chinese cities. *J. Clean. Prod.* **2018**, *172*, 1096–1110. [CrossRef]
52. Lozano, S.; Gutierrez, E. Non-parametric frontier approach to modelling the relationships among population, GDP, energy consumption and CO_2 emissions. *Ecol. Econ.* **2008**, *66*, 687–699. [CrossRef]
53. Baldwin, A.; Bax, H.J.; Lhermitte, M. How Can Europe Raise Its Game? EV Attractiveness Survey Europe 2020. 2019. Available online: https://www.ey.com/en_gl/attractivenessss (accessed on 15 December 2019).
54. Pan, H.; Page, J.; Cong, C.; Barthel, S.; Kalantari, Z. How ecosystem services driven urban growth: Integrating nature-based solutions. *Anthropocene* **2021**, *35*, 100297. [CrossRef]