A Two-stage Approach for Energy Efficiency Analysis in European Union Countries

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ABSTRACT

This paper evaluates the energy efficiency of EU countries over the period 2000–2010. At the first stage, data envelopment analysis (DEA) is used, combining multiple energy consumption data and economic outputs. The efficiency estimates obtained from the analysis are evaluated in a second stage through a multiple criteria decision aiding methodology (MCDA). The proposed non-parametric approach combining DEA with MCDA enables modeling of the problem in an integrated manner, not only providing energy efficiency estimates but also supporting the analysis of the main contributing factors, as well as the development of a benchmarking model for energy efficiency evaluation at the country level.

Keywords: Energy efficiency, Data envelopment analysis, Multiple criteria decision aiding

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1. INTRODUCTION

In the 1970s and early 1980s, energy efficiency emerged as a major issue for sustainable economic growth. Even after the 1986 counter oil shock and the decline in oil prices, environmental concerns continued to rise, especially in the context of the growing debates on global warming and climate change, which gave energy efficiency improvement a new perspective. The latter, along with the 1993 world energy crisis, and in combination with the sharp increase in oil prices during the 2000s, today have put energy efficiency on the policy agenda of many countries as a top priority issue.

Governments are increasingly aware of the urgent need to make better use of energy resources. The benefits of more efficient energy use are well known, including reduced investments in energy infrastructure, lower fossil fuel dependency, increased competitiveness, and improved consumer welfare. Efficiency gains also deliver environmental benefits by reducing greenhouse gas emissions and air pollution. Therefore, it is not surprising that tracking economy-wide energy

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efficiency trends is being undertaken in many countries on a regular basis (Ang, Mu and Zhou, 2010).

Energy efficiency has now been recognized as an essential component of sustainable development policies, which seek to achieve a well-balanced trade-off between economic growth and competitiveness, energy security, and environmental sustainability. As noted by Filippini and Hunt (2011), policy making in this area has adopted energy intensity (i.e., energy consumption to gross domestic product [GDP]) as the main indicator for evaluating energy efficiency. However, as Patterson (1996) noted, changes in energy intensity cannot be solely attributed to energy efficiency policies, as there are other important factors that affect energy intensity (e.g., the sector mix of the economy, the mix of the energy inputs, etc.). This is further confirmed by the empirical results presented by Filippini and Hunt (2011) for OECD countries, who also noted the importance of introducing alternative measures controlling for structural economic and energy-related factors. In a wider context, Ryan and Campbell (2012) emphasized the importance of going beyond the analysis of energy-related outcomes when evaluating energy efficiency policies. The framework proposed by the authors suggests the adoption of a broader socioeconomic perspective, which would enable policy makers to generate accurate impact assessments considering a comprehensive range of benefits and costs that result from energy efficiency programs.

Adopting the context introduced in such studies, in this paper the evaluation of energy efficiency is based on a multidimensional context, considering a disaggregated view of energy consumption and economic outputs. Furthermore, following the framework proposed by Ryan and Campbell (2012), we also consider the introduction of an evaluation model that enables policy makers and analysts to consider the trade-offs between the different benefits of energy efficiency. The analysis is based on data collected for European Union countries over the period 2000–2010.

On the methodological side, at the first stage, we use data envelopment analysis (DEA) to measure the relative efficiency of the countries. DEA is a popular, non-parametric efficiency analysis technique with many applications in energy management and environmental planning (see, among others, Boyd and Pang, 2000; Hu and Kao, 2007; Ramanathan, 2005; Zhou, Ang and Poh, 2008a). At the second stage, the DEA efficiency classifications are used as inputs to a MCDA approach, which is used to build an operational model that combines energy efficiency with economic and environmental indicators. Two-stage approaches are often employed in an explanatory setting to identify relationships between efficiency estimates and external factors using parametric regression methods (e.g., OLS, truncated or tobit regression), based mainly on linear models. Instead, in this study we follow a decision-making approach based on a non-parametric multicriteria additive model. The additive model retains the simplicity and transparency of linear models, but it provides the flexibility needed to consider possible nonlinear relationships between energy efficiency and a set of multiple factors that describe its drivers and benefits. The construction of the additive MCDA model is based on a non-parametric approach using linear programming, thus being in accordance with the non-parametric framework of DEA. The resulting multicriteria model complements and enhances the technical efficiency estimates of DEA through the introduction of a transparent composite indicator that enables the evaluation of all countries in a common setting. Thus, the proposed two-stage DEA/MCDA approach provides a framework that policy makers can use to construct a standardized and comprehensible composite energy efficiency and performance evaluation indicator, which can be easily used for benchmarking purposes, allowing the formulation of a complete ranking of all countries under consideration, as well as the monitoring of the performance of any country over time, without having to resort to relative efficiency analyses every time an evaluation is sought. The introduction of the multicriteria approach also enables policy makers to evaluate different types of benefits that result from energy efficiency programs, without restricting the analysis solely to an input/output energy-economic context.

The remainder of this paper has the following structure: In Section 2, a literature review is presented, followed in Section 3 by the presentation of the main methodological tools used in the analysis. In Section 4, the data and variables used in the analysis are described, and in Section 5, the results are presented and described. Finally, in Section 6, the paper concludes, and future research directions are outlined.

2. LITERATURE REVIEW

Energy efficiency is a difficult concept to define. It is often confused with energy conservation, but conservation simply means using less energy, whereas efficiency implies meeting a given demand of energy required to provide products and services with a lower use of resources (Gunn, 1997). The directive on energy end-use efficiency and energy services of the European Council and the Parliament defines energy efficiency as "a ratio between an output of performance, service, goods or energy, and an input of energy" (European Union, 2006). An even trickier task than defining energy efficiency is measuring it. To measure energy efficiency changes over time at the economy-wide level, and to be able to make cross-country comparisons, a rich body of research has emerged. On one hand, various efficiency-related indicators have been developed, with the ratio of total national primary energy consumption to GDP (energy intensity) among the most popular ones. On the other hand, most researchers focus on developing methods to decompose accurately the aggregate energy intensity into the true change in intensities at the disaggregated sectorial levels, and to understand the effects of structural changes in the economy.

Another line of research examines energy efficiency within a framework where energy is one of the many inputs of production, with the most widely used technique being DEA. A recent literature survey by Zhou, Ang and Poh (2008b) listed 100 studies published from 1983 to 2006 using DEA in energy and environmental analysis. According to the survey, 72 of these studies were published between 1999 and 2006, which shows a rapid increase in the number of studies using DEA. Zhou and Ang (2008) presented several DEA-type linear programming methods for measuring economy-wide energy efficiency performance using labor, capital stock, and energy consumption as inputs, and GDP as the desirable output. DEA has also been widely used in energy efficiency studies at the sector, sub-sector, and firm levels.

Bampatsou and Hadjiconstantinou (2004) used DEA to develop an efficiency index, which combines economic activity, CO_2 emissions, and energy consumption of the production process in 31 European countries for 2004. The study also provides estimates for the capability of the countries to achieve sustainable economic development through the reduction of their reliance on fossil fuels. In a similar context, Ramanathan (2005) used DEA to analyze the performance of 17 countries in the Middle East and North Africa in terms of four indicators of energy consumption and CO_2 emissions for the period 1992–1996. The authors concluded that oil-rich countries show no indication of following carbon-friendly policies for their economic development.

Lozano and Gutiérrez (2008) applied a number of non-parametric, linear programming models for measuring energy efficiency in 21 OECD countries from 1990 to 2004, using the environmental DEA technology concept. Lanfang and Jingwan (2009) proposed a non-parametric method based on DEA to measure energy efficiency, taking into account undesirable factors such as water, gas, and solid wastes. In another study, Yu (2010) used a panel data set of 16 OECD countries to estimate the relationship between overall energy efficiency and the behavior of households regarding energy consumption. Ceylan and Gunay (2010) analyzed Turkey's economy-wide

Table 1: Studies that use DEA to Measure Countries' Energy Efficiency

Authors	Year	Sample	Inputs	Outputs
Bampatsou, Papadopoulos and Zervas (2013)	1980–2008	EU-15	Energy consumption of fossil and non-fossil fuels, nuclear consumption	GDP
Chien and Hu (2007)	2001–2002	45 countries	Labor, capital stock, and energy consumption	GDP
Honma and Hu (2008)	1993–2003	47 regions in Japan	Labor employment, private and public capital stocks, electric power for commercial and industrial use, electric power for residential use, gasoline, kerosene, heavy oil, light oil, city gas, butane gas, propane gas, coal, and coke	GDP
Jia and Liu (2012)	2003–2009	30 provinces in China	COD and SO_2 emissions, energy consumption	GDP
Lu et al. (2013)	2005–2007	32 OECD	Value-added industry, population	GDP, fossil-fuel CO_2 emissions
Vlahinić-Dizdarević and Šegota (2012)	2000–2010	26 EU countries	Labor, capital stock, energy	GDP
Wei, Ni and Sheng (2011)	1980–2007	156 countries	Labor, capital, energy consumption	GDP
Yeh, Chen and Lai (2010)	2000–2007	Regions in China and Taiwan	Labor, capital stock, coal, oil, and electricity consumption	GDP, CO_2 and SO_2 emissions
Zhang et al. (2011)	1980–2005	23 developing countries	Labor force, energy consumption, capital stock	GDP

energy efficiency and its energy-saving potential with cross-country comparisons and benchmarking with EU countries, for the period 1995–2007, using a non-parametric frontier approach.

Table 1 presents a brief overview of other studies that used DEA in measuring energy efficiency at the country level.

Furthermore, DEA has gained popularity in environmental performance measurement. Färe, Grosskopf and Hernandez-Sancho (2004) provided a formal index number of environmental performance using DEA with three pollutants (CO_2, SO_X, and NO_X) as undesirable outputs. The proposed index suggests that there may be no clear-cut relationship between pollutants and per-capita income. Zhou, Ang and Poh (2008a) applied environmental performance measures to study the carbon emission performance of eight world regions, in 2002, under different reference technologies. The results show that the environmental performance index of a certain country may change under different environmental DEA technologies because different models are adopted under different situations. As a result, the choice of a specific environmental DEA technology would play an important role in environmental performance measurement. What is more, the study shows that the undesirable outputs' orientation DEA model is particularly attractive because it provides a pure environmental performance measure.

In addition to DEA models, multicriteria decision-analysis has been used extensively to evaluate energy management and efficiency. MCDA is involved with decision problems under the presence of multiple (conflicting) decision criteria, which require the selection of the best alternatives, the ranking of the alternatives according to their overall performance, or their classification into predefined performance groups.

Diakoulaki et al. (1999) used a multicriteria methodology to determine the relative contribution of different factors such as socio-economic indices, structural characteristics, and energy mix of countries in reaching a desired level of energy efficiency. The authors' analysis focused on 13 EU countries and the United States in three points in time, namely, 1983, 1988, and 1993, using data on economic growth, energy consumption, and its breakdown into energy forms and sectors. The results show that richer countries achieve better energy intensity than less developed ones. Appropriate pricing policies (mainly on electricity) and long-term structural changes in the energy system were the main effective means used to achieve efficient energy use in the late 1980s and early 1990s. These remarks agree with existing qualitative estimates about the relative importance of various factors related to energy efficiency at the national level, proving the capability of the proposed methodology to emphasize the examined problem through a detailed quantitative analysis.

Neves et al. (2009) used the soft systems methodology (SSM) and value-focused thinking to elicit and structure objectives in MCDA models for evaluating energy efficiency initiatives, thus illustrating how these two methodologies may be used fruitfully. The study showcases SSM as a useful tool, which helps to clearly define the decision problem context and support the main actors involved, as well as to unveil the relevant objectives for each stakeholder. For example, in the case of the government and regulators, the main society-related objectives could be reducing environmental impacts (emission of atmospheric pollution, water pollution and etc.), improving the quality of service, and improving domestic comfort and welfare, among others. Whereas, in the case of corporations the main objectives are minimizing cost, maximizing revenues (or minimizing revenue losses), etc. Moreover, Mavrotas and Trifillis (2006) used basic principles from DEA to facilitate the evaluation of the environmental performance of 14 EU countries through a MCDA approach. The analysis was based on energy intensity, emission intensity, acidifying gases intensity, and other indicators related to the composition of the countries' energy mix, use of land, and recycling. The results show that the overall evaluation of countries with dispersed performances along the criteria is more sensitive to modifications in the relative importance of the evaluation criteria.

Furthermore, Zhou, Ang and Poh (2006) attributed the increased popularity of MCDA, especially in decision-making for sustainable energy, to the multi-dimensional nature of the sustainability goal and the complexity of the socio-economic and biophysical systems. For example, Qin et al. (2008) developed an MCDA-based expert system to tackle the interrelationships between climate change and adaptation policies in Canada, and to facilitate the assessment of climate-change impacts on socio-economic and environmental sectors, as well as the formulation of relevant adaptation policies in terms of water resources management and other watersheds.

This overview indicates that despite the rich literature on the use of DEA and MCDA for energy efficiency analysis and planning, there has been almost no attempt to combine, in a unified context, the capabilities that the two approaches provide. Thus, this study contributes to the literature by adopting a two-stage DEA/MCDA approach. On the one side, the DEA model results provide efficiency classification estimates and facilitate the identification of the sources of inefficiencies. On the technical side, however, efficiency scores often have limited discriminating power when used for evaluation and do not allow a full ranking of the countries, which is important for benchmarking and comparative analyses purposes. Adler, Friedman and Sinuany-Stern (2002) provided a comprehensive review of different DEA-based ranking techniques, but according to Bouyssou (1999), many of these approaches (e.g., cross-efficiency and super-efficiency models) have significant methodological shortcomings. MCDA techniques, on the other hand, are particularly useful for evaluation problems under multiple (conflicting) criteria. Among others, MCDA provides several approaches for constructing composite indicators, which can be used to evaluate the energy performance and efficiency of a country and the impact of energy efficiency programs. Such composite indicators would be of interest to policy makers as these indicators introduce a transparent and easy-to-use framework that can support the decision-making process and the evaluation of the implemented actions and policies. The popularity of such composite indicators for sustainability assessment and environmental performance evaluation (Emerson et al., 2012; Munda and Saisana, 2007) indicates their usefulness. Furthermore, in the context of energy efficiency, MCDA models enable the consideration of a wider set of additional socio-economic issues related to the benefits and impacts of policy decisions. For instance, Ryan and Campbell (2012) presented a hierarchical typology of such issues, starting from international impacts (e.g., greenhouse gas [GHG] emissions, moderated energy prices, etc.), and also including national, sectoral, and individual impacts (e.g., job creation, macroeconomic effects, competitiveness, wellbeing, etc.). The consideration of these issues complements and enriches the results obtained from input/output energy-economic analyses, thus providing policy makers with a tool that enables them to quantify and evaluate the impacts of policy decisions in a wide context. However, in the MCDA framework the construction of evaluation models requires preferential information from the decision/policy makers (e.g., trade-offs and value judgments), which is often not available due to cognitive or time limitations.

Thus, DEA (and other frontier analysis techniques) and MCDA constitute useful tools for quantifying and measuring energy efficiency, each adopting a different perspective (for a comprehensive discussion in the context of DEA, see Belton and Stewart, 1999). Nevertheless, despite the differences, the combination of these approaches provides the advantages of both while addressing their limitations. Possible ways of combining the two paradigms have already been explored. For instance, Doyle (1995) suggested the use of the cross-efficiency analysis approach of DEA to rank a set of alternatives through a linear weighted evaluation model, whereas Sinuany-Stern, Mehrez and Hadad (2000) adopted a similar approach using the AHP method to rank the alternatives on the basis of the cross-efficiency pairwise comparisons. However, multicriteria evaluation methods based on cross-efficiency comparisons have been criticized for proving incoherent results (Bouyssou, 1999). In a different setting, Lahdelma and Salminen (2006) combined the ideas of DEA with the simulation framework of the SMAA multicriteria evaluation method (Lahdelma and Salminen, 2001), to obtain stochastic efficiency estimates in problems there input-output variables are uncertain or imprecise. As it is evident, the above approaches have focused either on introducing new multicriteria evaluation procedures inspired from ideas in DEA or on enhancing DEA with ideas from MCDA. Instead, in this study the adopted two-stage approach focuses on building a multicriteria model that will allow the evaluation of all alternatives (countries) on the grounds of their DEA efficiency classification (i.e., DEA and MCDA are used in combination instead of mixing ideas from both fields to introduce a new evaluation technique). Based on this framework, the next section discusses the two-stage approach DEA/MCDA used in this study.

3. METHODOLOGY

3.1 Data Envelopment Analysis

DEA, originally proposed by Charnes, Cooper and Rhodes (1978) is a non-parametric frontier technique that measures the inefficiency of a particular entity by its distance from the best practice frontier constructed by the best-performing entities within the group. This methodology is well-established for evaluating the relative efficiencies of a set of comparable entities (decision-making units, DMUs; e.g., countries) that transform multiple inputs (energy and non-energy inputs) into multiple outputs (desirable and undesirable). Relying on linear programming techniques, and without having to introduce any subjective or economic prices (weights, costs, etc.), DEA provides a non-parametric estimate of the efficiency of each DMU compared to the best practice frontier constructed by the best-performing DMUs (Zhou and Ang, 2008).

The assessment of energy efficiency in the context of DEA can be derived from a production theory point of view. In particular, in accordance with Zhou, Ang and Zhou (2012), assume that energy (E) and non-energy inputs (NE) inputs are used to produce outputs (Y) in an economy-wide context and let $T = \{(N, NE, Y)/(N, NE)$ can produce $Y\}$ be production technology set, which describes the feasible transformations of the inputs to outputs. From an energy efficiency point of view, the goal is to minimize energy use while keeping all inputs and outputs within the production technology set. Thus the following Shephard distance function can be defined:

$$D(E,NE,Y) = \sup\{a:(E/a,NE,Y) \in T\} \tag{1}$$

Countries for which $1/D(E,NE,Y) < 1$ are energy inefficient as their energy use could have been decreased within their production technology set and the ratio $0 < 1/D(E,NE,Y) \leq 1$ is a measure of energy-efficiency, with higher values corresponding to more efficient countries. Boyd (2008) analyzed the same modeling framework in the context of stochastic frontier analysis, which is used in the Energy Star program of the U.S. Environmental Protection Agency for assessing energy efficiency of consumer products, commercial buildings, and manufacturing.

To implement this framework in the context of DEA, assume that there are data on K_E energy inputs, K_{NE} non-energy inputs, and M outputs for N countries (DMUs). For the ith countries, these are represented by the vectors x_i^E, x_i^{NE}, and y_i, respectively. The $K_E \times N$ matrix X_E for the energy inputs, together with the $K_{NE} \times N$ matrix X_{NE} for the non-energy inputs, and the $M \times N$ output matrix Y represent the data for all available cases. Then, the energy efficiency of country i is estimated through the solution of the following linear program (Charnes, Cooper and Rhodes, 1978), which is referred to as the CCR model:

$$\begin{aligned} \min \quad & F = \theta_i - \varepsilon(\mathbf{1}\mathbf{s}_i^E + \mathbf{1}\mathbf{s}_i^O) \qquad (2) \\ \text{Subject to:} \quad & \mathbf{X}_E\boldsymbol{\lambda} - \theta_i \mathbf{x}_i^E + \mathbf{s}_i^E = 0 \\ & \mathbf{X}_{NE}\boldsymbol{\lambda} \leq \mathbf{x}_i^{NE} \\ & \mathbf{Y}\boldsymbol{\lambda} - \mathbf{s}_i^O = \mathbf{y}_i \\ & \boldsymbol{\lambda}, \mathbf{s}_i^E, \mathbf{s}_i^O \geq 0, \theta_i^C \in \mathbb{R} \end{aligned}$$

where **1** denotes a vector of ones. The solution of this linear program provides the energy efficiency estimate $\theta_i = 1/D(E,NE,Y)$ for each country i relative to other countries in the data, from the perspective of reducing the energy inputs, in accordance with the production framework discussed above. $\mathbf{s}_i^E$ and $\mathbf{s}_i^O$ are vectors of slack variables for the energy and non-energy inputs as well as the outputs, respectively, indicating the improvements that an inefficient country should achieve to become efficient. In the objective function $\varepsilon \approx 0$ is a small, positive constant that allows the solution procedure to give first priority to the optimization of θ_i. Denoting by F^* the value of the objective function of problem (2) at its optimal solution, country i is classified as efficient if and only if $F^* = 1$(i.e. if the efficiency score is $\theta_i = 1$ and the slacks are zero).

The above model (2) assumes constant returns to scale (CRS). Variable returns to scale (VRS) can be introduced by simply adding the convexity constraint $\lambda_1 + \cdots + \lambda_N = 1$. This constraint ensures that a country is benchmarked only against other units of similar size. The resulting model is known as the BCC model (Banker, Charnes and Cooper, 1984).

Although the CCR model is invariant to the orientation of the modeling approach (i.e., input/output oriented), in the BCC model the orientation plays an important role. Most studies dealing with applications of DEA models in energy efficiency and other related areas have adopted an input-oriented approach. This is line with the nature of energy efficiency management, as a country or organization has more control over its available resources (energy, labor, capital, etc.), rather than the level of outputs (e.g., GDP). Following this approach, we use an input-orientation for the CCR and the BCC model. In this study, we use a panel data set consisting of 286 country-year observations for the 26 EU countries over 11 years, thus measuring energy efficiency using a panel data set, based on a common frontier that characterizes the efficiency of the countries over all years, thus taking into account the correlation between the observations from a same country over whole period of the analysis. The adopted approach allows the comparison of the efficiency results over time and the identification of the observed efficiency trends.

3.2 Building an Operational Efficiency Evaluation Model through a Multicriteria Approach

As described earlier, in this study the results from the input/output frontier framework of DEA are combined with an MCDA modeling approach. The scope of the latter is to build an overall energy efficiency and composite performance indicator that will enable the evaluation of all countries in a common and standardized setting. Furthermore, such an indicator will have enough discriminatory power to allow the complete ranking of all countries (both DEA-efficient and inefficient). DEA efficiency scores often lack discriminatory power, as they do not differentiate among efficient cases. This difficulty also applies to inefficient cases, as making direct comparisons among such DMUs are generally meaningful only for those belonging to the same facet of the efficient frontier (Kao and Hung, 2005). Furthermore, increasing the number of input and output variables inflates the efficiency scores (thus yielding upward biased efficiency estimates) and leads to efficiency results with diminishing discriminating power (as more DMUs appear fully efficient). On the other hand, the multicriteria model is appropriate for benchmarking purposes, allowing the consideration of all pertinent factors that describe (direct or indirectly) energy efficiency and its multiple benefits, and enabling comparisons to be performed over time (for a single or multiple countries) based on a well-defined functional model without having to resort to relative estimates such the ones used in DEA. Of course, the linear programming formulations of DEA do not pose any computational issues as they are easy to solve. Nevertheless, the sample-dependent character of the relative efficiency estimates obtained with DEA is not an appealing feature in a benchmarking and evaluation context, as it makes it difficult to perform direct comparisons whenever the set of data observations is altered or the available data are updated. On the other hand, the multicriteria model enables analysts and policy makers to perform evaluations and monitor the performance of a country over time using data solely at the country level, without having to resort to relative assessments in comparison to data from a set of peer countries.

The second stage of the analysis is implemented using a multicriteria classification technique. In particular, the efficiency classifications, as defined from the DEA results, are used to build the multicriteria evaluation model. The countries are classified as efficient or inefficient according to their DEA efficiency scores and a multicriteria model is then constructed, which combines n criteria, so that the model's classifications are as close as possible to DEA's efficiency classification. The UTADIS multicriteria method is used for this purpose (Doumpos and Zopounidis, 2002). The UTADIS method leads to the development of an additive value function of the following form:

$$V(\mathbf{x}_i) = \sum_{j=1}^{n} w_j v_j(x_{ij}) \in [0,1], \tag{3}$$

where w_j is a non-negative trade-off constant for evaluation criterion j and $v_j(x_j)$ is the corresponding marginal value function normalized between 0 and 1. The marginal value functions provide a decomposition of the aggregate result (global value) in terms of individual assessments at the criteria level. According to its global value, a country i is classified as efficient if and only if $V(\mathbf{x}_i) > t$, where t is a cut-off point that distinguishes efficient countries from inefficient ones. The additive value function and the optimal cut-off point are estimated through linear programming techniques (a brief description is given in the Appendix). In contrast to parametric regression techniques, the use of linear programming provides flexibility to analysts and policy makers in building models that are not only based on historical trends and statistical relationships, but also take into account their expert judgments and policy objectives with respect to the properties of the final evaluation model (e.g., the tradeoffs between energy, socio-economic, and environmental factors).

4. DATA AND VARIABLES

For the empirical analysis, we used a panel data set for 26 EU countries[1] over the period 2000–2010. During this period, the EU formulated an energy policy based on the Kyoto Protocol, through numerous directives and actions plans focused on improving energy efficiency. At the same time, the introduction of the Euro has changed the economic environment and the global financial crisis that started at the end of 2007 had a strong negative effect, mainly in eastern and southern European countries that experienced recession, significant budget deficits, and high sovereign debt. In light of these developments, it is particularly interesting to examine energy efficiency in European countries over the selected period.

All data were obtained from Eurostat, except for labor force data, which were collected from the World Bank, and capital stock, which was obtained from the AMECO database of the European Commission. Choosing an appropriate set of indicators and evaluation criteria was clearly an important issue. The multidimensional character of energy efficiency and its multiple aspects (environmental, socio-economic, and technical) make it very difficult to specify a comprehensive set of relevant measurement indicators universally applicable under all contexts. In this study, the input and output variables, presented in Table 2, were selected based on data availability and the existing literature. All the economic variables are measured in constant prices, thus allowing comparisons over time eliminating the effect of inflation.

In the analysis, we considered two different settings for the input variables and two different settings for the output variables, thus leading to four DEA models (henceforth denoted as M1, M2, M3, and M4).

The first setting for the output variables uses only GDP, whereas in the second setting GDP is replaced by the value added from the industry and the services sectors, thus providing more

1. Malta is excluded due to unavailability of some data.

Table 2: Input and Output Variables

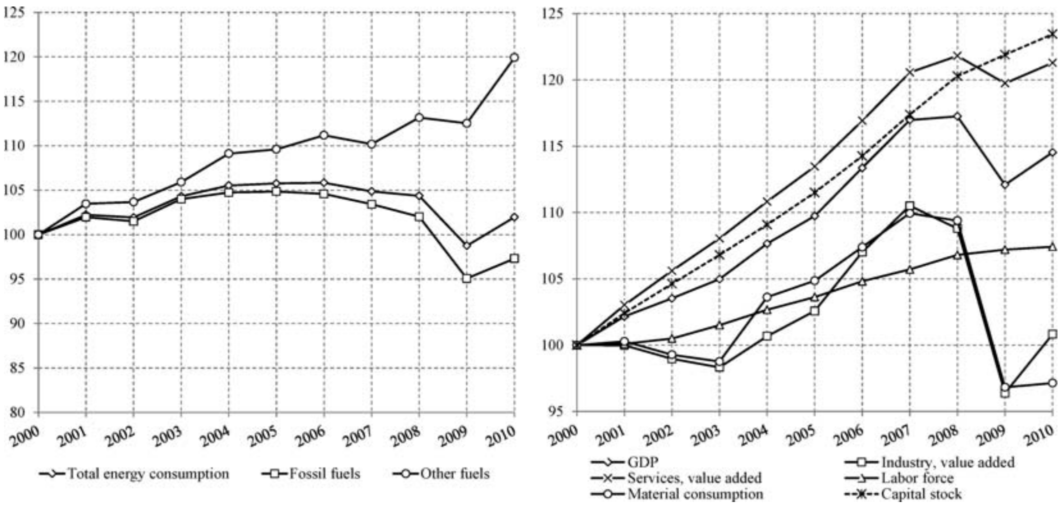
Type	Variable	Unit	M1	M2	M3	M4
Outputs	Gross domestic product	Million euros*	√	√		
	Industry, value added	Million euros*			√	√
	Services, value added	Million euros*			√	√
Inputs	Total energy consumption	Thousand tons of oil equivalent	√		√	
	Fossil fuels energy consumption	Thousand tons of oil equivalent		√		√
	Other fuels energy consumption	Thousand tons of oil equivalent		√		√
	Labor force	Economically active population	√	√	√	√
	Domestic material consumption	Thousand tons	√	√	√	√
	Capital stock	Billion euros*	√	√	√	√

* Constant prices

detailed insight into the economic output of each country. Generally, the industry sector is more energy intensive than the service sector. Therefore, a structural shift from high-energy-consumption secondary industry to low-energy-consumption tertiary industry may lead to an improvement in overall energy efficiency, solely due to structural changes in the economic activity of a country. Yu (2010), using the variations in the share of value-added from the industry and services sectors, in terms of GDP, showed that the service share has a significant positive impact on energy efficiency. However, he also showed that the industry share has an insignificant, small positive effect (less than 0.25%) and, as a result, may not affect energy efficiency at the country level substantially. Wei, Ni and Shen (2009) as well as Zhao, Ma and Hong (2010) examined energy efficiency in China and found that it is negatively associated with the secondary industry share in GDP, and that the simultaneous improvement of energy efficiency in energy-intensive sectors is mainly due to industrial policies. Furthermore, Zhao, Ma and Hong (2010) found that low energy prices have directly contributed to high industrial energy consumption, and indirectly to the heavy industrial structure. Arcelus and Arocena (2000) compared the multifactor productivity levels and the changes across countries and across time, using a nonparametric model. The evidence obtained from a sample of 14 OECD countries indicates a high degree of catching-up among the various countries for the total industry, manufacturing, and services sectors. Hu and Kao (2007) claimed that a newly industrialized economy will have lower total-factor energy efficiency than agriculture-dominant and service-dominant economies. Hence, the industrial structure of an economy is a crucial factor for energy efficiency, and thus the energy-saving ratio; an industry-dominant economy can improve its energy efficiency and save energy more efficiently and effectively by shifting the economy structure toward services. Therefore, it is important to decompose the influence of the value added to GDP by the industry and services sectors.

Similar to the outputs, two settings are also used for modeling the inputs. In particular, the first setting has four inputs, involving total energy consumption, capital stock, labor force, and materials consumption. Capital, labor, and material force are used as the non-energy (non-discretionary) inputs, in accordance with the KLEM production function framework. As discussed in section 3.1, the specification of these variables as non-discretionary inputs assumes that even though a country's outputs are produced through the utilization of such resources, the obtained energy efficiency estimates are obtained solely from the perspective of minimizing energy consumption. In the second setting, total energy consumption is replaced by fossil fuel consumption and the consumption of other energy sources (renewables and nuclear), thus providing a more refined view of the energy mix that each country uses. The majority of studies that measure energy efficiency

Figure 1: Evolution of the Selected Variables over the Period 2000–2010 (year 2000 = 100)



using the DEA framework choose inputs such as energy consumption, capital, and labor (see the studies listed in Table 1). Ramanathan (2005) also used fossil fuel energy consumption as a minimization indicator, in the sense that countries with lower values in this indicator are more preferred. Mandal (2010) used data related to capital, energy, labor, and raw materials as inputs, and claims that environmental regulation has the potential to positively affect energy use. Moreover, Hu and Wang (2006) observed a high correlation among the inputs (labor, capital stock, energy consumption, and total sown area of farm crops) and the single output (real GDP). In the same vein, Hu and Kao (2007) showed that labor employment, capital stock, and energy consumption actually do correlate with GDP performance. The authors also found that energy efficiency can be over-estimated or under-estimated if energy consumption is taken as a single input with a certain portion of GDP output produced not only by energy input but also by labor and capital. Hence, using a multiple-inputs framework is important to evaluate energy efficiency correctly (Hu and Wang, 2006).

Figure 1 presents the evolution of the selected variables aggregated over all countries over the period of the analysis. As far as the energy-related variables are concerned, the consumption of other fuels shows a steady increase throughout the examined period, mainly due to the increased use of renewable sources. However, total energy consumption and the consumption of fossil fuels increased slightly up to 2005–2006, followed by a decrease in the subsequent years. As far as the economic variables are involved, GDP and the services value added increased considerably up to 2008, before falling in 2009 due to the global economic crisis. Capital stock, on the other hand, increased considerably over the examined period (about 25% increase overall).

Figure 2 illustrates the time trends for the relative shares of the two energy inputs to the total energy consumption (fossil and other fuels – decomposed into nuclear and renewables). It is clear that the share of renewables in the energy mix has followed an increasing trend, starting from 2003. During the same period (2003–2010), the share of fossil fuels has declined, but it still ranges in levels that exceed 76%. The share of nuclear energy has also followed a slightly declining trend.

Although the selected input and output variables are meaningful in the context of DEA, they are not useful in a multicriteria setting, as they do not allow for direct comparisons among the

Figure 2: Evolution of the Shares of Fossil Fuels, Nuclear, and Renewables to Total Energy Consumption over the Period 2000–2010

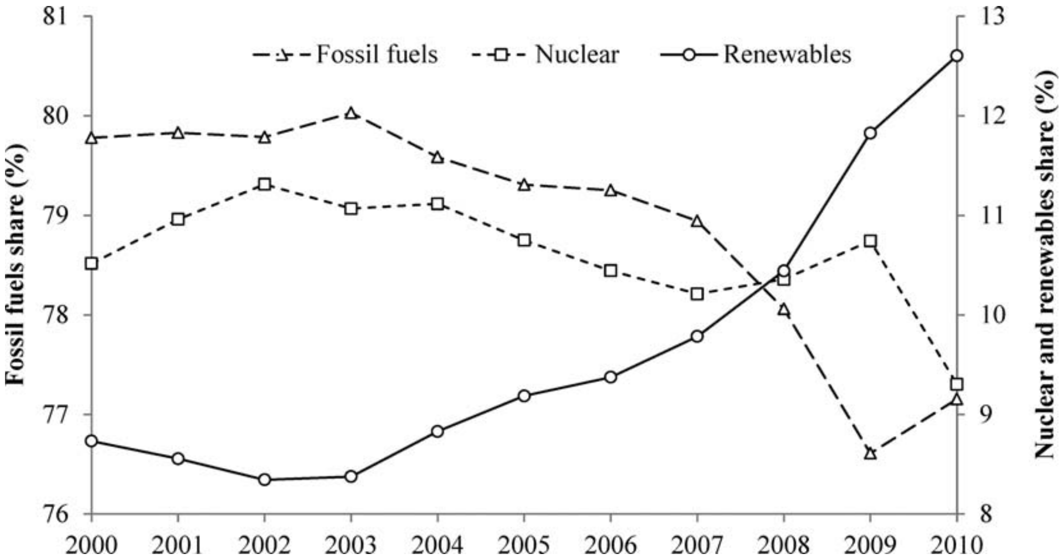


Table 3: Evaluation Criteria for Building the Second Stage Multicriteria Model

Energy intensity (Kgoe/€1000)	Current account balance/GDP
Gross fixed capital formation/GDP	Unemployment rate
Environmental taxes/GDP	Greenhouse gas emissions/GDP
Resource productivity (GDP/domestic material consumption, €/kg)	Primary energy source indicator
GDP growth	Economy focus indicator

countries. In particular, in DEA the countries are compared based on a ratio defined by each country's aggregate outputs to its aggregate inputs. However, the multicriteria evaluation context relies on the use of a set of indicators on which the countries are directly comparable. The multicriteria modeling framework provides flexibility in the specification of these indicators. In this study, their selection is based on the framework introduced by Ryan and Campbell (2012), who emphasized the need to analyze energy efficiency in a context much broader than the usual input/output energy-economic production model. Based on this framework, we use indicators that are relevant to the input/output modeling context discussed earlier for the DEA models, but also cover additional issues that policy makers may consider relevant for evaluating the impacts of energy efficiency programs as pointed out by Ryan and Campbell (2012).

In particular, the second stage of the analysis is based on a set of ten evaluation criteria. Similar to the modeling approach used in DEA, the selected criteria (Table 3) combine energy efficiency indicators, economic growth and competitiveness indicators, environmental indicators, and two original indicators related to the primary energy source and the focus of the economy in each country. Furthermore, the selected indicators cover the top three levels (international, national, sectoral) in the hierarchical structure of energy efficiency benefits presented in Ryan and Campbell's work (2012). In particular, energy intensity is used as the main proxy for energy efficiency as it is widely adopted by policy makers for assessing energy efficiency. GDP growth is used as the main indicator for measuring economic development, thus enabling the evaluation of the economy-wide impact of energy efficiency. However, economic output and growth are affected by many factors beyond energy use, and as explained, energy efficiency has multifaceted benefits. To consider these issues, we use additional variables, including resource productivity (for the effect of materials' use),[2] gross fixed capital formation/GDP (the effect of investments), and current account balance/ GDP (competitiveness).[3] In addition, we control for the effect of environmental taxes, which affect energy costs and consumption, as well as the labor dimension (unemployment rate). Furthermore, following the existing literature, we consider the environmental effects of energy use and economic activity, by considering the level of GHG emissions in relation to GDP. Ryan and Campbell (2012) also noted similar dimensions (GHG emissions, job creation, macroeconomic effects, competitiveness, among others) as important impacts of energy policies that must be introduced in a comprehensive evaluation framework. Finally, to control for the energy and economic mix, two additional indicators are introduced. The primary energy source indicator is used to consider the energy mix of a country in a particular year, indicating whether renewables, nuclear, natural gas, solid fuels, or petroleum consumption was the main energy source for the country. Economy focus is modeled as a binary indicator, designating whether the value added by the industrial sector of a country (as a percentage of GDP) in a given year is above or below the overall average of all countries. Introducing this indicator in the analysis enables the consideration of the differences among the various countries in terms of their level of industrial development (as industry is generally more energy intensive than services). The combination of the selected indicators in an additive evaluation model as described in section 3.2 not only provides policy makers and analysts with a comprehensive efficiency evaluation model, but also enables them to explore the trade-offs among the multiple aspects of energy efficiency (i.e., energy, economic, and environmental indicators).

5. RESULTS

5.1 DEA Results

Figure 3 illustrates the average constant returns-to-scale (CCR) and variable returns-to-scale (BCC) efficiency scores of the four models over the entire period of the analysis. The differences between the CCR and BCC scores are generally limited in most countries, thus indicating that overall the scale effect is weak (the scale efficiency defined by the ratio of CCR to BCC efficiency is on average more than 80% for the vast majority of the countries). However, some smaller countries such as Estonia, Bulgaria, and Cyprus, exhibit scale efficiency consistently below 65%, thus indicating that their scale size is a limiting factor. As far as the differences between the

2. Resource productivity is measured by Eurostat as the ratio of GDP to domestic material consumption and is reported in euros per kg. The same definition is also employed by OECD (2008). According to OECD this is a type of economic-physical measure which is suitable when the focus is on the decoupling of value added and resource consumption. Alternatively, physical or economic approaches can also be used to measure resource productivity (using physical or money values, respectively, for both the nominator and the denominator). The economic approach is more suitable when the focus is on the minimization of input costs, whereas the physical approach focuses on the maximization of outputs for a given level of inputs and a given technology. Dahlström and Ekins (2005) however, argue that such a physical measure is a resource efficiency indicator, rather than a measure of productivity.

3. Policies for improving energy efficiency can have a positive effect on current account balance through reducing energy dependency and energy imports.

Figure 3: Average Efficiency Scores for the Four Models (CCR left, BCC right)

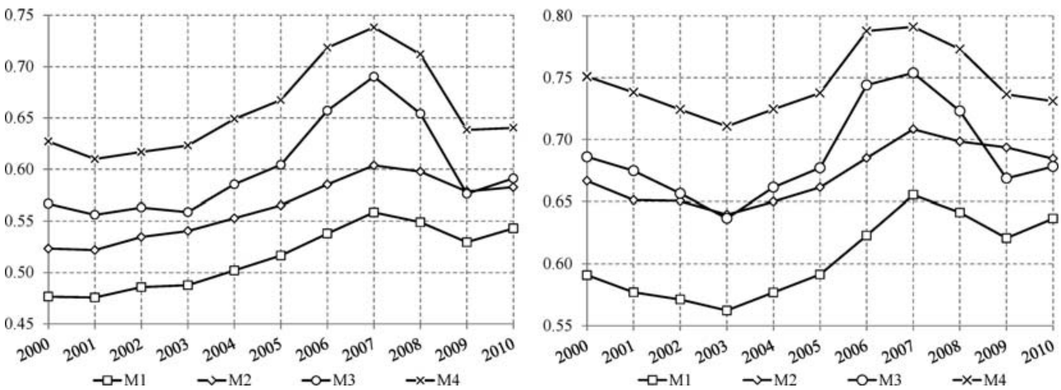


Table 4: Correlations between the DEA Efficiency Scores and Energy Intensity

	CCR				BCC			
	M1	M2	M3	M4	M1	M2	M3	M4
Pearson correlation	−0.79	−0.80	−0.74	−0.75	−0.69	−0.72	−0.64	−0.68
Kendall's τ	−0.83	−0.74	−0.64	−0.57	−0.62	−0.54	−0.46	−0.45

four models used in the analysis are concerned, it is evident that the models with more inputs and outputs lead to higher efficiency estimates, but this is fairly common in DEA (i.e., the DEA efficiency scores generally increase with the number of inputs and outputs). Generally, there are high correlations among the results of the four models. The correlations are stronger for the pairs M1-M2 (about 97% correlation for the CCR models and 94% for the BCC models) and M3-M4 (about 95–96% correlation coefficient under the CCR and BCC models). However, the similarities between each model M1 and M2 to M3-M4 are lower (correlation coefficient 84–92%). The pair of models M1-M2 differs from M3-M4 in the way that the outputs are defined, with the latter providing a more detailed breakdown of the economic output (M1-M2 consider only GDP, whereas M3-M4 consider the value added by services and industry as separate outputs). Thus, for European countries, the effect due to the consideration of the structure of their economic activity appears to be stronger than the effect due to the introduction of a breakdown by their energy mix.

When the efficiency estimates under the four modeling settings are compared with the energy intensity of the countries in the panel data set (Table 4), strong negative correlations are observed in all cases (all correlations are significant at the 1% level). The correlations are stronger for models M1 and M2, which use GDP to measure economic output (similarly to energy intensity). The same negative relationship between energy intensity and the obtained efficiency estimates was also observed (at different magnitudes) for each of the countries particularly under the CCR models, whereas for the BCC models the discrepancies were higher. However, in accordance with the suggestions of Filippini and Hunt (2011), the relationship between energy efficiency estimates obtained by frontier techniques and energy intensity needs further analysis, possible over extended time periods to derive conclusive evidence on the characteristics of the countries for which energy intensity might be a poor proxy for energy efficiency.

Table 5: Overall CCR Efficiency Scores (averaged over 2000–2010) and Percentage Changes (model M4)

	Average	2000–10	2008–10		Average	2000–10	2008–10
Luxembourg	0.998	0.0	0.0	Finland	0.749	−29.2	−44.4
Ireland	0.993	−4.4	−4.4	Poland	0.738	8.1	−19.8
Netherlands	0.978	0.0	1.7	Greece	0.591	26.4	2.1
Denmark	0.969	0.0	0.0	Cyprus	0.582	12.5	0.1
United Kingdom	0.967	0.0	0.0	Spain	0.561	10.8	5.2
Sweden	0.908	16.1	0.0	Portugal	0.523	12.0	10.5
Germany	0.859	13.3	−8.5	Belgium	0.505	6.9	−6.5
Latvia	0.850	−26.6	−47.5	Romania	0.296	24.0	−59.0
Austria	0.847	1.9	−0.9	Slovakia	0.287	107.3	−28.2
Slovenia	0.843	−49.8	−49.6	Hungary	0.252	16.8	3.5
Italy	0.832	1.2	−8.9	Czech Republic	0.226	36.0	4.8
Lithuania	0.758	2.8	−48.3	Estonia	0.147	16.4	−16.3
France	0.751	30.0	10.8	Bulgaria	0.107	81.3	−5.5

When the efficiency trends are examined over time, the period 2000–2007 is characterized by increasing global (CCR) efficiency scores according to models M1 and M2. A similar trend is also observed for models M3 and M4, particularly after 2003. The BCC efficiency scores obtained with the assumption of variable returns to scale also follow an increasing trend for the period 2003–2007. However, both during 2000–2003 and 2007–2009 an efficiency decline is evident. In both the CCR and BCC results the effect of the global economic crisis is clearly shown by the significant decrease of the efficiency scores during 2008–2009 (under all modeling settings), whereas signs of minor recovery are evident in 2010. The 2008–2009 decline is larger under the models M3-M4. Overall, the results indicate that when the structure of the economy is explicitly considered (i.e., separation of GDP into the value added by the industry and services in models M3 and M4), then the efficiency improvements appear to be more conservative. Based on these findings, the subsequent analysis focuses on model M4, which provides the most comprehensive consideration of the economic outputs of the countries and their energy mix.

Table 5 presents the countries' global CCR efficiency scores averaged over all 11 years of the analysis, as well as the percentage changes over the entire period of the analysis and during the recent economic crisis (2008–2010). Luxembourg, Ireland, the Netherlands, Denmark, and the United Kingdom (UK), achieved the highest efficiency scores overall, whereas Bulgaria, Estonia, the Czech Republic, and Hungary have the lowest scores. Similar efficiency estimates are reported for European countries in the recent study by Halkos and Tzeremes (2013), who applied DEA to 25 European countries using data from 2010. Similar to our results, the authors found countries such as Sweden and the UK had high efficiency scores, whereas countries such as Greece, Hungary, the Czech Republic, and Spain performed poorly (the correlation of our results with those reported in Halkos and Tzeremes (2013) for the CCR model M4 is 0.35). In another study, Vlahinić-Dizdarević and Šegota (2012) examined a set of 26 European countries (not identical to those in our study). Similar to our results, they found countries such as the UK, Luxembourg, Ireland, and Denmark performed consistently well over the period 2000–2010, whereas Bulgaria, the Czech Republic, Greece, and Hungary performed poorly. Chien and Hu (2007) reported similar results using DEA in a sample of OECD countries for 2001–2002 (e.g., Luxembourg, the UK, Denmark, Ireland had high efficiency). In contrast to these DEA-based studies, Filippini and Hunt (2011) used stochastic frontier analysis for a panel data set of 29 OECD countries over the period 1978–2006, using set of explanatory variables related among others to energy consumption, climatic conditions,

Table 6: Suggested Average Changes in Inputs and Outputs (% changes)

	Industry value added	Services value added	Fossil fuels	Other fuels
2000	0.80	6.01	−0.70	−2.22
2001	0.92	5.21	−0.60	−1.03
2002	1.61	5.60	−0.45	−1.49
2003	1.62	3.75	−0.51	−1.29
2004	1.78	4.91	−0.23	−0.32
2005	1.52	3.86	−0.15	−0.43
2006	1.15	3.25	−0.16	−1.05
2007	1.56	3.17	0.00	−0.44
2008	2.10	4.26	0.00	−0.68
2009	1.96	6.47	0.00	−3.70
2010	0.34	6.33	0.00	−2.08
Average	1.40	4.80	−0.26	−1.34

GDP, energy prices, and country size. Their results differ from the ones reported in the present study and other DEA-based studies. Except for the longer time period used by Filippini and Hunt, the discrepancies could be due to the differences in the variables used, the different sample of countries, and of course the method used for the analysis.

Table 6 summarizes the estimated energy inputs and economic outputs improvements (averaged by year) that inefficient countries should seek to achieve to improve their efficiency status (under the BCC model). The figures reported for the input variables involve the percentage reductions required for a country in a particular year to become efficient, whereas for the output variables the reported improvements involve the target percentage increase in the level of economic activity (industry/services value added). In terms of energy conservation, the results indicate that inefficient countries should implement policies that focus on energy consumption from non-fossil fuels (i.e., renewables and nuclear. A closer examination further indicates some time trends, which highlight the increasing importance of the consumption of non-fossil fuels, particularly after 2008 (the most recent time trends are clearly more relevant for policy making purposes). On the other hand, the inefficiencies of the countries with respect to the consumption of fossil fuels has followed a declining trend, and at the same time the suggested improvements with respect to other fuels increased. Thus, even though there has been an improvement of the energy mix from an environmental perspective (i.e., promotion of renewables), energy conservation still remains a challenge, with the relative importance of renewables increasing over fossil fuels. On the output side, the improvement targets for the services sector are consistently higher compared to the industry sector. This is in accordance with the increasing importance of services for the economic activity in EU countries, as evident by the time trends illustrated in Figure 1. Nevertheless, it should be noted that the design and implementation of policies for improving energy efficiency should also consider the interactions and synergies among different actions, the economic and environmental trade-offs, as well as complementarity and substitutability effects (Frondel and Schmidt, 2002; Neumayer, 2003), which may differ from country to country.

5.2 The Multicriteria Model

For the reasons explained in the previous subsection, the development of the multicriteria evaluation model in the second stage of the analysis is based on model M4. Given the CCR efficiency scores obtained with model M4, all countries are classified as efficient (efficiency score equal to 1) or inefficient (efficiency score lower than 1). The objective of the second stage analysis is to

Table 7: The Mean of the Selected Indicators for Efficient and Inefficient Countries

	Efficient	Inefficient
Energy intensity (Kgoe/€1000)	188.08	356.95
Gross fixed capital formation/GDP	3.32	3.12
Environmental taxes/GDP	3.08	2.63
Resource productivity (€/kg)	1.61	1.14
GDP growth (%)	4.00	2.42
Current account balance/GDP	0.88	−3.05
Unemployment rate (%)	5.41	8.80
Greenhouse gas emissions/GDP	0.48	0.92
Primary energy source indicator	2.06	1.84
Economy focus indicator	1.65	1.43

Notes: The primary energy source indicator is modeled through a 3-point scale (1 = solid fuels; 2 = gas, petroleum, nuclear; 3 = renewables), and the economy focus is a binary indicator (0 = industry focused; 1 = services focused).

Table 8: Criteria Trade-offs (weights in %)

Criteria	Weight	Criteria	Weight
GDP growth	21.46	Primary energy source indicator	9.28
Energy intensity	17.83	Environmental taxes/GDP	7.42
Resource productivity	11.84	Gross fixed capital formation/GDP	6.92
Unemployment rate	9.80	Greenhouse gas emissions/GDP	4.97
Current account balance/GDP	9.79	Economy focus indicator	0.69

construct an operational multicriteria evaluation model for evaluating the energy efficiency of all countries in a multidimensional context. The UTADIS multicriteria method is used to fit a model on the efficiency classifications of DEA, combining the selected set of criteria presented in Section 4 (Table 3).

Overall, the sample includes 49 efficient country-year observations and 237 inefficient cases. Table 7 presents the means of the selected indicators for each group. Most differences are statistically significant at the 5% level according to the non-parametric Mann-Whitney test, with the exception of the environmental taxes to GDP ratio. These comparative results indicate that energy-efficient countries have lower energy intensity, employ material resources in a more productive manner, experience higher GDP growth, are more competitive (lower current account deficits), have lower unemployment rates, lower GHG emissions, emphasize the use of renewables, and are more services-oriented.

Table 8 presents the estimated criteria trade-offs in the multicriteria additive model fitted to the above data. These trade-offs are proxies of the relative importance of the criteria. The indicators' trade-offs indicate that GDP growth and energy intensity are the two most important factors, followed by resource productivity, unemployment, current account balance/GDP, and the indicator involving the energy mix of the countries. These results are in accordance with the wider socio-economic impacts of energy efficiency that Ryan and Campbell (2012) noted, as they imply that except for increasing the value of economic activity and reducing energy intensity, additional factors such as strengthening the competitiveness of the economy, improving resources productivity, and promoting employment and the use of renewable energy, could also be part of the policy/decision-making process when it comes to analyzing energy efficiency and assessing its benefits and impacts.

Figure 4: Multicriteria Energy Efficiency Scores for Three Selected Indicators

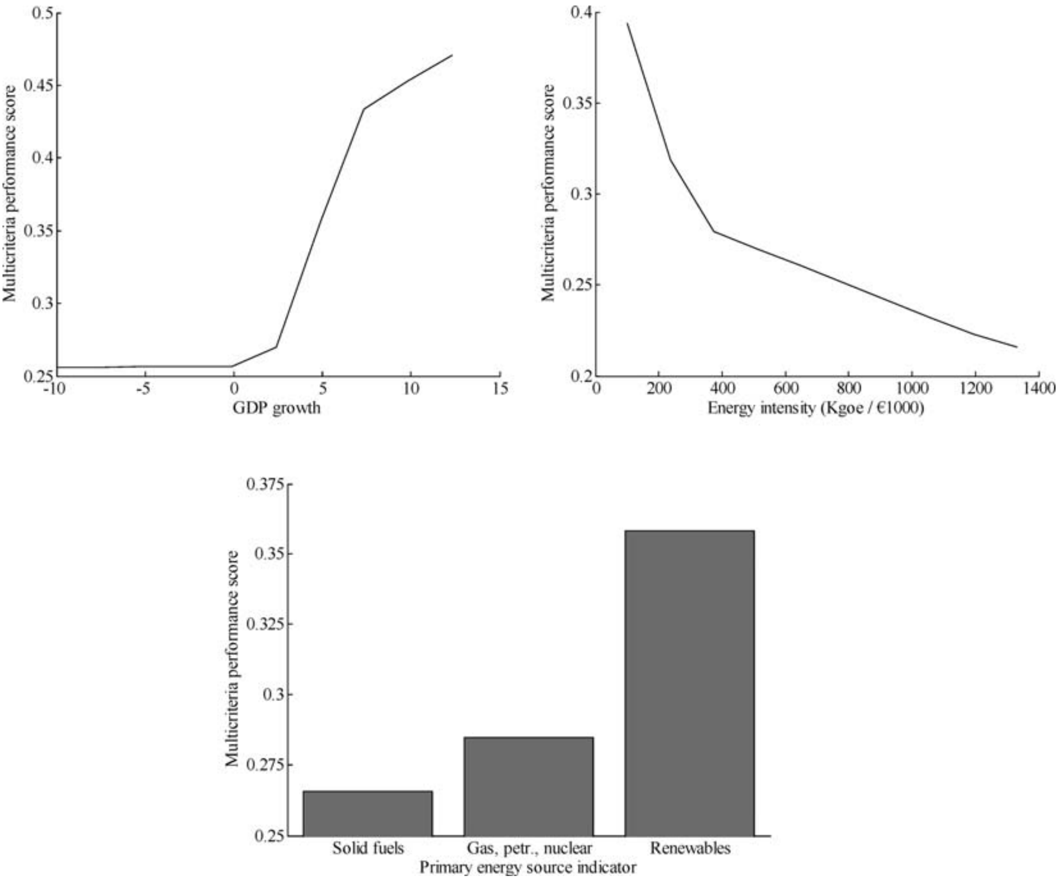


Table 9: Extreme Average Differences between the Annual Rankings of DEA and the Multicriteria Model

MCDA upgrades		MCDA downgrades	
Cyprus	7	Poland	−10
France	5	Slovenia	−6
Estonia	5	Germany	−5
Greece	3	Lithuania	−3

Figure 4 provides further details on the sensitivity of the multicriteria energy efficiency score regarding the three selected criteria, namely GDP growth, energy intensity, and the indicator of the primary energy source in each country. In accordance with the indicators' trade-offs, the sensitivity of the global (multicriteria) efficiency score is larger for the GDP growth ratio, with countries that achieve positive GDP growth rates receiving much higher scores compared to countries in recession. Furthermore, the multicriteria score improves at the highest rate when energy intensity falls below 400 Kgoe/€1000, and renewables are used as the main energy source. Such results and these levels on the selected indicators can support policy makers in setting target goals for the benefits that energy-efficiency programs should achieve.

The overall agreement between the efficiency classifications obtained with the DEA model (M4, CCR) and the ones of the MCDA model is 94%. In particular, 87.8% of the country-year observations classified by DEA as efficient are classified in the same group by the MCDA model, whereas the agreement level for the DEA inefficient cases is 95.4%. Table 9 provides a more detailed list of the countries with the largest differences in their annual rankings according to the DEA and MCDA models. In particular, Cyprus, France, Estonia, and Greece are better by the MCDA model compared to their rankings with the DEA model. For instance, Cyprus's position in the annual rankings obtained with the MCDA model improved by 7 grades (on average) compared to its ranking with the DEA model. On the other hand, the MCDA model significantly downgraded countries, such as Poland, Slovenia, Germany, and Lithuania. The downgrade for Poland is 10 grades (on average) in the annual rankings of countries. Interestingly, the group of countries significantly upgraded by the MCDA model have lower energy intensity compared to downgraded ones (310 Kgoe/€1000 vs. 344 Kgoe/€1000, on average; p-value = 1.8% according to the Mann-Whitney test), lower unemployment (8.3% vs. 10.2%, p-value < 1%), lower GHG emissions/GDP (0.89 vs. 0.96, p-value = 4.9%), and their economy is more services-oriented. These qualities compensate for the lower GDP growth rates that the upgraded countries have achieved (2.8% on average) as opposed to the downgraded ones (3.4% on average; difference insignificant at the 10% level). Thus, the MCDA model's results introduce some refinements in the estimates obtained with DEA based solely on a frontier-based input-output framework.

6. CONCLUSIONS

In this study, a two-stage approach to energy efficiency evaluation was developed and implemented in the context of EU countries. The proposed approach considers energy efficiency in a multidimensional context, combining multiple energy consumption data, economic outputs, structural indicators, and environmental factors. DEA was used under different modeling settings to perform a relative evaluation of the efficiency of the EU countries over the period 2000–2010. The results obtained with a more comprehensive consideration of economic outputs and energy consumption provided a better indication of true energy efficiency, compared to simpler models that consider only aggregate energy and GDP data.

Combining the results of DEA with a multicriteria classification technique enabled the construction of an operational model that provides analysts and policy makers with evaluations of the countries' energy efficiency in absolute terms, based on a common setting for all countries, without the need to resort to relative sample-dependent assessments (e.g., based on DEA) whenever an new evaluation must be performed. Furthermore, this modeling approach enables analysts and policy makers to consider a rich list of the impacts of energy-efficiency programs and actions, explore the underlying trade-offs, and ultimately reach more informed decisions. Of course, such a multicriteria evaluation model, which is built based on the results of a frontier technique such as DEA, needs to be periodically updated in accordance with the changes in the economic environment and the energy markets.

The results of the empirical analysis indicate that despite the considerable improvements achieved in terms of energy intensity, a more refined view of energy consumption and economic activity data shows that there is still much to be done to improve the actual energy efficiency of EU countries. The economic crisis of the past few years has had negative effects (on average).

Taking into account the results of this study, policy makers could identify the main steps that should be followed to improve each country's energy efficiency. Furthermore, the significance of each step can be measured, leading to more informed decisions in terms of priorities given. Weighing different policy measures is a challenging task; however, the results of this study could significantly help policy makers in their decision process. For example, the observation that a services-oriented economy is more efficient than an industry-oriented one or the fact that renewable energy sources should gradually displace fossil fuels could help regulators design policies to support certain sectors of the economy or certain energy sources. Furthermore, combining MCDA with frontier techniques, as suggested in this study, enables policy makers to consider a much wider range of impacts of energy efficiency programs, instead of focusing solely on an input-output energy-economic production framework.

Future research could examine a wide range of issues. Among others, these may involve more detailed data on structural factors, the analysis of specific energy-intensive business sectors, the enrichment of the data set with countries outside the EU, and a more extensive time period, as well as the evaluation of the actions and policies implemented to improve energy efficiency at the country level.

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APPENDIX

The multicriteria evaluation model developed with the UTADIS method is based on a sample of m observations (e.g., countries) each described over a set of n evaluation indicators. The observations are pre-classified into classes/categories defined in an ordinal manner. For simplicity, here it will be assumed that there are only two classes, involving m_E energy-efficient countries (denoted by E) and m_I inefficient countries (denoted by I). The UTADIS method fits an additive (nonlinear) model on the given classification of the observations in the sample.

The model optimization process is simplified by setting $v_j'(x_{ij}) = w_j v_j(x_{ij})$ in (2), which leads to the following equivalent alternative form of the additive evaluation model:

$$V(\mathbf{x}_i) = \sum_{j=1}^{n} v_j'(x_{ij}) \tag{4}$$

In this form, the marginal value functions $v_1', v_2', \ldots, v_n'$ are scaled between zero and the trade-off constants of the criteria $w_1', w_2', \ldots, w_n'$. No restrictions are imposed on the functional form of the marginal value functions, other than that they are piecewise linear functions, non-decreasing for maximization indicators (e.g., GDP growth) and non-increasing for minimization criteria (e.g., energy intensity).

The estimation of the additive model that best fits the given classification of the observations is performed through the solution of the following mathematical programming problem:

$$\min \quad \frac{1}{m_E}\sum_{i\in E}\sigma_i + \frac{1}{m_I}\sum_{i\in I}\sigma_i \tag{5}$$

$$\text{Subject to:} \quad \sum_{j=1}^{n} v_j'(x_{ij}) + \sigma_i \geq t+\delta \qquad \forall\, i\in E$$

$$\sum_{j=1}^{n} v_j'(x_{ij}) - \sigma_i \leq t-\delta \qquad \forall\, i\in I$$

$$v_j'(x_{kj}) - v_j'(x_{\ell j}) \geq 0 \qquad \forall\, k,l \text{ with } x_{kj}\geq x_{\ell j}$$

$$\sum_{j=1}^{n} v_j'(x_j^*) = 1, \sum_{j=1}^{n} v_j'(x_{*j}) = 0$$

$$v_j'(x_{ij}),\, \sigma_i,\, t \geq 0 \qquad \forall\, i=1,\ldots,m, j=1,\ldots,n$$

The objective of this formulation is to minimize the overall weighted classification error (controlling for the number of observations from each class). The non-negative variables σ define the classification error as $\sigma_i = \max\{t+\delta - V(\mathbf{x}_i), 0\}$ for the efficient cases and $\sigma_i = \max\{V(\mathbf{x}_i) - t + \delta, 0\}$ for the inefficient ones, where t is the cut-off point that distinguishes the two classes (to be estimated) and δ is a small positive constant. The first two constraints are used to define the error variables. The third set of constraints ensures that the marginal value functions are non-decreasing (assuming that all criteria are expressed in maximization form), whereas the next two equality constraints normalize the global scores in $[0, 1]$. The highest possible score is assigned to an ideal country defined by the best available data on all criteria $(x_1^*, \ldots, x_n^*)$, whereas an anti-ideal country that comprises of the least preferred available data on all criteria $(x_{*1}, \ldots, x_{*n})$ is assigned score equal to zero.

Introducing a piecewise linear form for modeling the marginal value functions allows expressing the above optimization model in linear form, which is easy to solve even for large data sets. Detailed descriptions of the resulting linear programming formulation can be found in the work of Zopounidis and Doumpos (1999) and Doumpos and Zopounidis (2002).