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Energy efficiency in the European Union: What can be learned from the joint application of directional distance functions and slacks-based measures?

Economics Department

Roberto Gómez-Calvet
David Conesa
Ana Rosa Gómez-Calvet
Emili Tortosa-Ausina

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Roberto Gómez-Calvet
Universitat de València
roberto.gomez@uv.es

David Conesa
Universitat de València
conesa@uv.es

Ana Rosa Gómez-Calvet
Universitat de València
ana.rosa.gomez@uv.es

Emili Tortosa-Ausina
Universitat Jaume I and IVIE
tortosa@eco.uji.es

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Abstract

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Roberto Gómez-Calvet
Universitat de València

David Conesa
Universitat de València

Ana Rosa Gómez-Calvet
Universitat de València

Emili Tortosa-Ausina
Universitat Jaume I and Ivie

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Communications to: Roberto Gómez-Calvet, Departament de Matemàtiques per a l'Economia i l'Empresa, Facultat d'Economia, Avinguda dels Tarongers s/n, 46022 València, Spain. Tel.: +34 963828369, fax: +34 963828370, e-mail: `roberto.gomez@uv.es`

1. Introduction

The operation of power plants for electricity and derived heat production during the past decades provided the energy required for technological progress and economic development, leading to a rise in the living standards of many countries around the world. This type of operation has both positive and negative effects for the society in general, as well as for the economy and the environment, in particular. For these and related reasons it is relevant to evaluate the electricity and derived heat generation process, bearing in mind not only the technical (and positive) aspects, but also the negative externalities which arise in the process.

This process involves consumption of resources, and is subject to several factors. Electricity is a secondary source of energy generated from other primary sources, the most important ones being: (i) coal; (ii) nuclear; (iii) natural gas; (iv) oil; and (v) renewable sources (mainly hydro power, wind and solar sources). As a consequence, the first decision a country should make is to choose among these available primary sources—ideally, those that provide a better fit for each country's energy strategy, or *mix* (Bousquet and Ivaldi, 1998)—certain countries might decide to emphasize the use of renewable sources, while others might either promote, or limit, the use of nuclear energy. This decision will ultimately be influenced by political, economic, technical and environmental factors. In this respect, there are many circumstances to consider such as the availability of natural resources, a crucial factor to bear in mind, and the lack of certain primary sources, which may constitute an important condition for the energy mix adopted. Whatever the primary energy involved might be, the final outcome will be generation of electricity power for the country.

Unfortunately, not all primary resources can be transformed into electricity, and a significant proportion is lost in the process, usually as unwanted heat—i.e. there is *inefficiency* involved in the process. Hence, an important issue to evaluate is the balance between the primary resources actually consumed and the final output available. Although the positive aspects—the beneficial impact on both economic activity and economic growth—usually prevail, there are also harmful effects such as the release of greenhouse gases and other emissions or radioactivity, all of them related to the rise in power plant operations that should also be considered.

In this particular respect, over the last two decades, there has been an ongoing tendency to care about (and, also, initiatives to address) the harmful effects of certain pollutants, such as carbon dioxide (CO_2), sulfur dioxide (SO_2), or nitrous oxide (NO_x). Pollutants like SO_2 have been controlled up to a certain level (Vestreng et al., 2007) and industrialized countries are trying to limit their amount, while attempting to simultaneously persuade developing nations about the importance of this issue.[1] In the particular case of Europe, in 1992 the former European Community reassessed its environmental policies for achieving the goal of sustainable development in the next century,[2] with a strategy and general approach of setting long term objectives and focusing on a more global approach.[3]

In this context, the main goal of this study is to analyse the efficiency in the electricity and derived heat generation process for 25 members of the European Union (EU25) during the early 2000s. In this regard, when focusing on power generation, an effective climate change mitigation strategy for the short and medium term calls for the production of energy in the most *efficient* possible way (Jaraitė and Di Maria, 2012). The starting point with regard to the electricity generating capacity in either emerging economies or developed countries is very different and, in the case of the EU, we find remarkable differences in the standards of living of its country members. However, in order to benefit the global environment, the cleanest technology should be available to all countries. Therefore, efforts should be made to analyse the energy consumption, CO_2 and other emissions, and development in different countries, in order to design and to implement the best environmental policies, or to introduce disciplinary measures when necessary. Our particular objective is to obtain a rank, index, or benchmark that will allow a comparison of EU countries which, in our case, will not only be based on finding a balance between the electricity and derived heat produced and the total primary energy consumed in the process, but will also control for relevant environmental and economic issues involved in the production process. This will be done by providing an explicit comparison of the different methodologies which have been considered for measuring efficiency in this specific context, with a special focus on those ones with better abilities to model the (likely) negative effects that may arise in the electricity and derived heat generation process.

There is a broad literature which has been analysing this and related issues, although in the particular case of the EU the available literature is not particularly large. Specifically, the

[1]For this reason, the United Nations Conference on Environment and Development (UNCED) held in Rio de Janeiro in 1992, pointed out two important sets of principles: (i) "Precautionary Principles" (15^{th} Principle); and (ii) "Internalization of Environmental Cost" (16^{th} Principle). The Kyoto Protocol (1997) and its latest review (2010) gave climate change an important role by increasing the number of countries concerned with the goal of achieving "stabilization of concentrations of greenhouse gases (GHG) in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system" (United Nations Framework Convention on Climate Change, UNFCC, Article 2, 1992).

[2]The long term goals were stated in the 5^{th} Environmental Action Programme, "Towards Sustainability".

[3]One of the target sectors of the programme was "Energy", and air quality is clearly linked to this sector. The Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC) shows that warming of the climate system is unequivocal, and provided compelling evidence that climate change is very likely to be due to the observed increase in anthropogenic greenhouse gas concentrations.

literature on the aggregated measurement of environmental performance can provide condensed information for analysts and decision makers dealing with energy and environmental-related issues (Zhou et al., 2007). Within this particular field, there have been two main approaches for constructing environmental performance indexes (EPIs) which, from the point of view of operations research, can be classified into *indirect* and *direct* approaches. According to the former, the key economic, energy and environmental sub-indicators are first identified, and then normalised and integrated into an overall index using a particular weighting scheme (see, for instance Esty et al., 2008). In contrast, in the latter, which has gained importance over the last few years (Färe et al., 1996; Färe et al., 2004; Tyteca, 1997; Zaim, 2004; Zhou et al., 2006; Zofio and Prieto, 2001), the indicators are directly obtained after defining a set of inputs and outputs of the environmental study under analysis using frontier approaches such as Data Envelopment Anaysis (DEA).

However, in the particular field of energy and environmental studies, following the survey by Zhou et al. (2008a), the assumption used by the traditional DEA models that all outputs should be maximised might be inappropriate when undesirable, or unwanted outputs are also generated as by-products in the production process (Zhou et al., 2007).[4] As indicated by Scheel (2001), several approaches have been proposed to deal with this issue, and most of them follow the concept of *radial* efficiency measures, which assume the reduction of inputs (and undesirable outputs), or the increase of desirable outputs, in the *same* proportion so as to become efficient; yet this assumption does not always match real production processes, where some variables may not have this proportional behaviour.

An alternative taxonomy of DEA models is to choose between oriented and non-oriented models, where the orientation (or its absence) refers to the variable to be optimised—inputs, outputs, or undesirable outputs. If there is a clear attempt to look for inefficiencies among a certain set of variables, oriented models may be an appropriate option. Yet if these concerns refer to more than one set of variables (which is usually the case in environmental performance analysis), then non-oriented models would represent the best alternative. In general, non-oriented efficiency measures provide more reasonable results for energy and environmental studies because of their enhanced ability to handle simultaneously both desirable and undesirable outputs. Because of these advantages, in recent years empirical research on efficiency measurement in this particular setting has focused more tightly on non-oriented models, in what is known as *the full space of inputs and outputs* or, more briefly, the <input-output> space. In this particular field, one of

[4] A review and systematic investigation on DEA model building with undesirable inputs and outputs can be found in Liu et al. (2010). The literature on undesirable outputs is evolving, and recent contributions (Førsund, 2009, such as) consider the traditional treatment of bad outputs suffer from serious weaknesses.

the most prominent contributions are those by Briec (1997), who introduced a graph measure of technical efficiency which is a special case of the directional distance function (DDF).[5]

Within this particular non-oriented approach, some other studies such as those by Chung et al. (1997), Färe et al. (2001) or, more especially, Chambers et al. (1996), have also been considering Directional Distance Functions (DDF). However, DDF approaches have the disadvantage of requiring the specification of a directional vector which is partly arbitrary. An alternative is provided by the slacks-based efficiency measures, which have been extensively developed by Tone and his collaborators (Tone, 1997, 2002, 2004a,b; Tone and Tsutsui, 2006; Tone, 2010; Tone and Tsutsui, 2010a,b, 2011).[6] These Slack-Based Measure (SBM) models share their basic underpinnings with DDF, since both are categorised as non-oriented models (in their basic form), and base their measures in the slacks of the optimized variables, although they differ in their definition of the objective function. The relationship between them has been analysed carefully in Färe and Grosskopf (2010). The main strengths of these measures relate to their ability to provide a more practical index with higher discriminating power than radial models, yielding specific inefficiency measures for each optimised variable. However, despite their advantages, SBM models have barely been used in this literature, with few exceptions (see, for instance Hu and Wang, 2006; Wei et al., 2011; Zhou et al., 2006, 2007). Taking into account the disparate number of applications in environmental studies using either DDF or SBM approaches, we consider it is interesting *per se* providing an explicit comparison of the results yielded by both methodologies in a relevant context as that of energy policy in the European Union.

According to the survey by Zhou et al. (2008a), benchmarking of electricity utilities accounts for the highest number of studies in the area of energy efficiency, however our analysis differs from previous contributions applied to the electricity sector in that we will be considering the electricity and derived heat production as a production process with high influence of environmental policies. In the particular context of the European Union, on which we focus, this issue is especially relevant. In this respect, using both the SBM and DDF models is particularly interesting due to their ability to account for undesirable outputs, as commented on above. In addition to this, as far as we know, there are no previous empirical contributions in the literature considering slacks in the DDF model.

Our results show that neglecting the role of slacks in the DDF model may overestimate the measured efficiency. As a matter of fact, comparing results between both the SBM and DDF

[5] See also more recent contribution by Russell and Schworm (2009).

[6] See also (Pastor et al., 1999).

models show a higher correlation when slacks are included in the latter. When the number of dimensions is large relative to the number of observations, slacks might be hiding an important part of inefficiency. Along this line, the available results one may find in the literature are scarce. Among them we can highlight those obtained by Picazo-Tadeo et al. (2011), who stressed the importance of slacks in explaining the total eco-efficiency by computing the weighting of slacks inefficiency on the total inefficiency in the context of a radial model.

The article proceeds as follows. Following this introduction, Section 2 briefly examines the energy generation in the European Union. Section 3 presents the methodology to compare the efficiency among countries. Section 4 provides data information, along with the definition of inputs and outputs, and Section 5 presents and discusses the results. Finally, Section 6 presents some conclusions.

2. Energy generation in the European Union

The electricity sector presents both a challenge and an opportunity for curbing the greenhouse gas emission into the environment.[7] On the one hand, it is a *challenge* because electricity is mostly generated from fossil fuels, which accounts for more than 40% of global energy-related CO_2 emissions. These are non-renewable resources that, when burnt, produce energy but also by-products that pollute when released into the environment. Among these undesirable products we find carbon dioxide (CO_2), which is a greenhouse gas[8] whose emissions do not result from inefficient combustion of fossil fuels—CO_2 is a product of ideal combustion of carbon. Considering that the emissions of carbon into the environment are directly proportional to the burnt carbon based fuels (coal, oil or natural gas, among others), the challenge comes from the fact that it is impossible to maintain the level of non-renewable fossil primary energy and, simultaneously, to decrease the amount of CO_2 released. This challenge is further stressed if we take into account that, under current trends, the annual carbon emissions associated with electricity generation and derived heat is projected to surpass the 4,000 Mt C level[9] worldwide by 2020 (Sims et al., 2003).

On the other hand, the electricity sector also represents an *opportunity* regarding GHG

[7] According to the International Energy Agency (2009), addressing climate change requires "nothing short of an energy revolution".

[8] Greenhouse gases in the atmosphere absorb and release radiation within the thermal infrared range. This process is the fundamental cause of the greenhouse effect. The most important greenhouse gases in the earth's atmosphere are water vapour (H_2O), carbon dioxide (CO_2), methane (CH_4), nitrous oxide (NO_x), ozone (O_3) and chlorofluorocarbon (CFCs). There is a broad consensus among scientists on the links between the increasing amount of greenhouse gas released into the atmosphere and global climate change.

[9] Mt C means millions of tonnes of carbon matter. Carbon matter accounts for 27.27% of total CO_2 mass.

emissions abatement because they are easier to monitor and control from a limited number of centralised, large power stations than from millions of vehicles, aircrafts, small boilers, or even ruminant animals. Therefore the electricity sector is likely to become a primary target in any future world where GHG emissions controls are implemented and GHG mitigation is valued.

In Table 1, obtained from Eurostat (2011) we can observe the figures corresponding to year 2009, and their shares of primary sources in the electricity generation for the European Union countries. The figures in Table 1 corroborate the importance of non-renewable sources in the European Union. The energy from conventional thermal power plants represents 44.05% of the total. This source relies exclusively on fossil fuels (coal, oil and natural gas) as a primary source. Once we add nuclear energy, the share is 78.79%. Considering the combined contribution of total conventional thermal and nuclear sources, coal has the largest share in the EU (23.36%), and also worldwide and, therefore, it seems difficult to shift electricity production to renewable sources (which represent 19.95%) in the near future. Natural gas has also a relevant share (17.30%), which is growing sharply in many regions of the world due to its increasing availability. In addition, the use of combined cycle gas turbine (CCGT) has increased its thermodynamic efficiency, making this source more appealing, and has also enabled the use of smaller power plants, which translate into benefits in the reduction of electricity transport losses.

As indicated above, nuclear power also represents a hefty share for the EU countries (34.74% of gross electricity generation), some of whom were planning to increase its use, yet in several cases these policies are being revised—especially after the earthquake and the subsequent tsunami in Japan in March, 2011. The main advantages of nuclear energy are the production stability, very low marginal cost (in terms of €/Mwh) and zero CO_2 generation. Hydro power (as well as pumped storage, which accounts for just 1.27%) has important limitations in the EU due to the orography and weather dependence. Finally, the item "other renewable sources" (basically wind, solar, biomass and geothermal) have been actively promoted by European governments and the European Union, but still have a low share on the overall set of sources—less than 20% including hydro, as indicated in Table 1. In this scenario, with close to 80% of electricity generation coming from fossil and nuclear power plants, in the short term those efforts devoted to increasing efficiency and reliable replacement with renewable energy are revealed as key objectives.

In this particular context, policies and efforts in the European Union designed to increase environmental protection can be classified into several categories. A possible classification is to consider, on the one hand, those aimed at increasing the saving and efficiency on the *demand* side (end-users) and, on the other, those aimed at shifting the production (*supply side*) to reduce, or to eliminate, carbon dioxide and radioactivity in the generation process.

Several methods for GHG abatement are available on the generation side, on which we focus. These would include: (i) to increase the efficiency conversion of fossil fuels into electricity, since the current EU conversion average was about 49.5% in 2009 (Eurostat, 2011), and technical progress may increase this amount up to 60% in the near future (co-generation, i.e. combined generation of electricity and heat, and combined cycle gas turbine, CCGT, can help to achieve these figures); (ii) shifting the electricity generation to low-carbon fossil fuel techniques, e.g. the use of natural gas instead of coal or oil; (iii) decarbonization of fuels and flue gases, and carbon dioxide sequestration.

If the goal is to remove the CO_2, some alternatives are:

- To use nuclear power stations. Nuclear energy can produce as much energy as fossil fuels with a low marginal cost. Concerns about safety, radioactivity waste disposal and proliferation make it a controversial alternative. During the last decades, a reduction in research and development in this field, along with political issues have relegated this source to a marginal position. Research initiatives into nuclear fusion or fuel reprocessing are necessary alternatives.

- To increase the use of renewable sources of energy. Much effort has been carried out in these fields, offering new opportunities and reducing the costs per KWh. Nevertheless there are several important difficulties related to these sources, among which we may highlight availability, storage of energy, and losses in transport.

The present economic crisis has contributed to deceleration of the fossil fuel consumption growth, but this is not a positive fact. The actual generation capacity in *developed countries* is much higher than their needs due to the economic stall, and efforts to shift to more efficient and environmentally friendly technologies have been deferred to the future. As the energy sector is characterised by high capital needs and long payback, there are fewer opportunities to change, update or modify technologies.

The scenario in *developing countries* is rather different, since their energy needs are increasing and the available technology is not always the best. Developed countries can invest in GHG reduction and make these technologies available to the other countries. With active participation of developed economies seeking new technologies, developing countries can achieve an important contribution in the fight against global warming which will contribute to global benefit.

For all these reasons, we consider it appropriate to carry out a benchmarking study of countries including the source of primary energy and negative effects in the environment and its conclusions should encourage countries to achieve a better performance in the electricity and derived heat generation process.

3. Models

In what follows, we present the nonparametric frontier techniques used to compare the performance of the 27 EU member states in our study.[10] One of the most popular nonparametric methods for measuring efficiency is the DEA framework. These have been widely used since the eighties after the influential work by Charnes et al. (1978), which developed the ideas of measurement of efficiency from Farrell (1957). DEA methods combine the estimation of the technology that defines a performance standard (usually called the technology), and the evaluation of the achievements against the established standard.

The background of the DEA literature is production theory, and the main underlying idea is that the units being compared have a common underlying technology. In particular, once the inputs and outputs are defined, the production possibilities set $\mathcal{S}$ which models the transformation of inputs $\mathbf{x} \in \mathbb{R}_{+}^{m}$ into good outputs $\mathbf{y}^g \in \mathbb{R}_{+}^{s_1}$ and bad outputs $\mathbf{y}^b \in \mathbb{R}_{+}^{s_2}$ is:

$$\mathcal{S} = \left\{(\mathbf{x}, \mathbf{y}^g, \mathbf{y}^b) : \mathbf{x} \text{ can produce } (\mathbf{y}^g, \mathbf{y}^b)\right\}. \tag{1}$$

Yet in real world applications we seldom know the technology $\mathcal{S}$, but all DEA variants (in particular DDF and SBM methods with undesirable outputs) overcome this problem by estimating the technology $\widehat{\mathcal{S}}$ from observed data. Clearly, this estimation process can also be performed using statistical methods (in what is usually called parametric methodologies). The particularities about the DEA approach are the way in which the approximation of the technology is constructed (performed using mathematical programming and an activity analysis approach instead of maximum likelihood or Bayesian estimation) and the resulting properties of the evaluations.

In our case, data consist of a known vector of inputs and outputs (both desirable and undesirable) of $L = 27$ countries, namely:

$$\mathcal{Z} = \{(\mathbf{x}_i, \mathbf{y}_i^g, \mathbf{y}_i^b), i = 1, \ldots, L = 27\}, \tag{2}$$

[10] Our presentation of this methodology closely follows those of Cooper et al. (2007) and Bogetoft and Otto (2011).

where $\mathbf{x}_i = (x_{i1}, \ldots, x_{im})' \in \mathbb{R}^m_+$, $\mathbf{y}^g_i = (y_{i1}, \ldots, y_{is_1})' \in \mathbb{R}^{s_1}_+$ and $\mathbf{y}^b_i = (y_{i1}, \ldots, y_{is_2})' \in \mathbb{R}^{s_2}_+$ are the input, good output and bad output vectors corresponding to country i, $i = 1, \ldots, L = 27$ respectively.

The basic DEA models mainly differ in the assumptions that they make about the technology, although most of them try to measure the efficiency of a DMU by a scalar measure ranging between zero (the worst) and one (the best). In particular, the estimate of the reference technology is constructed according to the minimal extrapolation principle: $\widehat{\mathcal{S}}$ is the smallest subset of $\mathbb{R}^m_+ \times \mathbb{R}^{s_1+s_2}_+$ that contains the data $\mathcal{Z}$ and satisfies certain technological assumptions specific to the given approach. By constructing the smallest set containing the actual observations, the method extrapolates the least. Then, when we combine this idea of minimal extrapolation with Farrell's (1957) idea of measuring efficiency as a proportional improvement, we obtain the corresponding mathematical programs that help us to measure the efficiency.

There are several DEA methods that differ in terms of the estimated technology and the efficiency concept used. Among them, and as indicated earlier, we will focus on two models. The first is the graph measure of technical efficiency introduced by Briec (1997), which is a special case of DDF, and its version with undesirable outputs by Chung et al. (1997); the second is the Slack-Based Measurement (SBM) models (Tone, 2001) which extend traditional DEA models by incorporating input excesses and output shortfalls into models that account for both inefficiencies at the same time. These methods are very helpful for our benchmarking analysis due to their ability to detect the sources of inefficiencies.

When analysing situations in which global environmental conservation is a concern (as in our case), undesirable outputs of productions and social activities (in our case CO_2 released into the environment and radioactivity) must be recognised as an important part of the analysis. Traditional DEA methods usually assume that producing more outputs relative to less input resources is a criterion for efficiency. In the presence of undesirable outputs, however, the beneficial effects in terms of efficiency of those technologies with more good (desirable) outputs and less bad (undesirable) outputs relative to less input resources should be taken into account. There are several methods for dealing with undesirable variables. Among them, we may highlight as some of the most relevant approaches the transformation of the original data and then considering traditional DEA models (Seiford and Zhu, 2002), treating the undesirable outputs as inputs and desirable inputs as outputs (Ramanathan, 2005), or modifying the DEA model by transforming it into a non-linear problem where normal outputs are maximised and undesirable outputs are minimised (Färe et al., 2004).

Complementarily to these methods, it is also common practice to assume weak disposability of undesirable outputs (Färe et al., 1989; Yaisawarng and Klein, 1994). The concept of weak disposable reference technology was originally suggested by Färe et al. (1996), leading to a technique that has been denoted as environmental DEA technology in Färe et al. (2004). The literature on this particular field is still evolving (Kuosmanen, 2005; Yang and Pollitt, 2007, 2009, 2010). Among its conclusions one finds the recommendation of assuming different types of disposability for different undesirable outputs in each efficiency measurement model. In our particular study, although the disposability of some undesirable outputs may not be without cost, it can be done with an acceptable increase in the costs of production. In other words, we can reduce CO_2 emissions to the detriment of a shift towards renewable sources. According to Yang and Pollitt (2010) "the null-joint relationship between undesirable outputs and desirable outputs is actually broken and the weak disposability assumption subsequently becomes inappropriate for undesirable outputs" such as, for instance, CO_2 in our model. In our case, we will take advantage of the fact that both SBM and DDF models can be easily adapted to take undesirable outputs into account by considering them as a third set of variables that appear in the linear problem without the need to transform them.

In particular, if we denote by $\mathbf{X} = [\mathbf{x}_1, \ldots, \mathbf{x}_m] \in \mathbb{R}_+^{m \times L}$, $\mathbf{Y^g} = [\mathbf{y}_1^g, \ldots, \mathbf{y}_{s_1}^g] \in \mathbb{R}_+^{s_1 \times L}$ and $\mathbf{Y^b} = [\mathbf{y}_1^b, \ldots, \mathbf{y}_{s_2}^b] \in \mathbb{R}_+^{s_2 \times L}$, then the estimate of the reference technology is:

$$\widehat{\mathcal{S}} = \left\{ (\mathbf{x}, \mathbf{y}^g, \mathbf{y}^b) | \mathbf{x} \geq \mathbf{X}\boldsymbol{\lambda}, \mathbf{y}^g \leq \mathbf{Y^g}\boldsymbol{\lambda}, \mathbf{y}^b \geq \mathbf{Y^b}\boldsymbol{\lambda}, e\boldsymbol{\lambda} \geq 0 \right\}, \tag{3}$$

where $\boldsymbol{\lambda}$ is the intensity vector and $e = (1, \ldots, 1) \in \mathbb{R}^L$. The latter condition in expression (3) indicates a constant return to scale (CRS) assumption, which is usual in country-level studies (Camarero et al., 2013; Arcelus and Arocena, 2005; Zofio and Prieto, 2001).[11]

Within this context, one particular country with data $(\mathbf{x}_0, \mathbf{y}_0^g, \mathbf{y}_0^b)$ is efficient in the presence of undesirable outputs if there is no vector $(\mathbf{x}, \mathbf{y}^g, \mathbf{y}^b) \in \hat{\mathcal{S}}$ such that $\mathbf{x}_0 \geq \mathbf{x}$, $\mathbf{y}_0^g \leq \mathbf{y}^g$ and $\mathbf{y}_0^b \geq \mathbf{y}^b$ with at least one strict inequality.

[11] Barla and Perelman (2005) have specifically tested for the validity of scale hypothesis in a similar study at a country level, corroborating its suitability. In our particular data set, the test proposed by Simar and Wilson (2002) has been applied for checking this assumption. The test has been performed individually for every year, and for the whole period, and we have found that there is no enough empirical evidence to reject the CRS assumption.

3.1. SBM model in the presence of undesirable outputs

In the SBM model, in order to obtain an estimate of the efficiency for each country while also controlling for undesirable outputs, we formulate the following fractional programming model:

$$
\begin{aligned}
\rho^* = \min_{(\boldsymbol{\lambda}\,,\mathbf{s}^-\,,\mathbf{s}^g\,,\mathbf{s}^b)} & \left\{ \frac{1-\dfrac{1}{m}\displaystyle\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1+\dfrac{1}{s_1+s_2}\left(\displaystyle\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g}+\sum_{r=1}^{s_2}\frac{s_r^b}{y_{r0}^b}\right)} \right\} \\
\text{s.t.}\quad \mathbf{x}_0 &= \mathbf{X}\boldsymbol{\lambda} + \mathbf{s}^- \\
\mathbf{y}_0^g &= \mathbf{Y^g}\boldsymbol{\lambda} - \mathbf{s}^g \\
\mathbf{y}_0^b &= \mathbf{Y^b}\boldsymbol{\lambda} + \mathbf{s}^b \\
& \mathbf{s}^- \geq 0\,, \mathbf{s}^g \geq 0\,, \mathbf{s}^b \geq 0\,, e\boldsymbol{\lambda} \geq 0
\end{aligned}
\tag{4}
$$

where the vectors $\mathbf{s}^- \in \mathbb{R}_+^m$, $\mathbf{s}^g \in \mathbb{R}_+^{s_1}$ and $\mathbf{s}^b \in \mathbb{R}_+^{s_2}$ (usally named slacks) correspond to excesses of inputs, shortages of desirable outputs, and excessive undesirable outputs, respectively. The objective value in linear programming problem (4) satisfies $0 < \rho^* \leq 1$. Then, one particular country with data $(\mathbf{x}_0, \mathbf{y}_0^g, \mathbf{y}_0^b)$ will be efficient if and only if $\rho^* = 1$; in such an optimal case, all input and output slacks will equal zero compared to other inefficient countries.

Taking into account the optimal solution for linear programming problem (4) if a particular country is found to be inefficient (i.e. its particular *energy mix* is inefficient), it might be possible to improve its efficiency by implementing several strategies, namely, by reducing the surplus input, by increasing the desirable outputs, or by reducing the excesses of undesirable outputs—or different combinations of these three alternatives. That is, an inefficient country has a *target* or projection reference point in the frontier that can be obtained as:

$$
\begin{aligned}
\hat{\mathbf{x}}_0 &= \mathbf{x}_0 - \mathbf{s}^{-*} \\
\hat{\mathbf{y}}_0^g &= \mathbf{y}_0^g + \mathbf{s}^{g*} \\
\hat{\mathbf{y}}_0^b &= \mathbf{y}_0^b - \mathbf{s}^{b*}
\end{aligned}
\tag{5}
$$

The fractional programming model in (4) can be solved via the following equivalent linear model in t, using the Charnes-Coopers' transformation (Charnes and Cooper, 1962):

$$
\begin{aligned}
\tau^* = \min_{(t\,,\boldsymbol{\Lambda}\,,\mathbf{S}^-\,,\mathbf{S}^g\,,\mathbf{S}^b)} & \left\{ t - \frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{i0}} \right\} \\
\text{s.t.} \quad 1 \quad & = t + \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{S_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2}\frac{S_r^b}{y_{r0}^b}\right) \\
\mathbf{x}_0 t \quad & = \mathbf{X}\boldsymbol{\Lambda} + \mathbf{S}^- \\
\mathbf{y}_0^g t \quad & = \mathbf{Y^g}\boldsymbol{\Lambda} - \mathbf{S}^g \\
\mathbf{y}_0^b t \quad & = \mathbf{Y^b}\boldsymbol{\Lambda} + \mathbf{S}^b \\
\mathbf{S}^- \geq 0\,, \mathbf{S}^g \geq 0\,, & \mathbf{S}^b \geq 0\,, e\boldsymbol{\Lambda} \geq 0\,, t > 0
\end{aligned}
\tag{6}
$$

In particular, if $(t^*, \mathbf{S}^{-*}, \mathbf{S}^{g*}, \mathbf{S}^{b*}, \boldsymbol{\Lambda}^*)$ is the solution for linear programming problem (6), then we can obtain an optimal solution for (4) using:

$$
\rho^* = \tau^*\,, \boldsymbol{\lambda} = \boldsymbol{\Lambda}^*/t^*\,, \mathbf{s}^{-*} = \mathbf{S}^{-*}/t^*, \mathbf{s}^{g*} = \mathbf{S}^{g*}/t^*\,, \mathbf{s}^{b*} = \mathbf{S}^{b*}/t^*\,. \tag{7}
$$

Among the desirable axioms to be met by efficiency indexes proposed by Färe and Lovell (2005), this model satisfies: (i) indication of efficiency; (ii) unit invariance; and (iii) weak monotonicity.[12]

3.2. DDF inefficiency index

The directional distance function (DDF) is an *inefficiency* index that measures the feasible contraction in inputs and bad outputs, and expansion of good output in a chosen direction. This approach is common when undesirable outputs are considered because of its flexibility in choosing the projection direction.[13]

The definition of DDF was introduced by Chambers et al. (1996), and their contribution allowed for an evaluation of the production process to be performed in a more realistic approach. Briec (1997) proposes an alternative DDF inefficiency function adapted from the shortage function of Luenberger (1992). Simultaneously, Chung et al. (1997) adapted it to the measurement of

[12] Axiomatization of (input) efficiency measurement was introduced by Färe and Lovell (1978) who initially proposed three axioms: (i) *indication of efficient* bundles, i.e. the efficiency index equals one if and only if the input vector is Koopmans (1951) efficient; (ii) *monotonicity* increasing input quantities reduces the value of the index; and (iii) *homogeneity*, proportionate change of all input quantities reduces the index proportionately. Later contributions from Russell (1990) introduced axioms of *continuity* in inputs and technologies. Russell (1990) argued that continuity is important because it provides some guarantee that "small" errors of measurement of output and input quantities do not result in "large" errors in the calculation of the efficiency index.

[13] A variety of empirical applications have used DDF DEA models to assess eco-efficiency, including Arcelus and Arocena (2005), Picazo-Tadeo et al. (2005), Picazo-Tadeo et al. (2011), Kumar (2006), Lozano and Gutiérrez (2008), Wang et al. (2012), Chiu et al. (2012), or Riccardi et al. (2012), among others.

inefficiency considering undesirable outputs. In this particular model, the directional distance is computed using the vector of the observed variables for each DMU to define a direction for optimisation. This index provides a measure of *inefficiency* in the $[0,1)$ interval, where zero is the benchmark for an efficient DMU.

Following the same notation as in the previous section, the model proposed by Chung et al. (1997) accounting for undesirable outputs with strong disposability is:

$$
\begin{aligned}
&\beta^* = \max \beta \\
&\text{s.t.} \quad \mathbf{X}\boldsymbol{\lambda} \quad \leq \mathbf{x}_0\,(1-\beta) \\
&\qquad\quad \mathbf{Y^g}\boldsymbol{\lambda} \quad \geq \mathbf{y}_0^g\,(1+\beta) \\
&\qquad\quad \mathbf{Y}^b\boldsymbol{\lambda} \quad \leq \mathbf{y}_0^b\,(1-\beta) \\
&e\boldsymbol{\lambda} \geq 0\,,\beta \text{ free}
\end{aligned}
\tag{8}
$$

However, the presented inefficiency index has a disadvantage derived from the lack of *indication of efficiency*.[14] This implies that model (8) can take a reference point in the frontier that may not be efficient in the sense of Koopmans (1951), and the presence of non-radial slacks should be considered for a *comprehensive* technical inefficiency measure.

To overcome this problem, we propose a second stage analysis so as to include the presence of these slacks as a source of inefficiency. To this end, we first maximise β and in this second stage, complement the inefficiency with a maximised sum of the average relative slack values, presented in the following mathematical program:

$$
\begin{aligned}
&\delta^* = \max \left[\beta^* + \frac{1}{m+s_1+s_2}\left(\sum_{r=1}^{m}\frac{S_r^-}{x_{r0}} + \sum_{r=1}^{s_1}\frac{S_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2}\frac{S_r^b}{y_{r0}^b}\right)\right] \\
&\text{s.t.} \quad \mathbf{X}\boldsymbol{\lambda}+\mathbf{S}^- \quad = \mathbf{x}_0\,(1-\beta^*) \\
&\qquad\quad \mathbf{Y^g}\boldsymbol{\lambda}-\mathbf{S}^g \quad = \mathbf{y}_0^g\,(1+\beta^*) \\
&\qquad\quad \mathbf{Y}^b\boldsymbol{\lambda}+\mathbf{S}^b \quad = \mathbf{y}_0^b\,(1-\beta^*) \\
&e\boldsymbol{\lambda} \geq 0\,,\mathbf{S}^- \geq 0\,,\mathbf{S}^g \geq 0\,,\mathbf{S}^b \geq 0
\end{aligned}
\tag{9}
$$

Considering the slacks in relative rather than absolute terms in the objective function, we keep the unit invariance of the model. In model (9), we propose an arithmetic average of relative

[14] In the operations research literature, an index satisfying this property is said to be *comprehensive*.

slacks to complement the first stage inefficiency score (β^*) and in a later stage (12) we check this proposal.

Following Russell and Schworm's (2009) axiomatic foundation of inefficiency measurement, the first stage of the inefficient model satisfies (1) weak monotonicity; (2) unit independence, and (3) continuity in production vector and technologies. Adding the second stage we have that it also satisfies (4) indication of efficiency.

Also, it is possible to define the targets, or reference in the frontier, for each DMU as:

$$\begin{aligned} \mathbf{x}_0^* &= \mathbf{x}_0 - \beta^* \mathbf{x}_0 - \mathbf{S}^- \\ \mathbf{y}_0^{g*} &= \mathbf{y}_0^g + \beta^* \mathbf{y}_0^g + \mathbf{S}^g \\ \mathbf{y}_0^{b*} &= \mathbf{y}_0^b - \beta^* \mathbf{y}_0^b - \mathbf{S}^b \end{aligned} \tag{10}$$

Using these targets, we can derive a measure of inefficiency for each variable, as the relative slack, in the following way:

$$\begin{array}{llll} \text{In inputs:} & \dfrac{\mathbf{x}_0 - \mathbf{x}_0^*}{\mathbf{x}_0} & = \dfrac{\beta_0^* \mathbf{x}_0 + \mathbf{S}^-}{\mathbf{x}_0} & = \beta_0^* + \dfrac{\mathbf{S}^-}{\mathbf{x}_0} \\ \text{In good outputs:} & \dfrac{\mathbf{y}_0^{g*} - \mathbf{y}_0^g}{\mathbf{y}_0^g} & = \dfrac{\beta_0^* \mathbf{y}_0^g + \mathbf{S}^g}{\mathbf{y}_0^g} & = \beta_0^* + \dfrac{\mathbf{S}^g}{\mathbf{y}_0^g} \\ \text{In bad outputs:} & \dfrac{\mathbf{y}_0^b - \mathbf{y}_0^{b*}}{\mathbf{y}_0^b} & = \dfrac{\beta_0^* \mathbf{y}_0^b + \mathbf{S}^b}{\mathbf{y}_0^b} & = \beta_0^* + \dfrac{\mathbf{S}^b}{\mathbf{y}_0^b} \end{array} \tag{11}$$

Based on specific inefficiencies for each variable presented in (11), we calculate their average in the following decomposition (12), and we prove that the presented efficiency measure (9) is well defined:

$$\begin{aligned} \delta^* &= \frac{1}{m+s_1+s_2}\left[\sum_{r=1}^{m} \frac{\beta_0^* x_{r0} + S_r^-}{x_{r0}} + \sum_{r=1}^{s_1} \frac{\beta_0^* y_{r0}^g + S^g}{y_{r0}^g} + \sum_{r=1}^{s_2} \frac{\beta_0^* y_{r0}^b + S^b}{y_{r0}^b}\right] = \\ &= \frac{1}{m+s_1+s_2}\left[\sum_{r=1}^{m}\left[\beta_0^* + \frac{S_r^-}{x_{r0}}\right] + \sum_{r=1}^{s_1}\left[\beta_0^* + \frac{S^g}{y_{r0}^g}\right] + \sum_{r=1}^{s_2}\left[\beta_0^* + \frac{S^b}{y_{r0}^b}\right]\right] = \\ &= \frac{1}{m+s_1+s_2}\left[m\beta_0^* + s_1\beta_0^* + s_2\beta_0^* + \sum_{r=1}^{m}\frac{S_r^-}{x_{r0}} + \sum_{r=1}^{s_1}\frac{S^g}{y_{r0}^g} + \sum_{r=1}^{s_2}\frac{S^b}{y_{r0}^b}\right] = \\ &= \beta_0^* + \frac{1}{m+s_1+s_2}\left[\sum_{r=1}^{m}\frac{S_r^-}{x_{r0}} + \sum_{r=1}^{s_1}\frac{S^g}{y_{r0}^g} + \sum_{r=1}^{s_2}\frac{S^b}{y_{r0}^b}\right] \end{aligned} \tag{12}$$

In the literature, the relationship between the DDF and the SBM models has been studied by Färe and Grosskopf (2010) and Fukuyama and Weber (2009). The latter accounts for the lack of indication of efficiency and defines a technical inefficiency bias as the difference between a proposed slack-based inefficiency measure and the directional distance distance function. Along this line, Asmild and Pastor (2010) have developed new slack-free efficiency measures for the Multi-directional Efficiency Analysis (MEA) model of Bogetoft and Hougaard (1999) and the Range Directional Model (RDM) of Silva Portela et al. (2004). Both of them are special types of linear directional distance function efficiency models.

Nonetheless, as far as we know, this second stage has never been considered in empirical applications, and as we will show later in the results' section, comparison of efficiencies yielded by DDF and SBM programs suggests that this stage is compulsory in order to obtain an appropriate performance measure.

3.3. Construction of the production frontier

In the DEA literature, one may find three proposed frontiers to evaluate efficiency in a panel data framework.[15] The first, and most usual, is the standard *contemporaneous frontier*, where the frontier for each year is built with only the observations of the considered period. The second type is the *sequential frontier*, which is based on observations from the present and previous years jointly. Finally, the *intertemporal frontier* bases the frontier on observations from all the considered periods.

In our study we evaluate the efficiency using the *contemporaneous* and the *sequential* frontiers. The last choice implies that the production possibility set can only expand each year, and any technological regress is penalised. To achieve the aim of this work, the *sequential frontier* seems a suitable approach for the analysis of the electricity and derived heat production, and the comparison of results from both frontiers will identify those countries and years for which there has been some sort of technological regress.

4. Data, sources, and selection of inputs and outputs

Since the study is focused on European Union *countries*, each of them will be considered as a DMU choosing among different alternatives, in order to produce both electricity and derived heat. The DMU set is completely determined by the scope of the study, i.e. 25 European Union countries (EU25), and it meets Dyson et al.'s criteria (2001), who claimed that a principle in a DEA analysis is that all the compared DMUs should have a common, or similar, underlying

[15] See Tulkens and Vanden Eeckaut (1995) for a detailed analysis about the different frontiers in DEA.

technology, determined by the social, political, technical and environmental issues in which the production process takes place. The country names, their respective abbreviations, and the most recent EU enlargements (since 1993) are reported in Table 2. The analysis has been computed with data from 2000 until 2007, which is an interesting period as it witnessed two EU enlargements after which the number of member countries almost doubled.

Few studies perform energy efficiency analysis controlling for environmental issues at the country level, and in many cases the selected variables differ from study to study—although in many cases this is due to the varying objectives. Among the studies at country level, we may highlight those by Hawdon (2003) and Edvardsen and Førsund (2003), who consider energy consumption as a positive output. However, other studies such as Färe et al. (2004) or Kumar (2006) consider this variable as an input. Actually, depending on the aims of the study, energy consumption might be considered either as an input (this is common practice in environmental studies), or as an output (this is more common practice in studies focusing directly on economic issues). Yet there is a broad consensus that all types of energies, even those from renewable sources, have some harmful effects on the environment, and must be included, in principle, as an input in environmental studies. On this respect, other country-level studies such as Arcelus and Arocena (2005) consider not only economic but also environmental issues. Similarly, Zhou et al. (2006) estimate the impact of environmental regulations over CO_2 emissions for 30 OECD countries, identifying two drivers for efficiency: on the one hand the economy and environment; on the other hand, regulations. Both factors had differential impacts depending on the evaluated country.

In our study, we consider six variables, namely, three inputs, one output, and two undesirable outputs, which are described in detail in the following subsections.

4.1. Inputs

Electricity and derived heat are a secondary source of energy that is only achievable using other primary sources, jointly with renewable energy, as well as human and technical resources. Therefore, the first physical input we use is the total primary energy involved in the generation of electricity and heat. All primary energies have been converted to the same units and, despite the fact that they belong to different generation systems, they serve the same purpose, i.e. to produce heat and, at a later stage, steam to move a turbine coupled to a generator. This aggregation has already been used by Tone and Tsutsui (2006) for the analysis of electric utilities (see also Cooper et al., 2007). It has also been followed by Ramanathan (2005), who focus on the countries from Middle East and North Africa, or Zhou et al. (2008b), who measure the carbon emission performance of eight world regions, among others. These primary energy sources, considered as an input variable in our DEA model, come exclusively from non-renewable sources. Since the renewable sources do not "consume" physical resources (for example, the wind and the sun are free in the atmosphere, or the water used to operate a hydroelectric power plant which depends on the weather, and later will also be available for other uses), they have no input consumption. The non-renewable sources come from fossil fuels (coal, gas and petrol), as well as nuclear reactors.

The total primary energy involved has been obtained from the Eurostat Database (section "Environment and Energy"). For simplicity, all energy data are expressed in the same units (Million Tonnes of Oil Equivalent, MTOE). Accordingly, to an estimate of the primary energy resources used, we aggregate the input data usage from different types of plants: conventional thermal power plant (coal, gas and petrol), combined heat and electricity plants (CHP), as well as heat produced in nuclear reactors. Aggregate energy consumption has also been adopted by Zhou et al. (2006) when modelling environmental performance.

Following related literature, we also use capital and labour as two additional inputs required for electricity generation. Analogous to Jaraitė and Di Maria (2012), we use the installed capacity, provided by Eurostat, as a proxy for capital. In the case of labour, which will be our third input, our data correspond to the number of employees provided by the EU KLEMS database.[16]

.

4.2. Outputs

Regarding the choice of outputs, one of them is *desirable*, or good, that is the electricity and derived heat generated from renewable and non-renewable sources. Its unit of measurement is MTOE. The non-renewable output comes from conventional thermal and nuclear power plants and the renewable from hydro, wind, solar and geothermal. In the year 2009, electricity and heat from non-renewable sources represented nearly 89.7% of the total electricity produced in the European Union. Reducing this share is an important challenge for the EU, with an 80% target

[16] EU KLEMS Database, March 2011, `http://www.euklems.net`. The data in the Statistical Classification of Economic Activities in the European Community, NACE (revision 1.1, section 40x, Electricity Supply) accounts for the total number of persons engaged in the electricity supply sector. Unfortunately, this section is not available for all countries and we have been forced to use the closest aggregated section (E, Electricity, gas and water supply). While this is not a precise estimation, we are comforted by the fact that a large share of employees belong to the electricity sector, and more interestingly, we have found that the share of Section 40x (Electricity supply) in this aggregation is very similar among the set of evaluated countries with available data, and due to the unit invariance of the proposed models, this can be a suitable proxy. A similar assumption has been adopted by Jaraitė and Di Maria (2012).

for year 2020 (see Eurostat, 2011).

Concerning the choice of outputs, it is worthwhile to comment that energy produced is higher than the energy consumed. The main differences are due to transport losses and import/export balances.[17]

There is a missing source of electricity (output) not considered in the study, namely the electrical energy generated from pumped storage. It is not really a "genuine" output because it is more like an energy storage rather than energy production.[18] For this reason, we have not considered it in the study.

Regarding the *undesirable*, or *bad* outputs of the process, the first one is the CO_2e[19] released into the environment. The units in which it is measured are million tonnes of *CO_2 equivalent released* into the atmosphere per year due to the energy sector. Data has been obtained from the European Environment Agency (EEA)[20], which provides data from 1990. Many authors have considered pollutants like CO_2 in their efficiency analysis such as Zhou et al. (2008b), Arcelus and Arocena (2005), Zofio and Prieto (2001), Zaim and Taskin (2000). Others have also considered SO_2 and NO_x as pollutants including Färe et al. (2004), Barla and Perelman (2005), Färe et al. (2004), Camarero et al. (2011) or Zhou et al. (2007).

The second bad output considered is radioactivity. Despite its relevance (the major concerns about nuclear energy are based on radioactive waste and the risk of contamination), the inclusion of radioactivity is not generalised in energy and environmental studies, mainly due to the difficulties of gathering reliable data. As CO_2 concentrates in the air, the risk of release into the environment of the anthropogenic radionuclides is becoming a latent problem. The presence of these substances is a normal fact of nature, but the problem arises when their concentrations exceed certain thresholds.

[17] A significant loss of energy takes place in the electric grid. In general, losses are estimated from the discrepancy between energy produced (as reported by power plants) and energy sold to final customers; the difference between what is produced, and what is consumed, constitutes transmission and distribution losses. In addition, due to the geographical proximity among EU countries, electric transmission networks are interconnected, and trade of electricity also takes place. For these two reasons, energy produced and energy consumed are not entirely coincidental. However, since our study is related to the generation process, losses in the network, or trade with other countries do not constitute an issue to control for.

[18] During periods of low electrical demand, water is pumped from a lower elevation reservoir to a higher elevation. Later during periods of peak demand, water is released through turbines to produce electricity. In any case, the amount of energy involved is not relevant for our study. According to the Eurostat database, in 2009, it was less than 1% in the EU.

[19] A metric measure used to compare the emissions from various greenhouse gases (i.e. Methane, Carbon Dioxide, Fluorine gas, HFCs, Nitrous oxide, PFCs and SF_6) based upon their global warming potential (GWP). Carbon dioxide equivalents are commonly expressed as "million metric tonnes of carbon dioxide equivalents ($MMTCO_2Eq$)." The carbon dioxide equivalent for a gas is derived by multiplying the tons of the gas by the associated GWP. Nevertheless, the most important greenhouse gas linked with the energy sector is CO_2, although most of the literature lacks a precise definition of this term.

[20] Emission source, IPCC sector 1.A.1A: Public electricity and heat production.

In the literature the contributions considering radioactivity as an undesirable output in efficiency studies are almost entirely yet to come, despite today's great concern about the risk of nuclear power plants. Only Arcelus and Arocena (2005) refer to nuclear power as a possible source of bad outputs. As indicated, this absence is generally due to the difficulties in gathering reliable data for this variable, and therefore we will proxy radioactive pollution by the amount of electrical energy produced by nuclear energy and coal. The amount of nuclear waste, nuclear spent fuel, and radiation released into the environment by nuclear power plants and coal combustion can be considered proportional to the energy produced by these two particular sources.[21] However, nuclear plants are not the only source of radioactivity. Actually, although less known, coal mining and combustion are the most important sources of radioactivity enhancement which are released into the environment. Even though in coal power plants there is greater concern over the possible environmental and health effects of chemical emissions than the traces of radioactivity, some studies such as Papastefanou (2010) have shown that the use of coal as fuel results in the enhancement of natural radioactivity, most of which (99%) escapes as very fine particles.[22]

It is also important to point out the assumption made that 1 MTOE of electricity generated from coal combustion produces the same amount of radioactivity pollution as 1 MTOE from nuclear power plants. According to some contributions (see, for instance Corbett, 1983; Papp et al., 2002; Chatzimouratidis and Pilavachi, 2008), this is a reasonable assumption as commented on previously. The units considered are MTOE, and the data have been extracted from Eurostat (environmental and energy theme).

For the sake of brevity a summary and some descriptive statistics of the inputs and outputs are shown in Table 3.

[21] It is not in the aim of this study to measure the amount of radioactivity released by nuclear power plants or the mining industry, but to consider the relevance of these sources due to the unsolved problem with spent nuclear fuel and the risk of pollution.

[22] Specifically, he found significant activity concentrations of natural radionuclides originated from coal mines in Greece. Other related studies such as Papp et al. (2002) concluded that mining and the utilization of uraniferous (rich in uranium) coal resulted in a remarkably high concentration of activity in the soil of a town (Ajka, Hungary) close to a power plant. Chatzimouratidis and Pilavachi (2008), based on the National Council of Radiation Protection and Measurements (NCRP) Report(1987) which estimated the effective dose equivalent from coal plants at 100 times higher than that of nuclear plants. Specifically, they estimated 4.9 man Sv/year for a coal power plant and 0.048 man Sv/year for a nuclear power plant (for a 1,000 MWe power plant) (Man Sv/Year is a radioactivity collective effective dose equivalent measure; MWe is MegaWatts of electrical power). Corbett (1983) shows a more conservative position, and established a similar collective dose from coal power plants and nuclear power plants of the same dimension.

5. Results

According to the rationale presented in the preceding paragraphs, our empirical application will provide results for the two DEA models considered (SBM and DDF) and the two reference frontiers, i.e. contemporaneous and sequential. Results for both SBM and DDF models are shown in Tables 4 and 5, respectively. The graphical counterparts to these tables are presented in Figures 1 and 2, where we report efficiency trends and differences between the contemporaneous and the sequential frontier for each pair country-year. In both figures the circles in black indicate efficiency yielded by the sequential frontier, whereas those in red correspond to the contemporaneous frontier. Due to the fact that the contemporaneous frontier is nested within the sequential frontier, the efficiencies (obtained using SBM) yielded by the latter are always equal or lower than those corresponding to the former, whereas the opposite holds for the inefficiencies (obtained using DDF). Considering the results for both frontiers, we have computed the correlation between SBM and DDF models, yielding high values in absolute terms (-0.91 and -0.92 for the sequential and the contemporaneous frontier, respectively). In contrast, the correlation between the SBM and the first stage results provided by the DDF model resulted in a much lower correlation (-0.65).

According to the results shown in Figure 1 and Figure 2, Denmark, France, Austria and Sweden are the countries with the highest efficiency differentials between the contemporaneous and the sequential frontiers. This might indicate that these countries could have been affected by some sort of technological *regress* in recent years—although this would require a more specific examination.

Considering the results for the sequential frontier, on which we focus for simplicity, the upper panel in Figure 3 reports mean results (considering all countries) for the SBM model (efficiency), whereas the lower panel provides analogous information for the DDF model (inefficiency). We also distinguish between unweighted and weighted means, which are reported in the left and right panels of Figure 3, respectively. We consider this distinction is relevant given the remarkable disparities among EU countries in both economic and population sizes, which ultimately affect the amount of electricity produced. Accordingly, for computing the weighted averages we have used total output (electricity and derived heat produced) as a weighting factor. Results for the unweighted average are relatively stable when compared to those obtained when weighting, for which we find a sudden change for year 2005, when the largest countries (in terms of energy production) perform much better. Specifically, this behaviour is highly influenced by Germany, whose efficiency under SBM in 2005 was 1.000—and its inefficiency under DDF was 0.000. This result is consistent with previous literature such as, for instance, Jaraitė and Di Maria (2012).

The explanations for these tendencies might be multiple, but some relevant facts occurred during these years which could partly contribute to shedding some light on these opposite trends—i.e. decreasing unweighted mean efficiency and increasing weighted mean efficiency, under SBM (the DDF inefficiencies show opposite tendencies, as expected). Specifically, both the EU enlargements (EU25 in 2004 and EU27 in 2007) as well as the Kyoto Protocol negotiations could underlie these tendencies. Regarding the Kyoto Protocol negotiations, the new EU members after the 2004 and 2007 enlargements were, in general, smaller economies and less technologically developed than their incumbent counterparts. The declining tendency for the (SBM) unweighted mean might be related to the inclusion in the computation of the mean of new entrants in years in which they were still non-EU countries. Since both enlargements took place in relatively recent years (especially taking into account that the last sample year is 2007), adopting EU energy regulations which attempt to enhance energy efficiency might be a slow process which is still far from over. In addition to this, the Kyoto negotiations may have also had an impact on these trends if we take into account that EU large economies are countries with binding obligations to reduce emissions of greenhouse gases.

The links between the different EU enlargements and their likely impact on the results obtained are explored further in Figure 4, where the upper and lower panels report unweighted efficiency averages according to the SBM and DDF models, respectively. In addition, Figure 4 is divided into two sub-figures: Figure 4(a) reports unweighted means, whereas its weighted counterpart is provided in Figure 4(b). All sub-figures have separate lines for the different country aggregates corresponding to the different EU enlargements. These descriptive results indicate that the EU15 enlargement in 1995 (when Austria, Finland and Sweden joined the EU) represented the inclusion of three countries whose environmental performance was much better than the rest, especially due to the presence of the two Nordic countries, as shown by comparing the dotted (EU15 excluding EU12) vs. the dashed (EU12 only) lines in both panels. This trend is robust across methods (SBM and DDF) as well as across weighting schemes (unweighted vs. weighted). In contrast, the 2004 enlargement, when Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia and Slovenia joined the EU shows opposite results, as shown by the visual comparison between the solid line (EU25) vs. the dashed-dotted line (EU25 excluding EU15) in both the upper an lower panels.

Regarding the differences found when comparing EU15 and EU25 results, the explanations might partly lie in the strong differences in terms of productive structure and development of electricity power markets comparing the acceding countries with the EU15 members. Regarding the latter, the regulated power markets in most of the new EU members still do not provide enough incentives for boosting efficiency. Among the 2004 acceding countries we find Hungary, Poland, Estonia and Lithuania, all of which still set regulated end-user prices for electricity (Bosch et al., 2009). Regarding the former, the average age of power plants in these countries is much higher than the average in EU15 countries, (see Graus and Worrell, 2009), with less incentives to update these plants during the last years of their life cycle, especially in the context of regulated power markets (Jaraitė and Di Maria, 2012). As shown by Pollitt (2012), the opening of the electricity markets in the in EU15 countries may have led to an efficiency enhancement of electricity utilities. Yet he concludes that, in terms of eco-efficiency, "it is not liberalisation *per se* what will determine the movement towards a low carbon energy transition, but the willingness of societies to bear the cost, which will be significant no matter what the extent of liberalisation."

One might of course consider whether the differences found among the different country's aggregates are significant or not. For this, we can consider several possibilities to test the null hypothesis that $H_0 : f(\text{EU15}) = f(\text{EU25} - \text{EU15})$, against the alternative that $H_1 : f(\text{EU15}) \neq f(\text{EU25} - \text{EU15})$, where $f(\cdot)$ corresponds to the density function of the aggregate being considered. However, if we take into account that efficiency scores obtained using nonparametric techniques such as those obtained in this paper do not generally meet the normality assumption (Simar and Wilson, 1998), then the number of available instruments shrinks substantially.

An appropriate tool to test the hypotheses considered above is the Li (1996) test, which compares two densities using kernel smoothing methods (see Silverman, 1986, for details).[23] The main advantage of using this test is that it compares the entire distributions of efficiencies, rather than a specific moment or moments. Although applications of the Li (1996) and related tests are still scarce, some evidence is available for a variety of fields (see, for instance Thieme et al., 2013).

The results of applying this test to the different country aggregates are provided in Table 7. Although there are several hypotheses we might be interested in testing, we will restrict the results to the comparison of EU15 vs. EU25-EU15, given that the differences between EU12 vs. EU15-EU12 are driven by two specific countries only—Finland and Sweden. The test has been conducted for both efficiency measurement methodologies considered, and for the two sub-periods,

[23]See also the relatively recent monograph by Li and Racine (2007), where an extensive revision of this and related tests is provided.

namely, 2000–2004 and 2005–2007, determined by the dates of the two EU enlargements.

Results are reported in Table 7 (including both the T-statistic of the Li test as well as the corresponding p-value). The differences found when testing $H_0 : f(\text{EU15}) = f(\text{EU25} - \text{EU15})$ are strongly significant (at the 1% level), although the value of the T-statistic is lower for DDF. The value of the T-statistic also varies between the two sub-periods, although we do not observe any particular tendency—in the case of SBM it is higher for 2000–2004, but in the case of DDF this happens for 2005–2007.

6. Concluding remarks

This study has analysed the efficiency in the electricity and derived heat generation process for the EU25 country members of the European Union, from year 2000 to 2007, also taking into especial consideration how the successive enlargements might have affected the results. The energy sector accounts for the largest contribution to GHG emission and studies assessing technical and environmental efficiency are crucial for policy makers and regulators. In particular, we have found that the first phase of the EU ETS concluded with positive results, but the beginning of the second phase does not seem so positive. As this sector, and set of countries, have pioneered the implementation of the EU ETS, our study may provide feedback for past analysis and help for future initiatives.

Given the great deal of inefficiency that can be involved in the process of electricity generation, previous studies have introduced a variety of proposals to evaluate the *balance* between the primary resources actually consumed, and the final output available, also factoring in the externalities that emerge in the process—such as the release of greenhouse gases and other emissions, as well as radioactivity. Despite the importance of this type of problem, the number of studies attempting to evaluate the efficiency in the electricity and derived heat generation process at the *country* level is relatively modest. Yet in some particular contexts such as that of the European Union, these questions are especially important due to the design of common energy policies for all countries.

Due to the variety of problems, positive and negative aspects (in terms of externalities) involved in the energy sector, the use of a multi input-multi output nonparametric frontier methodology represents a suitable tool for this type of analysis. Among these methodologies, slacks-based and directional distance function DEA models have prevailed. Our efficiency measurement approach considers these two models, namely, the slacks-based (SBM) model by Tone (2001), and the directional distance function (DDF) model by Briec (1997) and Chung et al. (1997), which provided highly correlated results.

Both measurements suit our analysis particularly well due to its ability to model bad outputs, and to provide inefficiency slacks for each variable, which is particularly interesting for detecting abatement opportunities. Our contribution to the present literature is twofold. On the one hand, the use of directional distance functions accounting for non-directional slacks clearly improves the reliability of results, and proves that neglecting this source of inefficiency may result in seriously biased efficiency measures. The literature analysing these specific issues is still evolving, and it offers an appealing research opportunity. On the other hand, the use of specific aggregate inefficiency slacks provide sound information about the absolute extent of inefficiencies, and helps in detecting abatement opportunities when undesirable outputs are factored in.

Our results indicate that there are large efficiency differentials among EU15 and later enlargements of the EU with a steady trend. Actually, one may also find strong efficiency differentials when focusing on EU15, although this occurs due to the effect of some particular (Nordic) countries, as acknowledged by the literature. However, the differences found between EU15 and the countries who joined the EU in 2004 were large and significant. Accordingly, opportunities for improvement terms of CO_2 abatement and primary energy saving in the EU are still present and are also great, especially for new EU members with highly regulated energy sectors. However, there are also dangers derived from these discrepancies, since the less efficient countries' growth prospects might be jeopardised by the need to converge. The differences, though, were not applicable to all bad outputs, since in the case of the second one (radioactivity) the accounted inefficiency is less important.

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Table 1: Gross electricity generation (2009), European Union (27 countries)

Source	In GWh	%
Total conventional thermal	1,101,693	44.05
Coal	584,401	23.36
Oil	52,192	2.09
Gas	432,658	17.30
Other power stations	32,442	1.30
Nuclear	869,057	34.74
Pumped storage	31,719	1.27
Renewable energies	499,091	19.95
Total	2,501,560	100.00

Data source: Eurostat Database, Energy (nrg_105a; August 2012).
GWh: Gigawatt Hour.

Table 2: European Union (27 countries)

Austria (AT)	Germany (DE)	Poland (PL)
Belgium (BE)	Greece (EL)	Portugal (PT)
Bulgaria (BG)	Hungary (HU)	Romania (RO)
Cyprus (CY)	Ireland (IE)	Slovakia (SK)
Czech Republic (CZ)	Italy (IT)	Slovenia (SI)
Denmark (DK)	Latvia (LV)	Spain (ES)
Estonia (EE)	Lithuania (LT)	Sweden (SE)
Finland (FI)	Luxembourg (LU)	Netherlands, The (NL)
France (FR)	Malta (MT)	United Kingdom (UK)

EU12: BE, DK, FR, DE, EL, IE, IT, LU, PT, ES, NL, UK (1-11-1993)
EU15: EU12 + AT, FI, SE (1-1-1995)
EU25: EU15 + CY, CZ, EE, HU, LV, LT, MT, PL, SK, SI (1-5-2004)
EU27: EU25 + BG, RU (1-1-2007)

Table 3: Inputs and outputs considered in the analysis. Some descriptive statistics

		2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
Inputs									
Primary Energy	Simple Mean	38,812.80	39,715.04	40,544.44	42,178.28	42,870.20	42,823.80	43,402.68	43,290.80
(MTOE)	Weighted Mean	109,730.96	112,170.48	103,938.80	116,926.82	118,977.49	118,521.83	119,994.40	119,865.85
	Standard Deviation	53,546.44	54,749.15	50,266.36	57,307.33	58,298.22	58,109.78	58,845.54	58,763.25
	Total	970,320	992,876	1,104,723	1,054,457	1,071,755	1,070,595	1,085,067	1,082,270
Proxy for Capital	Simple Mean	46,201.56	46,886.32	44,188.92	43,863.68	44,733.72	4,5472.76	46,694.48	47,689.80
Installed Capacity	Weighted Mean	119,407.27	120,265.20	103,938.80	103,053.28	105,156.04	106,974.93	110,336.19	113,000.05
(MW)	Standard Deviation	57,160.02	57,599.92	50,266.36	49,787.52	50,715.80	51,667.42	53,487.29	54,999.87
	Total	1,155,039	1,172,158	1,104,723	1,096,592	1,118,343	1,136,819	1,167,362	1,192,245
Labour	Simple Mean	63.09	62.39	61.48	59.79	60.06	59.43	60.13	59.67
(Thousand of Employees)	Weighted Mean	154.84	153.83	151.17	147.06	148.65	146.84	148.52	148.93
	Standard Deviation	77.13	77.36	77.10	74.95	74.93	73.79	74.47	74.24
	Total	1,577.28	1,559.63	1,537.03	1,494.66	1,501.49	1,485.64	1,503.13	1,491.67
Desirable Outputs									
Electricity and D.H.	Simple Mean	14,233.48	14,677.12	14,794.68	15,762.24	16,315.52	16,624.12	16,982.04	16,996.60
(MTOE)	Weighted Mean	35,974.54	36,846.86	36,967.35	40,604.83	42,039.12	43,166.79	44,273.52	43,765.98
	Standard Deviation	17,294.23	17,698.59	17,811.45	19,719.26	20,377.68	21,066.97	21,666.31	21,266.25
	Total	355,837.00	366,928.00	369,867.00	394,056.00	407,888.00	415,603.00	424,551.00	424,915.00
Undesirable Outputs									
CO_2e emissions	Simple Mean	49.18	50.44	51.30	53.40	52.92	52.46	52.86	53.05
(Tg of CO_2 equivalent)	Weighted Mean	136.39	140.87	140.22	146.15	144.82	143.03	144.73	146.57
	Standard Deviation	73.40	76.30	76.26	79.07	78.44	77.76	78.71	79.77
	Total	1,229.62	1,260.97	1,282.60	1,335.10	1,322.88	1,311.54	1,321.49	1,326.25
Proxy for radioactivity	Simple Mean	6,251.80	6,375.08	6,464.72	6,680.88	6,628.24	6,537.16	6,557.84	6,280.48
(MTOE)	Weighted Mean	19,237.91	19,472.72	19,488.34	19,999.60	19,653.22	19,651.97	19,561.38	18,296.15
	Standard Deviation	10,799.61	10,804.00	10,960.59	11,211.52	11,081.22	11,152.55	11,106.05	10,419.31
	Total	156,295.00	159,377.00	161,618.00	167,022.00	165,706.00	163,429.00	163,946.00	157,012.00

Table 4: SBM and DDF measures under contemporaneous frontier

SBM efficiency

	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
Austria	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Belgium	0.305	0.305	0.321	0.340	0.318	0.314	0.324	0.330
Cyprus	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Czech Republic	0.299	0.315	0.312	0.322	0.300	0.295	0.295	0.303
Denmark	0.489	0.610	0.607	0.568	0.635	0.588	0.527	0.572
Estonia	0.303	0.362	0.383	0.395	0.341	0.349	0.350	0.367
Finland	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
France	0.455	0.482	0.485	0.577	0.520	0.476	0.522	0.495
Germany	0.271	0.276	0.355	0.439	0.433	1.000	0.458	0.418
Greece	0.223	0.226	0.222	0.225	0.209	0.201	0.209	0.212
Hungary	0.293	0.288	0.270	0.253	0.264	0.270	0.265	0.290
Ireland	0.226	0.232	0.217	0.223	0.212	0.200	0.218	0.216
Italy	0.422	0.428	0.400	0.392	0.491	0.423	0.456	0.440
Latvia	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Lithuania	0.335	0.340	0.397	0.374	0.372	0.353	0.348	0.367
Luxembourg	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Malta	1.000	0.496	1.000	1.000	0.161	0.152	0.168	0.170
Netherlands	0.413	0.482	0.502	0.507	0.527	0.434	0.455	0.444
Poland	0.302	0.323	0.313	0.296	0.290	0.288	0.289	0.284
Portugal	0.405	0.514	0.473	0.532	0.465	0.379	0.486	0.558
Slovakia	0.346	0.300	0.302	0.279	0.297	0.293	0.287	0.300
Slovenia	0.361	0.348	0.338	0.355	0.358	0.334	0.335	0.318
Spain	0.271	0.294	0.295	0.361	0.331	0.312	0.314	0.314
Sweden	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
United Kingdom	0.262	0.266	0.280	0.281	0.247	0.251	0.240	0.240

DDF inefficiency

	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
Austria	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Belgium	0.402	0.370	0.374	0.356	0.377	0.320	0.367	0.362
Cyprus	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Czech Republic	0.461	0.443	0.455	0.449	0.449	0.238	0.457	0.447
Denmark	0.233	0.072	0.080	0.132	0.091	0.109	0.174	0.132
Estonia	0.463	0.405	0.401	0.402	0.427	0.226	0.450	0.401
Finland	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
France	0.247	0.234	0.240	0.229	0.230	0.256	0.243	0.247
Germany	0.464	0.449	0.415	0.370	0.365	0.000	0.352	0.361
Greece	0.531	0.524	0.531	0.534	0.539	0.477	0.538	0.533
Hungary	0.539	0.543	0.557	0.579	0.554	0.556	0.560	0.540
Ireland	0.488	0.478	0.489	0.408	0.398	0.528	0.478	0.479
Italy	0.341	0.332	0.341	0.178	0.142	0.278	0.288	0.208
Latvia	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Lithuania	0.422	0.418	0.373	0.386	0.384	0.404	0.419	0.403
Luxembourg	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Malta	0.000	0.249	0.000	0.000	0.540	0.580	0.623	0.626
Netherlands	0.288	0.258	0.249	0.107	0.084	0.279	0.223	0.267
Poland	0.512	0.508	0.536	0.552	0.530	0.485	0.546	0.541
Portugal	0.273	0.219	0.254	0.150	0.186	0.300	0.229	0.208
Slovakia	0.475	0.426	0.467	0.483	0.453	0.432	0.463	0.455
Slovenia	0.387	0.386	0.417	0.420	0.401	0.268	0.435	0.447
Spain	0.438	0.381	0.406	0.330	0.366	0.312	0.372	0.372
Sweden	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
United Kingdom	0.452	0.436	0.429	0.418	0.457	0.408	0.473	0.466

Table 5: SBM and DDF measures under sequential frontier

	SBM efficiency							
	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
Austria	1.000	0.925	1.000	0.815	1.000	1.000	1.000	1.000
Belgium	0.305	0.302	0.308	0.321	0.318	0.314	0.322	0.329
Cyprus	1.000	1.000	1.000	1.000	0.930	1.000	1.000	1.000
Czech Republic	0.299	0.311	0.307	0.321	0.300	0.295	0.295	0.303
Denmark	0.489	0.531	0.543	0.524	0.615	0.588	0.514	0.545
Estonia	0.303	0.351	0.366	0.388	0.341	0.349	0.346	0.367
Finland	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
France	0.455	0.475	0.460	0.476	0.479	0.476	0.481	0.482
Germany	0.271	0.273	0.355	0.439	0.433	1.000	0.458	0.417
Greece	0.223	0.222	0.221	0.224	0.209	0.201	0.209	0.212
Hungary	0.293	0.288	0.270	0.253	0.255	0.270	0.265	0.285
Ireland	0.226	0.226	0.212	0.214	0.212	0.200	0.213	0.211
Italy	0.422	0.409	0.380	0.370	0.451	0.423	0.430	0.425
Latvia	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Lithuania	0.335	0.339	0.366	0.374	0.362	0.353	0.344	0.358
Luxembourg	1.000	1.000	1.000	1.000	1.000	1.000	0.979	0.733
Malta	1.000	0.496	1.000	1.000	0.161	0.152	0.168	0.166
Netherlands	0.413	0.424	0.458	0.450	0.509	0.434	0.394	0.393
Poland	0.302	0.315	0.310	0.296	0.290	0.288	0.289	0.284
Portugal	0.405	0.463	0.417	0.450	0.417	0.379	0.429	0.524
Slovakia	0.346	0.289	0.284	0.279	0.284	0.293	0.286	0.293
Slovenia	0.361	0.337	0.321	0.321	0.345	0.334	0.326	0.314
Spain	0.271	0.288	0.280	0.334	0.331	0.312	0.309	0.311
Sweden	1.000	1.000	0.904	0.742	0.842	1.000	0.880	1.000
United Kingdom	0.262	0.264	0.271	0.279	0.247	0.251	0.240	0.240
	DDF inefficiency							
	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
Austria	0.000	0.019	0.000	0.030	0.000	0.000	0.000	0.000
Belgium	0.402	0.370	0.374	0.357	0.377	0.362	0.368	0.359
Cyprus	0.000	0.000	0.000	0.000	0.022	0.000	0.000	0.000
Czech Republic	0.461	0.443	0.455	0.449	0.449	0.249	0.457	0.447
Denmark	0.233	0.111	0.111	0.225	0.095	0.114	0.252	0.167
Estonia	0.463	0.405	0.401	0.402	0.427	0.230	0.450	0.401
Finland	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
France	0.247	0.235	0.246	0.248	0.249	0.256	0.250	0.247
Germany	0.464	0.449	0.415	0.370	0.365	0.000	0.352	0.362
Greece	0.531	0.524	0.531	0.534	0.539	0.492	0.538	0.533
Hungary	0.539	0.543	0.557	0.579	0.554	0.556	0.560	0.544
Ireland	0.488	0.478	0.499	0.473	0.418	0.528	0.500	0.496
Italy	0.341	0.344	0.200	0.192	0.142	0.273	0.231	0.241
Latvia	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Lithuania	0.422	0.418	0.375	0.394	0.401	0.408	0.419	0.402
Luxembourg	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.038
Malta	0.000	0.249	0.000	0.000	0.545	0.575	0.623	0.632
Netherlands	0.288	0.283	0.193	0.199	0.097	0.279	0.292	0.302
Poland	0.512	0.508	0.536	0.552	0.530	0.485	0.546	0.546
Portugal	0.273	0.245	0.191	0.181	0.195	0.300	0.257	0.227
Slovakia	0.475	0.426	0.467	0.483	0.453	0.445	0.463	0.454
Slovenia	0.387	0.386	0.417	0.420	0.401	0.280	0.435	0.446
Spain	0.438	0.386	0.409	0.330	0.366	0.333	0.372	0.374
Sweden	0.000	0.000	0.012	0.042	0.043	0.000	0.022	0.000
United Kingdom	0.452	0.436	0.429	0.418	0.457	0.430	0.473	0.463

Table 6: Mean efficiency (SBM) and inefficiency (DDF) for EU25

		2000	2001	2002	2003	2004	2005	2006	2007
SBM	Unweighted mean	0.519	0.501	0.521	0.515	0.493	0.516	0.487	0.488
	Weighted mean	0.436	0.442	0.447	0.452	0.468	0.584	0.466	0.468
DDF	Unweighted mean	0.297	0.290	0.273	0.275	0.285	0.264	0.315	0.307
	Weighted mean	0.336	0.321	0.305	0.299	0.288	0.219	0.308	0.305

Table 7: Distribution hypothesis tests

		SBM		DDF	
		2000–2004	2005–2007	2000–2004	2005–2007
f(EU25) vs. f(EU15)[a]	T-statistic	3.1278	2.1470	0.6767	0.9373
	p-value	0.0009	0.0159	0.2493	0.1743
f(EU15) vs. f(EU25 – EU15)[a]	T-statistic	15.4963	13.6568	8.3130	8.7470
	p-value	0.0000	0.0000	0.0000	0.0000

[a] The hypothesis tested is $H_0 : f(\cdot) = g(\cdot)$, $H_1 : f(\cdot) \neq g(\cdot)$.

Figure 1: Efficiencies by country using Slack-Based Measures (SBM)

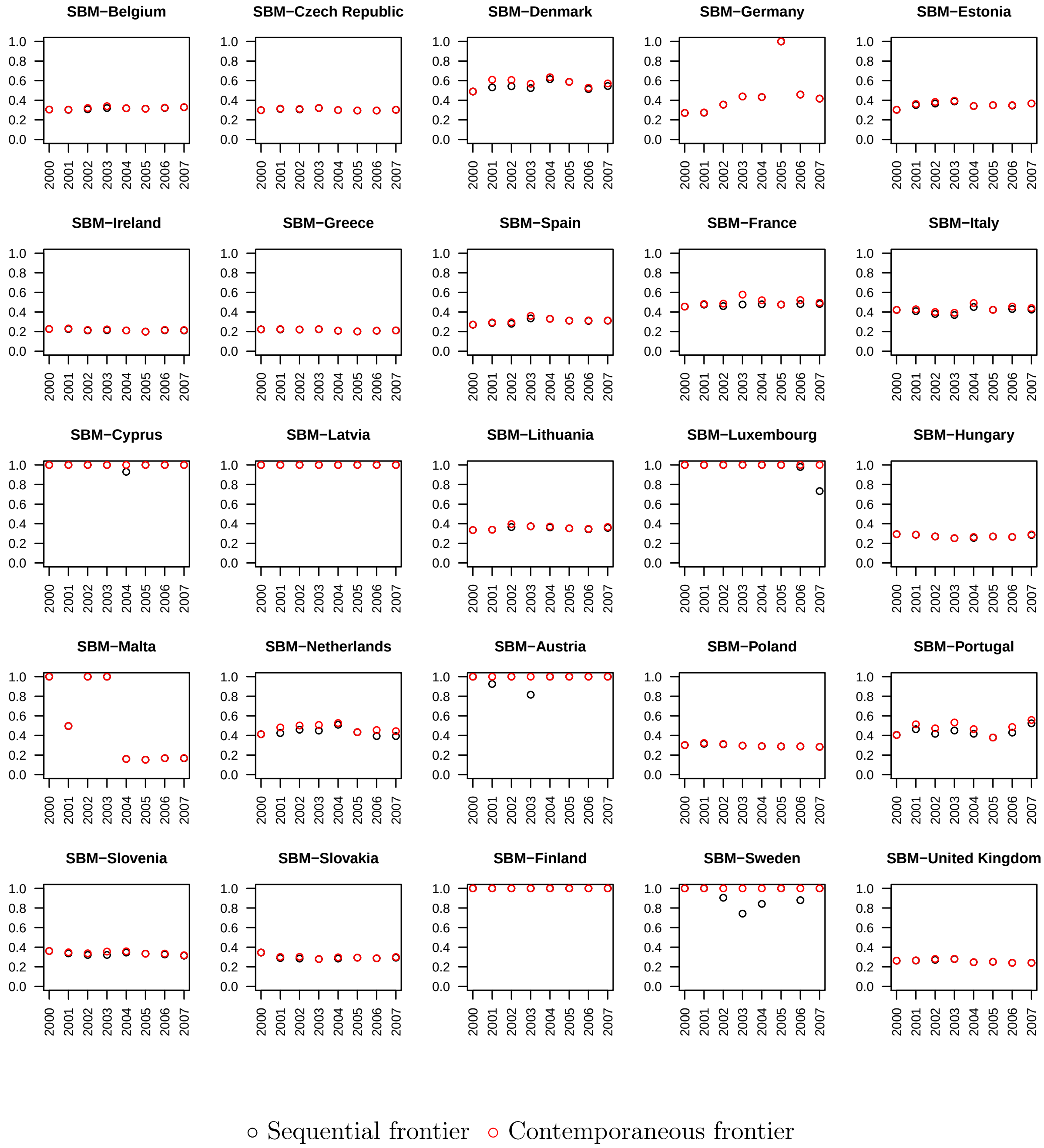


Figure 2: Inefficiencies by country using Directional Distance Functions (DDF)

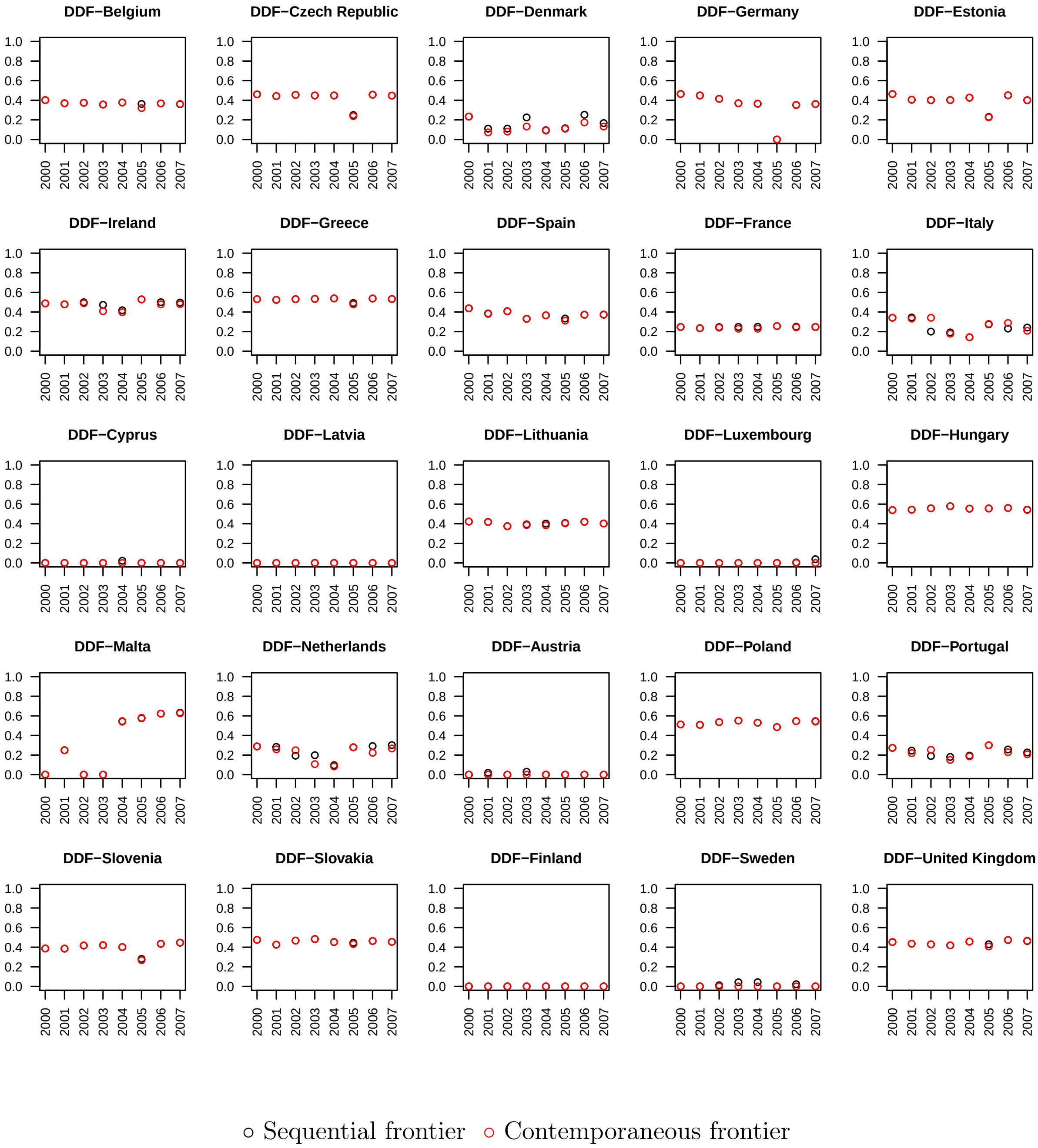


Figure 3: Mean efficiencies and inefficencies (unweighted and weighted)

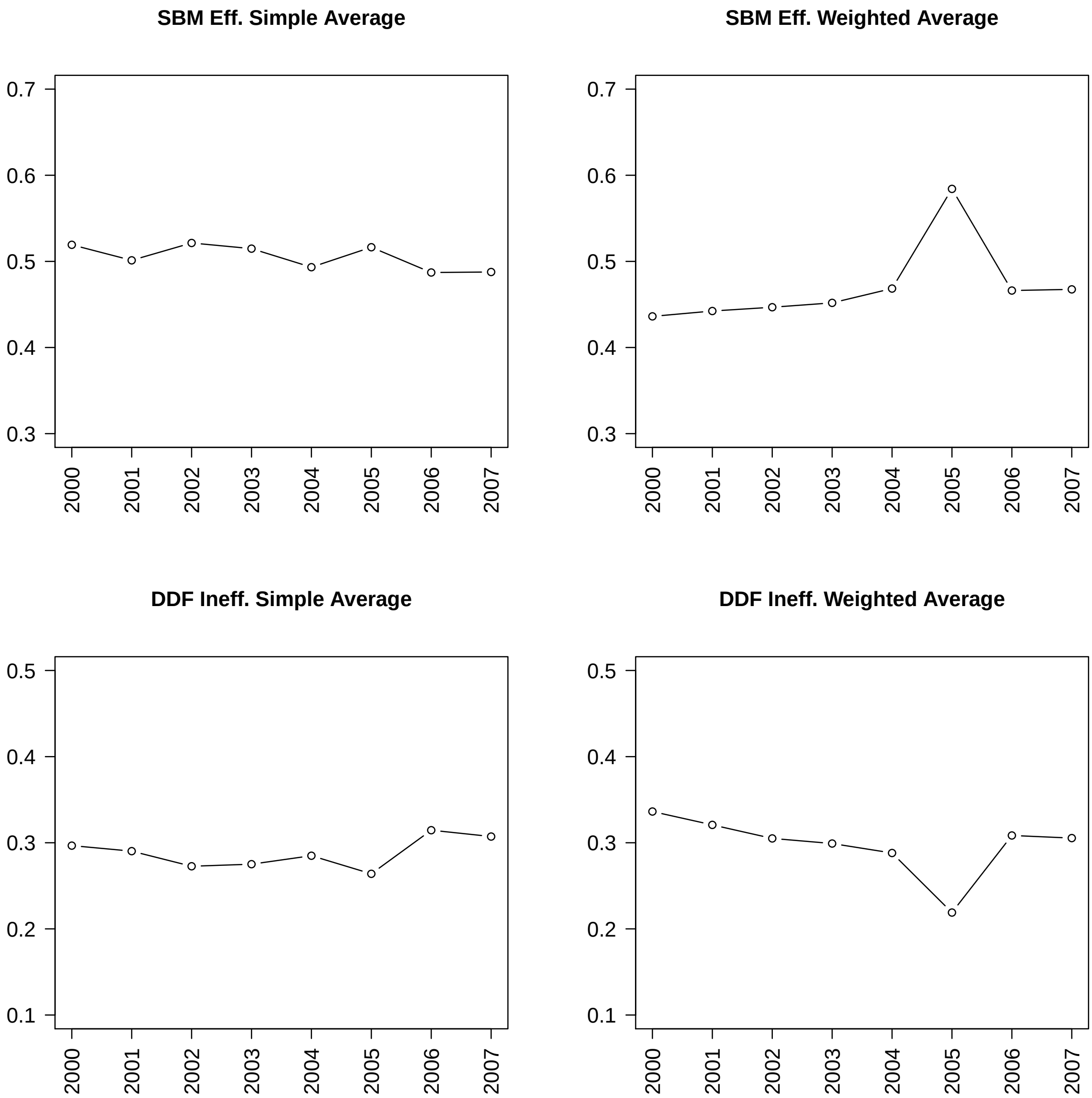
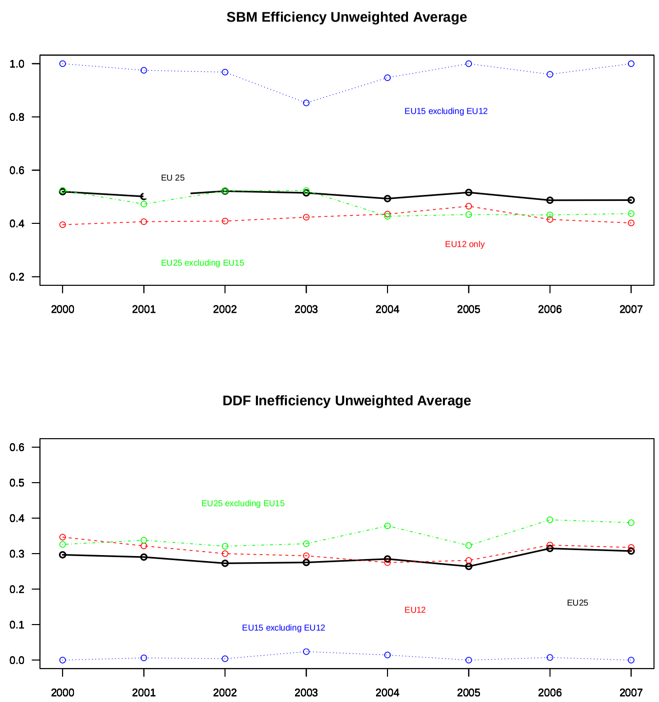


Figure 4: Efficiencies for different EU groupings

(a) Unweighted



(b) Weighted