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Evaluating environmental performance using data envelopment analysis: The case of European countries

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ABSTRACT

Environmental efficiency is considered to be a critical pillar of sustainable development; consequently, improving environmental performance has aroused attention at both the local and global level. This study evaluated the environmental performance of European Union (EU) countries using the data envelopment analysis (DEA) approach and the global Malmquist-Luenberger index. Although literature using the DEA approach to measure environmental performance exists, this study's main contribution was considering different types of undesirable outputs and using long-term panel data on EU countries. In particular, the DEA window analysis technique was applied to evaluate the environmental performance of 27 EU countries in cross-sectional and time-varying data during the period 2000–2017. Three DEA models were examined; labor, capital, and energy were used as common inputs with a combination of different outputs, including gross domestic product, carbon dioxide and particulate matter emissions, and waste. The empirical results revealed that the trends in the environmental performance of the entire EU and its individual countries were similar under all examined models. Environmental performance was indeed negatively affected by the financial crisis of 2007–2008; this impact was mainly observed in eastern EU countries. Furthermore, both economic and environmental variables significantly influenced countries' overall efficiency. The analysis using the global Malmquist-Luenberger index elucidated that overall, EU countries experienced the efficiency improvement during the study period, although fluctuations were observed. These results enable countries and policymakers to understand their environmental performance, identify strengths and weaknesses, and set targets for further improvement based on the current best practices of comparable peers.

1. Introduction

Environmental efficiency and energy efficiency are the two critical pillars of sustainable development. The links between climate change and sustainable development are strong. Sustainable Development Goal 13 aims to "take urgent action to combat climate change and its impact." Climate change is considered to be an inevitable and urgent global challenge with long-term implications for the sustainable development of all countries. There has been growing concern about climate change due to carbon dioxide (CO_2) emissions worldwide. Improving environmental performance has attracted attention at the local and global levels—it has often been regarded as one of the most cost-effective ways of reducing CO_2 emissions and increasing potential benefits of sustainable development (Ang et al., 2010). Indeed, the term *environmental performance* has been globally promoted and quoted by environmental policy analysts, especially due to the growing concerns about global warming (Labuschagne et al., 2005). *Environmental performance* is defined as "the measurable results of an organization's management of its environmental aspects" (ISO, 2013). Although this definition is concisely written and broadly applicable, it is fuzzy enough to impose no clear conceptual boundaries (Dragomir, 2018). This explains the dilemma of how to measure environmental performance when research is conducted

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in fields such as ecology, environmental management, and sustainability studies.

More and more economies have generally recognized the importance of evaluating environmental efficiency. Developing an environmental policy statement and a plan to achieve environmental objectives involves, among other things, measuring and reviewing environmental performance. Indeed, the careful measurement of environmental trends and performance provides a foundation for effective policymaking, especially when issues such as climate change are considered. In particular, it can provide stakeholders and policymakers with quantitative information with strong practical implications, thereby making the decisions contained in environmental policymaking more scientific, empirical, and systematic. Governments have been using a combination of regulation, economic instruments, and voluntary agreements to meet targets of environmental performance, such as climate change mitigation. For example, by the early 1990s, governments of the Organisation for Economic Co-operation and Development (OECD) countries had enacted a wide variety of environmental laws and signed on to a multitude of environmental treaties and declarations. The Environmental Performance Review (EPR) was launched in 1992; since then, the OECD has conducted over 90 EPRs of its member and partner countries.

A country should measure, monitor, and evaluate its environmental performance. It must monitor the key characteristics of its operation as well as activities that may have a significant impact on the environment, establishing records for the same. An environmental performance index, usually used for the aggregated measurement of environmental performance, can provide valuable information for analysts and decision makers dealing with energy and environment-related issues (Esty et al., 2006). A large collection of wide-ranging environmental indicators has been developed and used by different organizations based on their individual characteristics (Tyteca, 1996; Olsthoorn et al., 2001).

This paper aimed to assess the environmental performance of 27 European Union (EU) countries over the period 2000–2017.[1] Rapid economic development and population growth in the EU have placed heavy pressure on the environment, with consequent deterioration in recent years. The EU has adopted a series of environmental policies and regulations with the intention of improving environmental quality among EU member states. As such, environmental performance among EU countries is worthy of further study. Under such circumstances, this study employed a data envelopment analysis (DEA) approach to identify the trends of the countries' environmental performance by considering socioeconomic and environmental variables. In particular, labor, capital, energy consumption, gross domestic product (GDP), CO_2 emissions, particulate matter ($PM_{2.5}$) emissions, and waste were the variables used for its evaluation. At the second stage of the analysis, the global Malmquist-Luenberger (GML) index was applied to further evaluate changes in environmental performance over time.

This study made a twofold contribution to the literature. First, this study attempted to evaluate the environmental performance in the context of EU countries using a DEA window approach that considered desirable and undesirable outputs and energy and non-energy inputs. DEA only deals with cross-sectional analysis, and it does not review efficiency over time. Therefore, the DEA window approach was used to eliminate this limitation. Also, when this approach is applied, the number of observations that can be considered is multiplied by a factor equal to a window's width, increasing the discrimination capability of the method. Thus, the DEA window approach provides more accurate results than traditional analysis. In particular, the main contribution of this study was to provide an evaluation and comparison index of countries' environmental efficiency trends over time. This allowed for the documentation of the practicality of the proposed approach, as policymakers could use it to construct a standardized and comprehensible environmental indicator for benchmarking purposes.

Second, this study utilized panel data composed of EU countries for 2000–2017, which contained many more observations than most of the previous DEA studies that applied panel data. Indeed, this study aimed to overcome a limitation of previous studies examining CO_2 emissions by incorporating CO_2, $PM_{2.5}$, and waste emissions as outputs. Given the pressure of holding pollution in check and of improving environmental quality, reducing air pollutant emissions is urgent and reasonable for protecting the environment. Thus, incorporating air pollutants into the analysis was necessary to investigate environmental performance. Therefore, this study beneficially supplemented the existing research and body of knowledge in the environmental sciences.

The rest of the paper is structured as follows. In Section 2, the relevant literature is briefly reviewed. Section 3 provides the methodology description, and Section 4 describes the variables and data used in the analysis. In Section 5, the estimation results are presented and discussed. Finally, Section 6 concludes and raises some related policy implications and directions for future research.

2. Literature review

The international literature contains many studies dealing with assessing energy and environmental performance using various methodologies. One of the most used methodologies in these studies is DEA. Zhou et al. (2008a), Song et al. (2012), and Sueyoshi et al. (2017) reviewed the studies in which DEA was applied to environment and energy analysis.

DEA is a widely employed approach in measuring environmental performance at the macro-economic level, as it enables researchers to consider undesirable outputs through composite environmental performance indicators (Zofio and Prieto, 2001; Zaim, 2004; Zhou et al., 2007; Song et al., 2012; Kounetas, 2015; Zhang et al., 2015). Considering undesirable outputs is important because, as Mandal (2010) noted, neglecting undesirable outputs when evaluating energy efficiency could result in biased energy efficiency estimates.

Sarkis and Talluri (2004), and more recently, Mardani et al. (2018), provided a detailed summary of the applications of DEA in environmental efficiency research. Researchers have developed a variety of DEA models that consider undesirable outputs, including environmental performance evaluation, environmental regulation impact assessment, pollutant emission quotas, shadow prices of pollutants estimation, and other environmental system assessment problems (Song et al., 2012). A more recent approach in handling undesirable outputs for the DEA framework is the slacks-based measurement model (Tone, 2001; Hu and Wang, 2006; Zhou et al., 2006; Cook and Seiford, 2009; Lozano and Gutiérrez, 2011; Makridou et al., 2015).

Many studies that used the DEA approach for environmental assessment focused on a particular period of time and geographical zone (Färe et al., 2004; Kortelainen, 2008; Kuosmanen et al., 2009; Hu et al., 2011; Menegaki, 2013; Jin et al., 2014; Vlontzos et al., 2014; Suzuki et al., 2015; Chen et al., 2015; Balezentis et al., 2016; Suzuki and Nijkamp, 2016; Sanz-Díaz et al., 2017). Färe et al. (2004) applied DEA to evaluate the environmental performance of 17 OECD countries in 1990. GDP was the desirable output, whereas CO_2, nitrogen oxide (NO_X), and sulfur oxide (SO_X) emissions were used as the undesirable outputs. Energy consumption, capital stock,

[1] Malta was excluded due to the unavailability of certain data.

and labor were the inputs used in this research. Zhou et al. (2006) developed two slacks-based DEA techniques for the environmental performance measurement of 30 OECD countries from 1998 to 2002 using total primary energy supply and population as inputs and GDP and CO_2 emissions as desirable and undesirable outputs, respectively. Zhou et al. (2007) used a non-radial DEA approach to measure the environmental performance of 26 OECD countries from 1995 to 1997. They used labor force and primary energy consumption as inputs; GDP was the only desirable output, whereas CO_2, SO_X, NO_X, and carbon monoxide (CO) were the undesirable outputs. Kortelainen (2008) applied frontier efficiency techniques to assess the overall environmental performance of 20 EU countries from 1990 to 2003 using real GDP and various air pollutant emissions, including emissions from 12 different pollutants.

Jin et al. (2014) used a DEA model to evaluate the carbon emission performance of 20 members of the Asia Pacific Economic Cooperation (APEC) economies in 2010 under random conditions. Total energy consumption and labor force were used as the input variables, GDP was used as the desirable output variable, and CO_2 emissions were used as the undesirable output variable. They concluded that the stochastic pure environmental performance of APEC economies was affected by random factors. Woo et al. (2015) also examined the environmental efficiency of renewable energy in 31 OECD countries with a DEA method. Labor, capital, and renewable energy supply were the inputs, GDP was the desirable output, and carbon emissions were the undesirable output. They concluded that undesirable environmental factors should be considered when examining environmental efficiency, as they were significantly related to energy performance. Guo et al. (2017) performed the DEA method to measure the environmental performance of 109 strictly environmentally monitored cities in China. They concluded that there was a large gap between the level of economic development and environmental protection among these cities.

Studies that have used the DEA model to evaluate environmental performance can be divided into the following two groups. The first includes studies using CO_2, SO_2, NO_2, waste gas, wastewater, and waste as undesirable outputs (Wu and Wu, 2009; Hua et al., 2013; Sun et al., 2014; Lee et al., 2014; Wang et al., 2015; Li et al., 2015; Zha et al., 2016; Zhang et al., 2016). The second group uses $PM_{2.5}$ and PM_{10} as research indexes on the basis of traditional pollutants (Kang et al., 2010; Sueyoshi and Yuan, 2015; Reyes et al., 2016; He et al., 2016; Zhou and Zhou, 2017). Most studies handled a single air pollutant—such as CO_2, SO_2, NO_2, or waste gas—as undesirable outputs. Studies using undesirable outputs such as $PM_{2.5}$ and PM_{10} were rarely seen, let alone literature analyses on the regional differences of environmental pollution (Guo et al., 2017). Table 1 summarizes representative studies that used DEA methodology to evaluate environmental performance.

Combined with DEA, several authors have employed the Malmquist productivity index (MPI) to assess the changes in environmental performance (Kumar, 2006; Zhou et al., 2007; Kortelainen, 2008; Sueyoshi and Goto, 2013; Woo et al., 2015; Ding et al., 2019; Zhu et al., 2019). Lin et al. (2013) used the generalized metafrontier MPI approach to measure environmental productivity in 70 countries from 1981 to 2007. Menegaki (2013) applied DEA and the Malmquist index to measure efficiency in 31 European countries from 1997 to 2010 with respect to their renewable energy performance. The research used variables such as the GDP, renewable energy, fuel energy consumption, CO_2 emissions, employment, and capital. Sanz-Díaz et al. (2017) used both DEA and the Malmquist index to evaluate Spain's and all EU-28 countries' efficiency from 2005 to 2012. They used employment, energy consumption, and gross fixed capital formation as inputs, GDP as a desirable output, and greenhouse gas emissions as an undesirable output. Wu et al. (2017) and Du et al. (2018) applied the DEA-based Malmquist index to assess China's environmental productivity. Carboni and Russu (2018) and Mavi and Mavi (2019) used the MPI to analyze the economic and ecological performance of the 20 Italian regions from 2004 to 2011, and of OECD countries, from 2012 to 2015, respectively.

The Malmquist-Luenberger index has also been widely used to measure the environmentally sensitive productivity growth of countries (Yoruk and Zaim, 2005; Fan et al., 2015; Emrouznejad and Yang, 2016). Oh (2010) and Kumar (2006) used it to analyze the performance of 26 OECD countries from 1990 to 2003 and of 41 countries from 1973 to 1992, respectively. Yang and Zhang (2018) used an extended DEA model in combination with the GML index to evaluate eco-efficiency trends in China from 2003 to 2014.

3. Methodology

Environmental performance measurement, defined as the ratio of value added to the environmental damage index, is difficult to interpret. It is not helpful, for example, to compare the environmental performance of a heavily polluting energy firm with that of a firm in the service sector due to different industry-specific factors, technologies, and environmental challenges. Indeed, to obtain insights about the relative performance of the evaluated unit, its performance must be compared with the best performers of the group (Kortelainen, 2008). In this study, an input-oriented DEA approach was chosen to measure environmental efficiency using a model that could consider both desirable and undesirable outputs; a window analysis approach was applied to assess trends over time. Furthermore, the GML index (Oh, 2010) was used to further evaluate efficiency improvements over time.

3.1. DEA model

DEA has been widely and extensively used to measure environmental performance at different levels (Jin et al., 2014). It is a nonparametric linear programming technique to evaluate the efficiency of comparable production units (decision-making units [DMUs]). In the context of DEA, efficiency is measured as the ratio of a DMU's aggregate outputs to its aggregate inputs. The aggregation of multiple inputs and outputs is done through an endogenous weighting scheme in which the input/output weights are defined for each DMU so that it maximizes its efficiency compared to its peers. The derived efficiency scores for all units lie between 0 and 1, with higher scores indicating more efficient DMUs.

The main advantages of DEA involve incorporating multiple inputs and outputs, its applicability (as it does not come up with a priori assumptions for the function that links inputs and outputs), and its amenability to modifications, which provides sufficient flexibility for adapting the method to different studies.

This study used the directional distance function model of Chung et al. (1997) and Färe and Grosskopf (2004), which allowed the consideration of both desirable and undesirable outputs.[2] Denoted by $\mathbf{X}\in\mathbb{R}_{\geq 0}^{n\times m}$, the matrix of m inputs for n DMUs; $\mathbf{Y}\in\mathbb{R}_{\geq 0}^{n\times d}$, the data matrix of d desirable outputs for n DMUs; and $\mathbf{U}\in\mathbb{R}_{\geq 0}^{n\times s}$, the matrix of s undesirable outputs for n DMUs, the model involves the solution of the following linear program for each DMU $i = 1, 2, \ldots, n$, described by the input and output vectors $\mathbf{x}_i, \mathbf{y}_i, \mathbf{u}_i$:

[2] For a review of other models for handling undesirable outputs in environmental and energy performance benchmarking models, see the review papers of Dakpo et al. (2016) and Sueyoshi et al. (2017). See also the models based on range-adjusted efficiency measures, such as those proposed by Sueyoshi and Goto (2011) and Ramli and Munisamy (2015).

Table 1
Summary of studies that used DEA to measure environmental performance.

Authors	Sample/Year	Inputs	Outputs
Zaim and Taskin (2000)	25 OECD countries, 1980–1990	Total labor, total capital stock	GDP, CO_2
Zofio and Prieto (2001)	14 OECD countries, 1990 and 1995	Total net stock of fixed capital, total labor	Manufactured production, CO_2
Zaim (2004)	US state manufacturing sectors, 1974–1986	Manufacturing employment, capital stock	Gross state product in manufacturing, SO_X, NO_X, and CO
Färe et al. (2004)	17 OECD countries, 1990	Energy consumption, capital stock, labor	GDP, CO_2, NO_X, SO_X
Zhou et al. (2006)	30 OECD countries, 1998–2002	Total primary, population	GDP, CO_2
Zhou et al. (2007)	26 OECD countries, 1995–1997	Labor force, primary energy consumption	GDP, CO_2, SO_X, NO_X, CO
Zhou et al. (2008b)	8 world regions, 2002	Energy consumption	GDP, CO_2
Zhou et al. (2010)	18 top CO_2-emitting countries, 1997–2004	Total capital stock, total labor, total primary energy consumption	GDP, CO_2
Oggioni et al. (2011)	21 countries' cement industries, 2005–2008	Total labor, capacity material, energy consumption	Cement production, CO_2 from clinker process
Meng et al. (2013)	Industrial sectors in different provinces of China, 1998–2009	Industrial labor force, industrial energy consumption	Industrial value added, industrial CO_2, industrial waste gas, industrial wastewater, industrial solid waste
Xie et al. (2014)	26 OECD and BRICS countries, 1996–2010	Total labor, installed capacity, fuel and nuclear inputs	Power generation, CO_2
Jin et al. (2014)	20 members of APEC economies, 2010	Total energy consumption, labor force	GDP, CO_2
Vlontzos et al. (2014)	Primary sectors of the EU member states, 2001–2008	Energy consumption, labor, capital	CO_2, gross nutrient balance
Woo et al. (2015)	31 OECD countries, 2004–2011	Labor, capital, renewable energy supply	GDP, CO_2
Sueyoshi and Yuan (2015)	30 provinces in China, 2003–2014	Capital, labor, energy	Gross regional product, CO_2, SO_2, soot, wastewater, chemical oxygen demand, ammonia nitrogen
Guo et al. (2017)	109 strictly environmentally monitored cities in China, 2014	Total population, investment in pollution control, total electricity consumption, per capita consumption	GDP, $PM_{2.5}$, PM_{10}, SO_2, NO_2
Sun et al. (2018)	283 cities in China, 2010–2014	Labor force, current assets, fixed assets, industrial electricity	Gross industrial output, industrial wastewater, industrial SO_2, industrial soot
Han et al. (2018)	42 industrial departments in China	Energy consumption	Total output, CO_2

$$
\begin{array}{ll}
\max & \beta \\
\text{subject to:} & \boldsymbol{\lambda}\mathbf{X} \le \mathrm{x}_i \\
& \boldsymbol{\lambda}\mathbf{Y} \ge (1+\beta)\mathbf{y}_i \\
& \boldsymbol{\lambda}\mathbf{U} = (1-\beta)\mathbf{u}_i \\
& \boldsymbol{\lambda} \ge \mathbf{0}
\end{array}
\tag{1}
$$

In Eq. (1), β denotes the percentage increase in the desirable outputs of the DMU under consideration and the decrease in its undesirable ones that could be achieved using at most the level of inputs of this DMU. At the optimal solution of the above linear program, the optimal value β^* of the objective function defines the efficiency score of DMU i as $1-\beta^*$. This efficiency index ranges from 0 to 1, with higher values indicating more efficient DMUs.

3.2. Window analysis

Efficiency scores were obtained through a five-year window analysis approach, which enabled the measurement of efficiency in a panel data setting (Cooper et al., 2007). Under the window analysis approach, a DMU's performance (i.e., country) in period t was evaluated against all other DMUs in year t and against the observed data for previous time periods $t-1, t-2, \dots, t-T$, where $T+1$ was the window period of the analysis (the present analysis set $T=4$ for a five-year window). This approach enabled the analysis of efficiency trends over time. Moreover, it overcomes the limitation of using small cross-sectional data sets, which are prohibitive to applying DEA and deriving meaningful efficiency estimates. This is particularly relevant for the present analysis, which focused on 27 EU countries—a small number of DMUs with which to obtain reliable efficiency estimates with DEA. Extending the analysis to multiple annual instances of the countries (i.e., five years of data for 27 countries results in 135 country-year observations) can overcome this limitation.

3.3. GML index

In DEA models, efficiency changes over time are usually evaluated using the Malmquist index, which allows for the identification of efficiency improvement or deterioration in one period compared to the previous one (Malmquist, 1953; Hadad et al., 2015). However, as Chung et al. (1997) noted, the standard Malmquist index is not meaningful when undesirable outputs are present in the analysis, as it is based on the Shephard output distance function, which assumes that all outputs should be maximized. To address this limitation, Chung et al. (1997) introduced the Malmquist-Luenberger (ML) index, which was based on direction distance functions, allowing for the consideration of both desirable and undesirable outputs. Formally, the ML index ML_t^{t+1} between periods t and $t+1$ is defined as the product of efficiency and technology change (EFF_t^{t+1} and $TECH_t^{t+1}$), respectively:

$$ML_t^{t+1} = EFF_t^{t+1} TECH_t^{t+1} = \frac{(1+\beta_{t+1}^t)}{(1+\beta_t^t)} \sqrt{\frac{(1+\beta_{t+1}^t)}{(1+\beta_{t+1}^{t+1})} \frac{(1+\beta_t^t)}{(1+\beta_t^{t+1})}} \tag{2}$$

In Eq. (2), $\beta_{t_1}^{t_2}$ is the optimal objective function value (i.e., the directional distance function) of the problem in Eq. (1) for a country in period (i.e., year) t_1 when benchmarked against the reference technology (inputs/outputs) of period t_2.

However, the ML index as defined above is often not computable because the linear program in Eq. (1) may not be feasible when applied to the mixed-period data needed to calculate β_{t+1}^t and β_t^{t+1} (Färe et al., 2001). In order to overcome this issue, this study used Oh's (2010) GML index:

$$GML_t^{t+1} = \frac{1+\beta_t^T}{1+\beta_{t+1}^T} \tag{3}$$

In Eq. (3), β_t^T and β_{t+1}^T represent the directional distance functions derived from the solutions of Eq. (1) for a country in periods t and $t+1$ when benchmarked against the global reference technology defined by the inputs/outputs for all years. Similar to the standard Malmquist index, GML index values greater than one indicate improvement, and values lower than one correspond to deterioration.

4. Variables and data

To measure environmental performance, this study used panel data for 27 EU countries over 18 years (2000–2017). Due to the urgent need for environmental protection, and the multiple factors that affect environmental performance, performing a model that combines economic, environmental, and energy-related factors was a necessity. Therefore, this study considered three models with different output variables. The selection of variables was based on the literature review, data availability, and their significant impact on countries' environmental efficiency. Table 2 summarizes the variables used for the DEA as well as their sources.

Regarding input variables for the DEA models, this study used variables related to the countries' economic activities similar to those used in many previous studies (see Table 1), such as labor, capital, and energy consumption; these three variables were applied to all the examined models. Labor and capital are the most basic inputs of production functions in economics. Furthermore, labor, capital, and energy consumption are commonly used as the inputs of economic models' production functions (Menegaki, 2013; Zhang et al., 2014; Makridou et al., 2015, 2016; Kounetas, 2015; Matsumoto et al., 2016; Octaviano et al., 2016; Matsumoto, 2019).

Output variables can be divided into two categories: desirable and undesirable (e.g., Färe and Grosskopf, 2004). Desirable output variables are those that generate positive socioeconomic effects. In this study, GDP was used as the positive output variable because GDP is the most common variable to explain a country's overall economic activity. In particular, without the production of intermediate outputs, GDP is used as a measure of the value added of a national economy. The value added is the numerator of the eco-efficiency ratio. This explains the use of GDP data in a cross-country eco-efficiency analysis.

In contrast, undesirable output variables are those that produce negative socioeconomic effects and represent environmental impacts. This study used CO_2 emissions as a basic negative output variable because climate change caused by CO_2 emissions has a broad range of impacts on socioeconomic activities—not only atmospheric but also hydrological, terrestrial, and ecological impacts (IPCC, 2014). This variable was used for all models. In addition to CO_2 emissions, $PM_{2.5}$ emissions were also employed (a proxy for atmospheric pollution). $PM_{2.5}$ is an important air pollutant that has been found to have strong health and economic impacts, particularly in recent years (Yin et al., 2017; Ciarelli et al., 2019). Although NO_X and SO_X have often been used to evaluate environmental performance with DEA (e.g., Färe et al., 2004; Zaim, 2004; Sueyoshi and Yuan, 2015), studies including $PM_{2.5}$ are still rare in the literature (see Table 1), even though it is a significant environmental issue, particularly recently, and thus important in determining countries' environmental performance. This study focused on two different air pollutants—CO_2 and $PM_{2.5}$ emissions (undesirable outputs)—due to the importance and transboundary character of air pollution at the global level.

Mitigating air pollutant emissions is one of the most important environmental policy issues there is. There are many regulations and international environmental agreements concerning air pollution, including the Geneva Convention on Long-Range Transboundary Air Pollution Reduction Protocol of 1979 and the Kyoto Protocol of 1997. In the case of the EU, several directives have also been focused on the emissions and the concentrations of air pollutants. Even before the early 1990s, EU policymakers were concerned about air pollution. However, the first program with long-term environmental objectives for both air quality and acidification was the fifth Environmental Action Program ("Towards Sustainability") of 1993. Later, the Kyoto Protocol, by which the EU was required to reduce greenhouse gas emissions by 8% from the level of 1990 to the average for the period 2008–2012, may explain the amounts of greenhouse gases in the sample period. It is worth mentioning that environmental policies can affect air pollutant emissions as well as economic growth. Therefore, it is important to consider different types of air pollutants in environmental performance measurement; this is because policies that reduce, for example, CO_2 emissions, can increase other emissions.

Waste is another important environmental burden throughout the world. Although waste management has been rarely used in

Table 2
Input and output variables used for the DEA models and their data sources.

Type	Variable (unit)	Model	Data Source
Input	Labor (population)	All	World Bank[b]
	Capital (million Euros)	All	Eurostat[c]
	Energy consumption (tons of oil equivalent)	All	Eurostat[c]
Output[a]	GDP (million Euros)	All	Eurostat[c]
	CO_2 emissions from energy consumption (thousand tons)	All	Eurostat[c]
	$PM_{2.5}$ emissions (tons)	1 and 3	Eurostat[c]
	Waste (tons)	2 and 3	Eurostat[c]

[a] GDP is the desirable output, whereas the others are the undesirable outputs.
[b] World Development Indicators (https://datacatalog.worldbank.org/dataset/world-development-indicators)
[c] https://ec.europa.eu/eurostat/.

Table 3
Descriptive statistics of the examined input and output variables.

Variable	Mean	Standard Deviation	Minimum	Maximum
Labor (population)	8,991,692.8	11,136,021.9	201,394	43,473,204
Capital (million Euros)	101,332.3	142,648.6	2,311.4	562,045.2
Energy consumption (tons of oil equivalent)	63,889.0	83,309.5	2,188.2	351,599.5
GDP (million Euros)	482,883.2	705,629.7	13,730.6	2,918,821.9
CO_2 emissions from energy consumption (thousand tons)	132,972.6	181,367.1	5,715.5	830,695.6
$PM_{2.5}$ emissions (tons)	56,269.3	58,338.6	1,147	280,594
Waste (tons)	92,711,554	106,184,985.1	1,248,723	406,455,657.4

Note: The data for the 27 countries from 2000 to 2017 were used for the calculations.

DEA to evaluate environmental performance compared with air pollutants, it is crucial to target circular economies (Malinauskaite et al., 2017). Therefore, waste was also selected as a negative output variable. Thus, on the methodological side, this study considered three different settings for the input and output variables, leading to three DEA models (denoted as Model 1, Model 2, and Model 3). The three DEA models shared the same inputs (i.e., labor, capital, and energy consumption); however, some outputs differed by model. Among the outputs, GDP as a desirable variable and CO_2 emissions as an undesirable variable were common. In addition to these output variables, Model 1 included $PM_{2.5}$ emissions, Model 2 included waste emissions, and Model 3 included both $PM_{2.5}$ and waste as undesirable variables. Table 3 summarizes the descriptive statistics, and Table 4 shows the correlation coefficients among the examined variables; all values were calculated based on all observations (i.e., 27 countries from 2000 to 2017).

Table 4 showed that energy consumption and labor force had a strong positive relationship with GDP and CO_2 emissions. In particular, the correlation between energy consumption and CO_2 emissions was 0.96, while that between labor and CO_2 emissions was 0.97, showing that the more energy and labor force were consumed, the more CO_2 emissions were generated. Furthermore, capital was also significantly related to energy consumption (0.98) and CO_2 emissions (0.91).[3] Jin et al. (2014) reported similar findings, stating that energy consumption and labor force were significantly related to GDP and CO_2 emissions. In particular, they noted that there was a strong positive relationship between energy consumption and CO_2 emissions and between labor force and CO_2 emissions. Although the GDP per capita has been found to be positively related to CO_2, many of the other pollutants that were considered individually, such as CO_2, SO_X and NO_X, had an eventually negative impact on per capita income (Färe et al., 2004).

Fig. 1 shows the aggregate time-series trends of the variables for all the examined countries. For the input variables, energy consumption decreased during the study period (around 10%), whereas the other variables increased slightly (Fig. 1a). For the output variables, GDP steadily increased, except for the financial crisis (2007–2008). Environmental burdens decreased, particularly CO_2 and $PM_{2.5}$ (Fig. 1b). In 2017, CO_2 emissions and $PM_{2.5}$ were around 80% and 70% of the 2000 levels, respectively.

5. Results and discussion

This section begins by reporting the aggregated results (EU; western and eastern EU). The results of individual countries and their comparisons are then presented.

5.1. Overall trends in the EU

Fig. 2 illustrates the average efficiency scores of the examined EU countries from 2000 to 2017. Note that because the waste data were only available for 2004, Models 2 and 3 were calculated beginning with 2004. The three models had similar average efficiency scores; they were stable throughout the study period at around 0.8 (minimum: 0.70, maximum: 0.85 for Model 1; minimum: 0.74, maximum: 0.88 for Model 2; minimum: 0.79, maximum: 0.93 for Model 3). All the models showed similar overall trends in terms of efficiency scores. The average efficiency scores declined until 2007–2008 and tended to improve afterward. The efficiency scores declined due to the global financial crisis of 2007–2008 and the fact that GDP considerably affects CO_2 emissions. After the financial crisis, the efficiency scores rapidly recovered for all the models, peaking around 2012–2013. After 2012, the efficiency scores were relatively stable. This observation was consistent with the findings of some previous studies. For example, Woo et al. (2015) found that environmental efficiency was influenced by the financial crisis. Sanz-Díaz et al. (2017) concluded that the global economic crisis had a negative impact on countries' efficiency performance.

5.2. Trends in the western and eastern EU countries

Comparing the western and eastern EU countries,[4] the average efficiency scores were much higher in the west than in the east (Fig. 3). In particular, the differences were relatively large for Model 1, in which CO_2 and $PM_{2.5}$ were used as the undesirable output variables. Vlontzos et al. (2014) came to the same conclusion, finding that eastern European countries achieved low efficiency scores due to the low levels of technology being implemented in these countries. Sanz-Díaz et al. (2017) also observed that the EU's west-block countries presented higher levels of efficiency compared to its eastern countries.

In this study, the trends of the average scores of the eastern countries were similar to the average for all EU countries. As discussed above, the minimum efficiency scores were observed around 2008, recovering after that year. However, the western EU countries' trends differed from the eastern countries. Although their efficiency scores declined until around 2007–2008, the degree of the decline was very small (e.g., the scores were 0.90 in 2000 and 0.86 in 2008 for Model 1). The efficiency scores were relatively stable and continuously increased after the crisis period (e.g., 0.94 in 2017 for Model 1). This means that the financial crisis of 2007–2008 clearly affected the efficiency scores of the eastern EU countries but not of the western countries. This may be because the eastern EU countries were more susceptible to economic

[3] Input variables used in DEA are often highly correlated (Smith, 1997).

[4] The western EU countries include the countries that became members in or before 1995.

Table 4
The correlation coefficients among the examined input and output variables.

	Capital	Energy Consumption	GDP	CO_2	$PM_{2.5}$	Waste
Labor	0.95	0.97	0.96	0.97	0.83	0.87
Capital		0.98	0.99	0.91	0.75	0.83
Energy consumption			0.98	0.96	0.78	0.87
GDP				0.94	0.72	0.84
CO_2					0.74	0.83
$PM_{2.5}$						0.75

Note: The data from the 27 countries from 2000 to 2017 were used for the calculations.

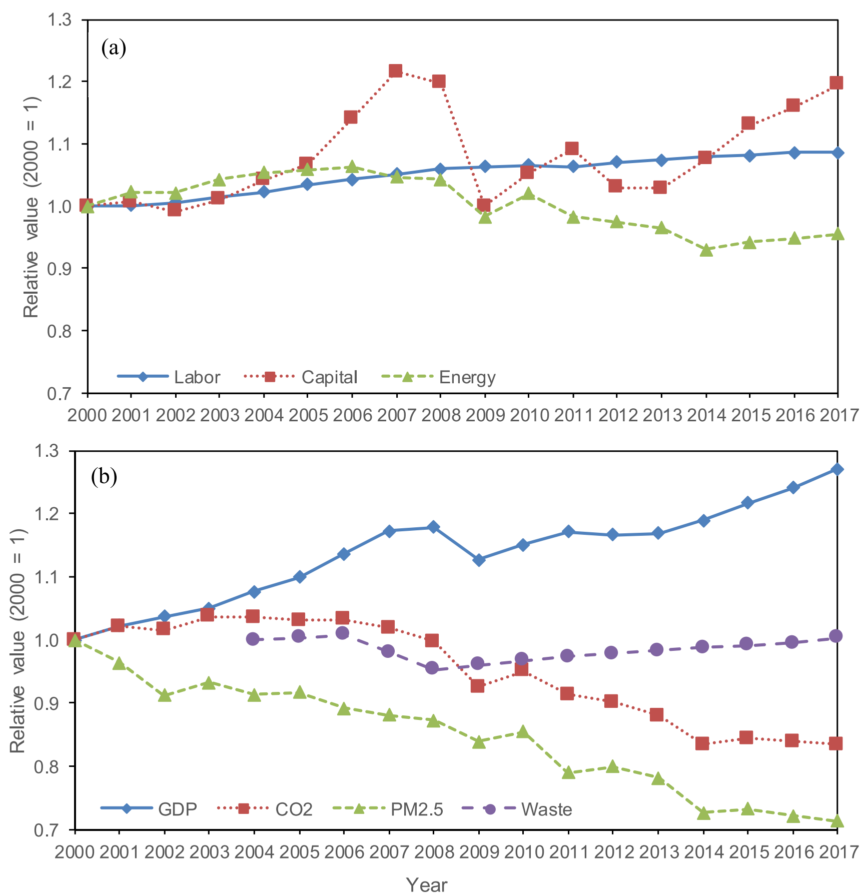

Fig. 1. Aggregate time-series trends for variables for all of the examined EU countries over the study period; (a) input variables, including labor, capital, and energy consumption; (b) output variables, including GDP (desirable), CO_2 emissions from energy consumption, $PM_{2.5}$ emissions, and waste (undesirable); 2000 = 1 for variables other than waste; 2004 = 1 for waste.

fluctuations than the western EU countries. Indeed, eastern countries were hit first by the global liquidity crisis, followed by dramatic declines in capital inflows and plunging demand for their exports.

The reason that the differences between the western and eastern EU countries were larger for Model 1 compared with the other models was the trends in the reduction of $PM_{2.5}$ and waste. During the study period, $PM_{2.5}$ decreased more in the western countries than in the eastern countries (63.7% and 91.4% in 2017 compared with the 2000 level in the western and eastern countries, respectively), while total waste increased in the western EU countries but decreased in eastern countries (114.4% and 65.8% in 2017 compared with the 2000 level in the western and eastern countries, respectively). Although GDP seemed to be a major factor in determining the efficiency scores, selection of environmental variables may also have significantly affected the results.

5.3. Individual countries' analysis

Fig. 4 showed the boxplot for the efficiency scores of individual countries over the study period (see Tables A1–A3 in the Appendix for the time-series efficiency scores of the countries). Tables 5–7 showed the GML index of the EU countries for the three models. Overall, the results for all the models showed similar trends. On average, Luxemburg was the most efficient country (being consistently efficient throughout the study periods), followed by Denmark and Sweden for Models 1 and 2. For Model 3, Luxemburg was also the only country that was consistently efficient in all the years, closely followed by Denmark, Germany, and the Netherlands, which were also found to be fully efficient in most of the years in

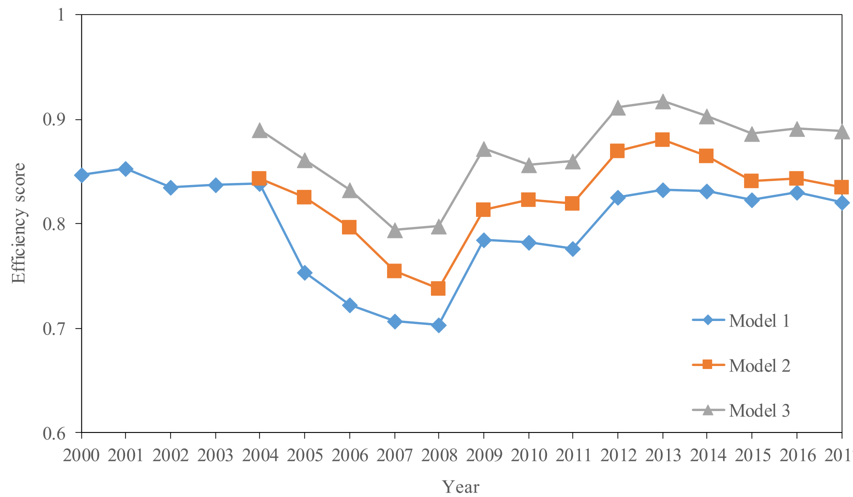

Fig. 2. The EU's average environmental performance (efficiency score) for the three DEA models during the study period. Because of the data availability for waste emissions, Models 2 and 3 began from 2004.

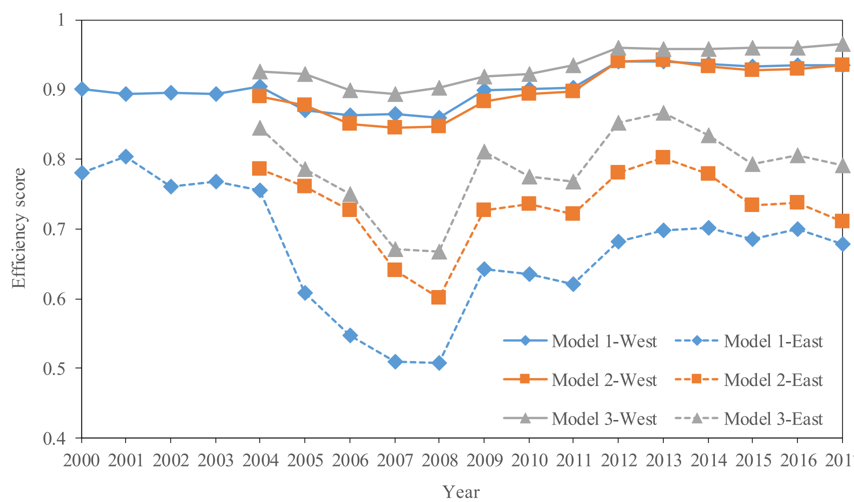

Fig. 3. Average efficiency scores of western and eastern EU countries for the three DEA models during the study period. Because of the data availability for waste emissions, Models 2 and 3 began from 2004. The western EU countries include the countries that became members in or before 1995.

the examined period. Zhou et al. (2006) reported similar conclusions, finding that among 30 OECD countries, Luxembourg had the best environmental performance over the period 1998–2002. Menegaki (2013) also found that Luxemburg was one of the most technically efficient European economies. Sanz-Díaz et al. (2017) concluded that Denmark and Luxembourg were efficient in every year during their study period. In addition, the efficiency scores were stably high in such highly efficient countries. These results suggest that the countries mentioned above generated higher GDP and smaller environmental burdens with relatively fewer inputs. Particularly, Luxemburg's efficiency score was 1, and its GML index was mostly 1 over the study period, indicating that the country was the most stable and efficient in all three models (Fig. 4 and Tables 5–7). During the study periods, per capita GDP among the EU countries was highest in Luxemburg. Furthermore, CO_2 emissions per GDP and $PM_{2.5}$ emissions per GDP in Luxemburg were lower than the EU average; it had one of the lowest per GDP emissions in the EU. Although its per GDP waste was not low, its waste level was similar to the EU average. Consequently, Luxemburg's economic variable would be an important factor, but taken together with its environmental variables, that country was the most environmentally efficient country in the EU.

In contrast, Estonia was the least efficient country for all the models (average efficiency scores: 0.43 for Model 1, 0.35 for Model 2, and 0.37 for Model 3), followed by the Czech Republic and Bulgaria in Model 1 and Poland and Slovakia for Models 2 and 3. Although some differences did exist, the inefficient countries were similar in all three models. In the case of Estonia, the environmental variables were not favorable. The per capita CO_2 emissions, $PM_{2.5}$ emissions, and waste were among the worst levels for EU countries. In addition, its economic level was also much lower than the EU average. Therefore, the environmental variables together with the economic variable made Estonia the country with the poorest environmental performance.

It would also be interesting to investigate the possible relationship between relative efficiency and income among countries. To this end, correlation coefficients between efficiency scores and real GDP per capita were calculated separately for each year. The

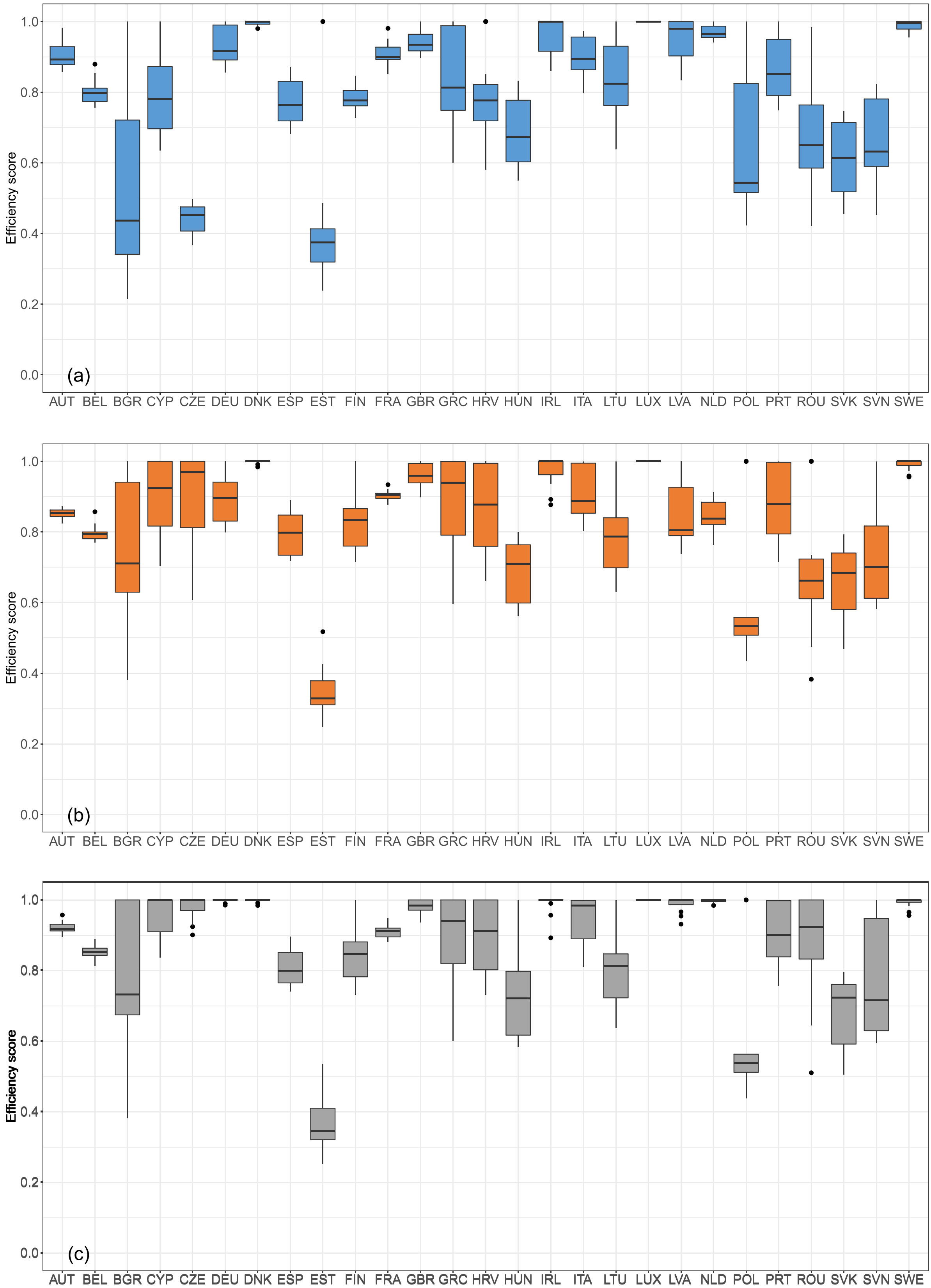

Fig. 4. Boxplots for each country's efficiency scores over the study period. (a) Model 1; (b) Model 2; and (c) Model 3. These boxplots were created based on the data shown in Tables A1–A3. The dots represent the outliers.

Table 5
GML index for 27 EU countries (Model 1).

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Average
AUT	0.993	1.020	0.970	1.010	1.006	1.025	1.012	1.013	1.030	0.998	1.000	1.015	1.001	1.027	0.990	0.996	1.006	1.007
BEL	1.017	1.033	1.002	0.975	0.982	1.004	0.992	0.996	1.041	1.002	1.010	1.012	1.012	1.005	0.983	0.992	1.006	1.004
BGR	0.602	1.019	0.975	1.003	0.975	0.979	0.987	0.986	1.064	1.048	0.999	1.011	1.036	0.983	1.000	1.044	1.005	0.977
HRV	0.946	0.922	0.973	1.014	0.999	0.959	0.980	0.986	1.082	1.069	0.995	1.034	0.993	1.012	0.982	0.974	0.984	0.994
CYP	1.061	0.949	1.005	0.965	1.000	0.966	1.003	0.950	1.080	0.986	1.102	1.099	1.135	1.000	0.953	0.926	0.890	1.002
CZE	0.993	1.004	1.012	0.998	1.013	1.001	0.983	1.013	1.046	0.995	1.006	1.016	1.024	0.989	0.983	1.023	1.005	1.006
DNK	1.007	1.017	1.000	0.992	1.025	0.944	1.032	1.023	1.086	0.997	1.003	1.006	0.986	1.018	1.000	0.988	0.992	1.006
EST	0.984	0.979	0.968	1.008	1.014	0.968	0.983	1.050	1.104	0.953	0.978	0.967	1.007	0.999	1.053	0.988	0.975	0.998
FIN	0.996	1.008	0.978	1.012	1.028	0.985	0.997	1.043	1.054	0.959	0.998	1.045	1.013	1.024	1.012	0.965	0.982	1.005
FRA	1.005	1.018	0.999	0.984	0.991	1.000	0.996	1.005	1.062	0.992	0.998	1.011	1.003	1.017	0.994	1.002	0.991	1.004
DEU	1.034	1.056	0.997	1.029	1.021	0.983	0.990	1.010	1.083	0.949	0.982	1.095	0.994	1.019	1.035	1.013	1.000	1.016
GRC	1.003	1.013	0.959	1.031	1.048	0.945	0.983	1.045	1.133	1.021	1.036	1.142	1.000	0.973	1.027	1.000	0.972	1.018
HUN	1.026	1.001	1.012	0.984	1.029	1.016	1.011	1.002	1.095	0.990	1.047	1.052	1.017	0.962	1.020	1.013	0.962	1.014
IRL	1.007	1.016	0.980	1.024	0.963	1.012	1.018	1.009	1.113	1.110	1.014	0.937	1.038	0.974	1.054	0.988	1.013	1.015
ITA	0.999	0.975	0.995	0.997	1.009	0.994	1.006	1.015	1.064	0.982	1.010	1.080	1.035	1.008	0.988	1.007	1.002	1.009
LVA	0.887	1.016	1.022	1.085	0.857	0.934	0.980	1.023	1.245	0.895	0.928	1.095	1.010	1.079	0.945	1.013	0.951	0.994
LTU	0.968	0.985	1.004	0.951	1.014	0.996	0.954	1.005	1.261	0.877	0.988	1.077	1.039	1.016	0.915	1.031	1.002	1.002
LUX	1.007	1.000	1.000	1.000	1.000	1.000	1.000	0.986	1.014	1.000	1.000	0.958	1.007	1.037	1.000	1.000	1.000	1.000
NLD	1.006	1.033	1.021	1.013	1.005	1.003	1.009	1.020	1.020	1.031	1.001	1.023	1.035	1.000	0.967	1.021	1.013	1.013
POL	1.036	1.028	0.995	0.988	1.007	0.983	0.972	1.013	1.056	0.982	0.990	1.022	1.027	0.988	1.001	1.016	0.998	1.006
PRT	1.002	1.014	1.050	0.986	0.995	1.026	1.019	1.004	1.040	1.026	1.064	1.082	1.007	0.990	0.954	1.017	0.993	1.015
ROU	0.943	1.018	1.002	0.997	1.030	0.954	0.944	1.020	1.111	1.002	0.962	1.033	1.046	1.015	0.987	1.040	1.035	1.007
SVK	0.964	1.026	1.044	0.988	0.996	1.016	1.025	1.004	1.116	0.962	0.997	1.086	1.007	1.011	0.968	1.032	1.006	1.014
SVN	1.011	1.008	0.991	0.983	1.016	0.983	0.979	0.995	1.128	1.029	1.011	1.084	0.985	1.021	1.015	1.013	0.983	1.013
ESP	1.000	0.986	0.989	0.989	0.990	1.003	1.001	1.036	1.076	1.030	1.027	1.029	1.036	0.983	0.969	1.018	1.004	1.009
SWE	1.003	1.025	0.997	1.016	1.010	0.991	0.986	1.011	1.074	0.952	1.005	1.035	1.010	1.000	1.000	1.000	1.000	1.006
GBR	1.002	1.018	1.009	1.018	1.013	0.997	1.017	1.028	1.072	0.949	1.022	0.980	0.979	0.992	1.000	1.019	1.023	1.008

Note: Each value shows the change from the previous year; "Average" shows the geometric mean during the study period.

Table 6
GML index for 27 EU countries (Model 2).

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Average
AUT	1.006	1.024	1.008	1.012	1.035	1.003	0.990	1.017	1.003	1.024	0.990	0.992	0.989	1.007
BEL	0.974	1.000	1.000	1.004	1.019	1.000	0.997	1.016	1.016	0.983	0.987	0.999	1.008	1.000
BGR	0.734	0.866	0.955	0.966	1.210	1.103	0.944	1.050	1.288	0.942	0.821	0.996	0.953	0.976
HRV	1.024	1.018	1.065	1.089	1.048	1.116	1.000	0.986	0.951	0.992	0.911	0.951	0.976	1.008
CYP	1.094	1.186	0.864	0.905	1.030	0.953	1.123	1.131	1.026	1.000	0.952	0.930	0.902	1.003
CZE	1.040	1.021	0.975	0.995	1.086	1.075	0.925	1.016	1.016	0.964	0.971	1.023	1.002	1.007
DNK	0.992	1.008	0.961	1.008	1.032	1.000	1.000	1.000	0.992	1.008	1.001	0.991	0.993	0.999
EST	1.016	0.980	0.983	1.044	1.124	0.939	0.971	0.975	1.007	1.001	1.061	0.989	0.971	1.004
FIN	1.021	0.990	0.994	1.044	1.077	0.957	0.988	1.051	1.021	1.035	1.042	0.967	1.124	1.023
FRA	0.995	1.004	0.998	1.005	1.056	0.992	1.002	1.011	1.003	1.019	0.994	1.002	1.001	1.006
DEU	0.995	0.952	0.995	1.003	1.058	0.968	0.989	1.044	0.991	1.011	1.010	1.002	0.994	1.001
GRC	1.351	0.719	0.980	1.039	1.119	1.028	1.050	1.131	1.000	0.969	1.032	0.998	0.976	1.021
HUN	1.033	1.017	1.013	1.018	1.069	0.988	1.030	1.031	1.005	0.982	1.024	1.022	0.968	1.015
IRL	0.963	1.000	1.036	1.027	1.083	1.121	1.007	0.978	1.011	0.963	1.028	1.003	1.018	1.017
ITA	0.994	0.988	0.987	1.003	1.066	0.986	1.014	1.071	1.028	1.002	0.990	1.005	1.001	1.010
LVA	0.884	0.948	1.125	1.060	0.928	1.133	0.772	0.988	1.012	1.050	1.003	1.013	0.969	0.987
LTU	1.016	1.001	0.959	1.005	1.349	0.816	0.990	1.068	1.033	1.016	0.929	1.026	1.002	1.010
LUX	1.000	1.000	1.000	1.000	1.000	1.000	0.951	0.993	1.029	1.029	1.000	1.000	1.000	1.000
NLD	1.000	0.995	0.956	1.023	1.038	1.004	1.014	1.026	1.001	1.025	0.887	1.050	0.997	1.000
POL	0.786	0.827	0.966	1.014	1.058	0.975	0.990	1.019	1.029	0.984	1.002	1.013	0.999	0.971
PRT	0.999	1.021	1.021	1.054	1.023	1.005	1.066	1.091	1.000	0.988	0.988	1.003	0.983	1.018
ROU	0.987	0.833	0.813	0.963	1.144	1.004	0.988	1.072	1.025	0.973	0.988	1.045	1.036	0.986
SVK	0.970	1.011	1.031	1.030	1.096	0.990	1.000	1.081	0.995	0.985	0.963	1.029	1.009	1.014
SVN	1.010	0.999	1.014	1.026	1.033	1.024	1.020	1.303	0.831	1.000	1.008	1.007	0.984	1.016
ESP	0.999	1.011	1.009	1.029	1.048	1.030	1.031	1.034	1.032	0.983	0.969	1.014	0.999	1.014
SWE	1.009	0.991	0.988	1.014	1.067	0.950	1.007	1.034	1.011	1.000	1.000	1.000	1.000	1.005
GBR	1.014	0.997	1.015	1.024	1.063	0.961	1.018	0.982	0.982	0.994	1.002	1.017	1.019	1.007

Note: Each value shows the change from the previous year; "Average" shows the geometric mean during the study period.

correlation coefficients ranged from 0.31 to 0.75 for Model 1, 0.34–0.66 for Model 2, and 0.24–0.61 for Model 3 over the examined period. A clear positive relationship between the efficiency scores and wealth level was observed. For example, Luxemburg had the highest GDP per capita and also the highest relative efficiency score. Zhou et al. (2010) also concluded that GDP per capita had a positive effect on the total factor carbon emission performance (Malmquist carbon emission performance).

In countries with very high average efficiency scores, the time-series efficiency scores were stable, whereas the time-series scores fluctuated for other counties, particularly those with low efficiency scores (Fig. 4 and Tables 5–7). Such inefficient countries were mainly in eastern EU. For example, the range of efficiency scores was wide in Bulgaria, Estonia, Poland, and Romania (Fig. 4). The

Table 7
GML index for 27 EU countries (Model 3).

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Average
AUT	1.006	1.024	1.008	1.012	1.035	1.003	0.990	1.017	1.003	1.024	0.990	0.992	0.989	1.007
BEL	0.974	1.000	1.000	1.004	1.019	1.000	0.997	1.016	1.016	0.983	0.987	0.999	1.008	1.000
BGR	0.734	0.866	0.955	0.966	1.210	1.103	0.944	1.050	1.288	0.942	0.821	0.996	0.953	0.976
HRV	1.024	1.018	1.065	1.089	1.048	1.116	1.000	0.986	0.951	0.992	0.911	0.951	0.976	1.008
CYP	1.094	1.186	0.864	0.905	1.030	0.953	1.123	1.131	1.026	1.000	0.952	0.930	0.902	1.003
CZE	1.040	1.021	0.975	0.995	1.086	1.075	0.925	1.016	1.016	0.964	0.971	1.023	1.002	1.007
DNK	0.992	1.008	0.961	1.008	1.032	1.000	1.000	1.000	0.992	1.008	1.001	0.991	0.993	0.999
EST	1.016	0.980	0.983	1.044	1.124	0.939	0.971	0.975	1.007	1.001	1.061	0.989	0.971	1.004
FIN	1.021	0.990	0.994	1.044	1.077	0.957	0.988	1.051	1.021	1.035	1.042	0.967	1.124	1.023
FRA	0.995	1.004	0.998	1.005	1.056	0.992	1.002	1.011	1.003	1.019	0.994	1.002	1.001	1.006
DEU	0.995	0.952	0.995	1.003	1.058	0.968	0.989	1.044	0.991	1.011	1.010	1.002	0.994	1.001
GRC	1.351	0.719	0.980	1.039	1.119	1.028	1.050	1.131	1.000	0.969	1.032	0.998	0.976	1.021
HUN	1.033	1.017	1.013	1.018	1.069	0.988	1.030	1.031	1.005	0.982	1.024	1.022	0.968	1.015
IRL	0.963	1.000	1.036	1.027	1.083	1.121	1.007	0.978	1.011	0.963	1.028	1.003	1.018	1.017
ITA	0.994	0.988	0.987	1.003	1.066	0.986	1.014	1.071	1.028	1.002	0.990	1.005	1.001	1.010
LVA	0.884	0.948	1.125	1.060	0.928	1.133	0.772	0.988	1.012	1.050	1.003	1.013	0.969	0.987
LTU	1.016	1.001	0.959	1.005	1.349	0.816	0.990	1.068	1.033	1.016	0.929	1.026	1.002	1.010
LUX	1.000	1.000	1.000	1.000	1.000	1.000	0.951	0.993	1.029	1.029	1.000	1.000	1.000	1.000
NLD	1.000	0.995	0.956	1.023	1.038	1.004	1.014	1.026	1.001	1.025	0.887	1.050	0.997	1.000
POL	0.786	0.827	0.966	1.014	1.058	0.975	0.990	1.019	1.029	0.984	1.002	1.013	0.999	0.971
PRT	0.999	1.021	1.021	1.054	1.023	1.005	1.066	1.091	1.000	0.988	0.988	1.003	0.983	1.018
ROU	0.987	0.833	0.813	0.963	1.144	1.004	0.988	1.072	1.025	0.973	0.988	1.045	1.036	0.986
SVK	0.970	1.011	1.031	1.030	1.096	0.990	1.000	1.081	0.995	0.985	0.963	1.029	1.009	1.014
SVN	1.010	0.999	1.014	1.026	1.033	1.024	1.020	1.303	0.831	1.000	1.008	1.007	0.984	1.016
ESP	0.999	1.011	1.009	1.029	1.048	1.030	1.031	1.034	1.032	0.983	0.969	1.014	0.999	1.014
SWE	1.009	0.991	0.988	1.014	1.067	0.950	1.007	1.034	1.011	1.000	1.000	1.000	1.000	1.005
GBR	1.014	0.997	1.015	1.024	1.063	0.961	1.018	0.982	0.982	0.994	1.002	1.017	1.019	1.007

Note: Each value shows the change from the previous year; "Average" shows the geometric mean during the study period.

standard deviations of Bulgaria and Poland, the two countries showing high standard deviations, were 0.27 and 0.21 in Model 1 and 0.19 and 0.20 in Model 2, respectively. Interestingly, the range was wide in the eastern EU countries, but it was relatively stable in the western and northern EU countries. This may be because the latter were in more stable economic condition than eastern countries; thus, their efficiency scores, calculated based on the variables related to countries' economic activities, were also stable (see Fig. 3).

Observing the GML index (Tables 5–7), on the one hand, the EU overall experienced efficiency improvement over the study period, although the degrees were small (1.006). While the environmental performance deteriorated in some countries (mean of 0.971–0.999, depending on the model), mainly in eastern EU countries, performance improved in most countries (mean of 1.000–1.023, depending on the model). On the other hand, the GML index averaged over all countries for each examined year (i.e., the efficiency trends over time) showed that the index was higher than one in 10 out of 17 periods for Model 1, indicating that the EU as a whole has improved its environmental performance in these periods. Similar performance was presented for Models 2 and 3. Over the study period, the index values fluctuated in most of the countries, and all the countries experienced both periods of improvement and deterioration. Interestingly, in most countries, environmental performance improved; average improvement was highest in 2008–2009 for all three models. This may be largely due to economic recovery from the financial crisis of 2007–2008. Observing the index of each country over the examined period, only Bulgaria, Croatia, Estonia, and Latvia presented average deterioration in their performance under Model 1. In contrast, the countries with the highest average improvements from 2001 to 2017 were Germany, Greece, Ireland, and Portugal, whereas Luxemburg and the Netherlands showed steady improvement in their performance in most of the examined years (Model 1). Similar conclusions were obtained for Models 2 and 3.

Finally, the efficiency scores calculated by Models 1 and 2 were strongly correlated (correlation coefficient: 0.75). Therefore, there was a strong correlation between the efficiency scores calculated with the negative output variables $PM_{2.5}$ emissions and waste. Apparently, $PM_{2.5}$ and waste are different types of environmental burdens; however, these results suggest that similar tendencies in $PM_{2.5}$ and waste emissions at the national level exist.

6. Conclusions

In this study, a DEA window analysis technique was applied to measure environmental performance in 27 EU countries from 2000 to 2017. In particular, three DEA models were run using labor, capital, and energy consumption as inputs and GDP and CO_2, $PM_{2.5}$, and waste emissions as outputs. Furthermore, the GML index was applied to evaluate changes in environmental performance over time. The results, which were obtained with comprehensive consideration of energy and economic variables as well as environmental variables, provided a clear indication of countries' environmental performance. In particular, the empirical results indicated that average environmental performance was higher in western EU countries compared to eastern countries. In terms of improvement of environmental performance over time, the greatest improvements were observed in western EU countries, whereas deteriorations were found in some eastern EU countries. Moreover, the economic crisis of 2007–2008 had negative effects (on average) on all EU countries' environmental performance. This negative effect was stronger for eastern EU countries.

The EU has put forward a strategic objective to build an environmentally friendly society in order to improve energy efficiency, combat climate change, and realize sustainable development. To this end, measuring environmental performance is a significant step in decision-making in energy and environmental systems, as it can provide condensed information and insights for monitoring progress and conducting benchmarking comparisons. An analysis such as the one presented in this study enables countries to understand their environmental performance, identify strengths and weaknesses, and set targets for further improvement based on the current best practices of comparable peers. Considering the results of this study, policymakers could identify the main steps that should be followed to improve each country's environmental performance. For example, the observation that a wealthy country was more environmentally efficient than a poor one could help regulators to design policies that promote economic development, helping countries to reach ecological balance and sustainable development. Furthermore, policymakers might understand how environmental efficiency can be influenced by economic shocks.

There are several issues with the present study's application and methodology that should be addressed in future research. For example, the analysis could be extended to examine the driving factors of environmental performance, focusing on the effects of policy measures, environmental research and development, as well as various socioeconomic factors. The relationship between environmental aspects and related topics, such as energy efficiency and security, is also worthy of investigation. Considering that the use of renewable energy is crucial to boosting environmental efficiency, it could be interesting to introduce renewable energy into the analysis. Finally, the extension of the analysis to a global context is also important. On the methodological side, beyond DEA, other similar approaches could also be considered, such as multi-criteria decision aid techniques and stochastic frontier analysis. Moreover, combining methods for environmental performance assessment with scenario and simulation analysis techniques could help researchers to examine various uncertainties that are inherent to long-term environmental policy planning and decision-making.

CRediT authorship contribution statement

Ken'ichi Matsumoto: Conceptualization, Data curation, Validation, Formal analysis, Investigation, Writing - original draft, Visualization, Funding acquisition. **Georgia Makridou:** Conceptualization, Investigation, Validation, Writing - original draft. **Michalis Doumpos:** Methodology, Software, Formal analysis, Writing - original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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