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On the dynamics of environmental performance in the European Union

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Abstract

This article evaluates the evolution of environmental performance in the context of the European Union (EU), over the period 1993–2010. The context is particularly relevant, due to the traditionally high concerns of the EU about these issues, which has triggered off several initiatives and regulations on environmental protection. In this setting, we conduct a two-stage analysis which develops environmental performance indicators in the first stage for each pair country-year, and evaluates its evolution in the second. More specifically, in the first stage we estimate specific efficiencies for three air-pollutants (CO_2e, SO_2, NO_x), along with an eco-efficiency indicator, for which we use the slack-free directional distance functions in the Data Envelopment Analysis framework (as opposed to the more extended intensity ratios), whereas in the second stage we propose using a model of explicit distribution dynamics which takes into account how the entire distributions of these indicators evolve. Our results indicate that the dynamics underlying the evolution of the indicators analyzed are indeed remarkable. Although the eco-efficiency indicator has improved over the last two decades, it has been during the last decade when performance has shown a more convergent path. However, in the case of the more traditional indicators (CO_2e, SO_2, NO_x) the abatement opportunities are still remarkable, especially in the case of SO_2e.

Keywords: distribution dynamics, efficiency, energy, environmental performance, European Union

JEL classification: Q4, Q43

On the dynamics of environmental performance in the European Union

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October 15, 2014

Abstract

This article evaluates the evolution of environmental performance in the context of the European Union (EU), over the period 1993–2010. The context is particularly relevant, due to the traditionally high concerns of the EU about these issues, which has triggered off several initiatives and regulations on environmental protection. In this setting, we conduct a two-stage analysis which develops environmental performance indicators in the first stage for each pair country-year, and evaluates its evolution in the second. More specifically, in the first stage we estimate specific efficiencies for three air-pollutants (CO_2e, SO_2, NO_x), along with an eco-efficiency indicator, for which we use the slack-free directional distance functions in the Data Envelopment Analysis framework (as opposed to the more extended intensity ratios), whereas in the second stage we propose using a model of explicit distribution dynamics which takes into account how the entire distributions of these indicators evolve. Our results indicate that the dynamics underlying the evolution of the indicators analyzed are indeed remarkable. Although the eco-efficiency indicator has improved over the last two decades, it has been during the last decade when performance has shown a more convergent path. However, in the case of the more traditional indicators (CO_2e, SO_2, NO_x) the abatement opportunities are still remarkable, especially in the case of SO_2e.

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1. Introduction

There is compiled evidence about the relationship between global warming/climate change and the amount of greenhouse gases (GHG) released into the atmosphere (IEA, 2010). Similar anthropogenic interactions have been established between acid rain, acidification, eutrophication[1] or ground-level ozone and certain pollutants like sulphur dioxide (SO_2), nitrogen oxides (NO_x), non-methane volatile organic compounds (NMVOC) and ammonia (NH_3).[2] These problems are closely linked to the fact that pollution is mainly a by-product of the manufacturing activity, and as a result of this, there is a branch of studies suggesting that a correct assessment of economic performance should also incorporate costs resulting from environmental degradation or benefits of environmental improvements (Zaim, 2004). Environmental performance measurement can provide the public decision-makers with meaningful information so as to implement relevant economic and/or regulatory instruments. Also, their results can be used to evaluate the effectiveness of environmental regulations, taxes or any other economic instruments used to improve the quality of the environment and to account for these costs. As a matter of fact, environmental preoccupations have come to the top of international and domestic policy agendas and academic literature is paying increasing attention to assessing environmental performance.

The complexity of the interactions among global environmental changes and its influence on economic and social life has motivated a significant response to this challenge among the scientific community, with an increasing concern according to which, unless a principle of sustainability is included in productive processes, the long term growth of human welfare will be jeopardised by environmental destruction (Zofio and Prieto, 2001).

In recent years, we find a series of studies dealing with economic and ecological efficiency, more popularly known as eco-efficiency, with the aim of measuring the ability of firms, industries, regions or economies to produce more goods and services with less impact on the environment and less consumption of natural resources (Korhonen and Luptacik, 2004; Camarero et al., 2013a; Figge and Hahn, 2004; Kuosmanen and Kortelainen, 2005). In particular, some of these assessments of environmental performance have been carried out by specific ratios or intensity indicators such as CO_2e over GDP emission at a macro level, or units of outputs per unit of waste (or environmental pressure) at the micro-level.

Jointly with these intensity indicators, there are compilations of them, as for instance, the *Environmental Sustainability Index* (ESI) defined by Esty et al. (2008). This particular index is obtained at the country level and is based on 21 indicators, which in turn are assessed from 76 data sets, and computed as a weighted average of indicators with equal weights. Other indicators follow the same structure, but give more emphasis to certain aspects (either the environment, the society, or the economy) such as the *Ecological Footprint* introduced by Rees (1992) or the *Sustainable Society Index* (SSI) due to Van de Kerk and Manuel (2008), an index based on 22 environmental and societal indicators that are aggregated into 5 main categories using equal weights. These 5 categories are then aggregated into SSI using unequal weights and the 150 evaluated countries are ranked accordingly. In line with this, Prescott-Allen (2001)

[1]Eutrophication is defined as an increase in the rate of supply of organic matter in an ecosystem. When their effects are undesirable, eutrophication may be considered a form of pollution. Eutrophication is a natural, slow-aging process for a water body, but human activity greatly speeds up the process.

[2]The Gothenburg Protocol, also known as the Multi-effect Protocol, was a multi-pollutant protocol aimed to set emissions ceilings for the most important pollutants, to be accomplished by 2010. This Protocol is part of the Convention on Long-Range Transboundary Air Pollution. Its geographic scope includes Europe, Noth America and countries of Eastern Europe, Caucasus and Central Asia.

propose a *Barometer of Sustainability*. This approach was introduced by the International Union for the Conservation of Nature (IUCN), and is an intuitive tool of sustainability assessment. In this index, the sustainability of a country has two fundamental components, Ecosystem Well-Being and Human Well-Being, and the primary indicators lie in the [0,100] range, where 0 is the worst performance and 100 the best performance of an indicator. These scores are computed by a straightforward aggregation. The development of all these indicators is not free of controversy due to its multidimensionality and the discrepancies among scientists, governments and agencies, about how to balance the most important factors involved.

Complementary to the *indirect* methods presented above, there is a trend development of indicators where the theory of productive efficiency (Färe and Primont, 1995) plays an important role. Pollutants arise as negative externalities linked with production processes where a bundle of inputs is transformed into desirable outputs. For this reason, environmental performance may be properly assessed in the context of production theory. This *direct* approach provides a synthetic *performance* index based on the observed data using mathematics as an aggregating tool. The advantage of this methodology is that, based on the observed quantities of inputs and outputs, it is possible to establish a benchmark or ranking among the evaluated units with very few assumptions.

The development of Environmental Performance Indicators (EPI) originates from the idea of incorporating pollutants (also called, undesirable outputs) within the well established productive efficiency measurement techniques. In recent years, there has been an ongoing research that has gained popularity in measuring environmental performance with this methodology and examples of these studies include Färe et al. (1996), Tyteca (1997, 1998), Zaim and Taskin (2000), Zofio and Prieto (2001) or Zhou et al. (2007). A comprehensive review of the literature involving environment and pollution related to the energy sector can be found in Zhou et al. (2008a), which complements a previous survey from the same authors (Zhou et al., 2006) in this field. In the literature, we can find environmental performance indicators not only at firm or industry level (Tyteca, 1996, 1998; Olsthoorn et al., 2001; Chung et al., 1997; Kuosmanen and Kortelainen, 2005), but also at a country or regional level (Zaim and Taskin, 2000; Zofio and Prieto, 2001; Färe et al., 2004; Arcelus and Arocena, 2005; Camarero et al., 2013a).

In this context, the aim of this study is to jointly evaluate the economic and ecological performance of EU countries (EU27) during the 1993–2010 period. This analysis is carried out in two stages. In the first stage, we compute an eco-efficiency score and pollutant pressures-specific indicators, through the proposal by Picazo-Tadeo et al. (2011), but making use of the Directional Distance Function (DDF), instead of a radial approach, both of them considering Data Envelopment Analysis (DEA) techniques. Throughout this analysis we obtain specific pollutant pressure indicators for three pollutants: Carbon Dioxide equivalent (CO_2e) and Nitrogen Oxides (NO_x), which are the main sources of GHG, as well as Sulphur Oxides (SO_x), responsible for acidification of soil and the decrease in the richness of plant species. Secondly, we study the dynamics of these specific pollutant pressure indicators using the model of explicit distribution dynamics initially devised by Quah (1993) for analysing their convergence (or divergence) patterns.

Our contribution to the eco-efficiency literature is therefore at two levels. Firstly, although DEA-DDF models have been applied in the pollutants literature (Kumar, 2006; Yörük and Zaim, 2005; Picazo-Tadeo et al., 2011), as far as we know, none of them have considered the presence of non-directional slacks on this particular model. Recent theoretical contributions (Fukuyama and Weber, 2009; Asmild and Pastor, 2010) have pointed out that neglecting the existence of slacks leads to over-estimated efficiency indicators. Our eco-efficiency score is developed using DDF, but it also includes a proposal of a balanced influence of these slacks in the final indicator, leading to a *comprehensive* technical efficiency measure.[3]

Secondly, several research initiatives have analysed convergence in emissions using econometric techniques using either indirect (Lanne and Liski, 2004; Aldy, 2006; Westerlund and Basher, 2008; Romero-Ávila, 2008) or direct approaches (Camarero et al., 2013b; Panopoulou and Pantelidis, 2009). In our case, we analyse the convergence and dynamics of these indicators using an explicit model of distribution dynamics which operates in three stages, namely, analysing the evolution of the external shapes of the distributions, examining if intra-distibution mobility (or churning) exists, and computing the stationary distribution of the efficiencies. This detailed analysis of how distributions evolve over time encodes meaningful information which is usually difficult to summarise considering other methodologies.

The paper is organised as follows. After this introduction, Section 2 is devoted to the development of the model, methodology and construction of the indicators. Section 3 briefly explains the model of distribution dynamics. Section 4 describes the data and sources, followeb by Section 5 which focuses on the results. Finally, Section 6 outlines some conclusions.

2. Model and methodology

One of the most popular nonparametric methods for measuring efficiency is the DEA framework. It has been widely used since the eighties after the influential study by Charnes et al. (1978), who developed the ideas on efficiency measurement by Farrell (1957). DEA methods combine the estimation of the technology that defines a performance standard (usually referred to as 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 technology set or 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:

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

The technological frontier represents best practice, whereas the distance to the frontier from each Decision Making Unit (DMU) in the sample is used to compute a measure of its relative performance. In the particular context of eco-efficiency, DEA models are being increasingly applied. For instance, Korhonen and Luptacik (2004) propose a two-tier approach, firstly a two DEA model to evaluate economic and ecological efficiency and from this, a new DEA model that determines the eco-efficiency performance is developed. The second approach, proposed by the same authors, consists of building up a ratio which simultaneously takes into account both desirable and undesirable output in a unique model.

In this line of research, two contributions worth mentioning are Kuosmanen and Kortelainen (2005) and Picazo-Tadeo et al. (2011). Both find a definition for eco-efficiency as a quotient between one unique

[3]In the operations research literature, models that may not provide Pareto-Koopmans efficiency measure are considered as *lacking for indication*. See Russell and Schworm (2009).

desirable output (economic output) and environmental pressures (undesirable outputs or pollutants). Based on this characterisation of technology, we borrow their formal definition, and with all the feasible combinations of economic results (v) and environmental pressures ($\mathbf{p}$) we build a *pressure generating technology* (PGT) as follows:

$$\mathrm{PGT} = \{(v, \mathbf{p}) : v \text{ can be generated with pressures } \mathbf{p}\} \tag{2}$$

Following Kuosmanen and Kortelainen (2005), the eco-effiency of a particular DMU is formally defined as:

$$\text{Eco-efficiency}_o = \frac{v_o}{P(\mathbf{p_o})} \tag{3}$$

P being a function that aggregates a set of K environmental pressures into an scalar. In the literature a common approach consists of taking a linear weighted average of the particular environmental pressures as an aggregating function in the following way:

$$P(\mathbf{p_o}) = \sum_{i=1}^{K} w_n p_n \tag{4}$$

where w_n is the weight assigned to pressure n.

Yet in real world applications we seldom know the technology PGT, but all DEA variants overcome this problem by estimating the technology $\widehat{\mathrm{PGT}}$ from observed data. Clearly this estimation process can also be performed using statistical methods. The particularities about the DEA approach are the way 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.

For this purpose, there are L DMUs each having two sets of factors: good, or desirable outputs, and bad, or undesirable outputs. Regarding the former, we will only consider one output, $v \in \mathbb{R}_{+}^{1\times L}$, whereas regarding the latter they will be represented by $\mathbf{p} = [\mathbf{p}_1, \ldots, \mathbf{p}_L] \in \mathbb{R}_{+}^{s\times L}$, which will be the most relevant pollutants.

In the DEA approach, the estimation of PGT will consist of a linear convex combination together with free disposability as:

$$\widehat{\mathrm{PGT}} = \left\{ (v, \mathbf{p}) | v \leq \sum_{j=1}^{L} \lambda_j v_j,\ \mathbf{p} \geq \sum_{j=1}^{L} \lambda_j \mathbf{p}_j,\ \ l \leq e\boldsymbol{\lambda} \leq u \right\} \tag{5}$$

where $\boldsymbol{\lambda} \in \mathbb{R}_{+}^{L}$ is the intensity vector, and the l and u parameters determine the return to scale assumption.

For the aim of this analysis, the best practice, or benchmark, of the production process is defined considering the set of all possible DMUs showing maximum output, and minimum environmental pressure combinations. In addition, the production process has three characteristics of interest: how to measure the efficiency, disposability of undesirable outputs and scale of operations.

The efficiency measure for each unit is calculated relative to a reference point on the best practice frontier, on the basis of the Pareto-Koopmans efficiency concept, i.e. a DMU would be deemed as fully efficient, if and only if, it is not possible to improve any good or undesirable outputs without worsening some good or undesirable outputs (Cooper et al., 2007).

Regarding the second characteristic, although weak disposability is a common practice when undesirable outputs are present, we have to assume this when there is a clear dependence between good outputs production and bad output generation. Conversely, when there are opportunities to either reduce, decouple, or even eliminate bad outputs without reduction of good output or increase of input consumption, this assumption might be dropped. In this vein, Yang and Pollitt (2010) or Førsund (2009) have presented some guidance on this issue, showing that the disposability assumption must be established when there is a functional relationship or dependence between bad outputs and other factors. In our particular analysis, we do not assume weak disposability of undesirable outputs as, at a country level, there are alternatives to minimise emissions within the present input consumption and output production.

Regarding the scale of operations, constant returns to scale (CRS) is a common assumption in studies at the country level (Camarero et al., 2013b; Korhonen and Luptacik, 2004; Zofio and Prieto, 2001). Barla and Perelman (2005) have tested for the robustness of the returns to scale hypothesis in a similar study at a country level, concluding that CRS is the right assumption. In our particular data set, the test proposed by Simar and Wilson (2002) has been applied for every year, and we have found that there is no evidence to reject the CRS assumption.

The next step in the theoretical background is the measure of the distance to the frontier. For this aim, we follow the theory of directional distance functions proposed by Färe and Grosskopf (2000). This distance is computed for each inefficiency unit as the distance to the PGT frontier defined as:

$$\overrightarrow{D_0}\left\{v, \mathbf{p}; \mathbf{g}=(g_v, -\mathbf{g_p})\right\} = \sup\left\{\beta \,/\, (v+\beta\, g_v, \mathbf{p}-\beta\, \mathbf{g_p}) \in \mathrm{PGT}\right\} \tag{6}$$

where $\mathbf{g}=(g_v, -\mathbf{g_p})$ is commonly defined as the direction vector. The parameter β provides the measure of this distance, and can be understood as an *inefficiency* score, i.e. if $\beta = 0$ then the DMU lies on the frontier and it is said to be efficient, and the higher the β, the higher the inefficiency.

Any efficiency analysis implies optimisation of a certain set of variables, and the direction vector has an influence on its choice. When there is a clear interest in the optimisation of a particular variable, the *direction vector* points toward this variable, and these models are known as *oriented* models. Conversely if our concern is in more than one variable, the direction vector should account for all of them. In recent years, empirical research on efficiency measurement has focused much more on *non-oriented* models, in what is known as the full space of inputs and outputs. Authors such as Russell and Schworm (2009) or Briec (1997) refer to it as ⟨input-output⟩ space. In environmental performance analysis, it is a common practice to evaluate the performance in the space of good and bad outputs, or even the full space of inputs and all outputs. In our case, we propose to apply a Directional Distance Function (DDF) with orientation to the outputs space (desirable and undesirable outputs) for an overall eco-efficiency indicator, and based on the total slacks for each pollutant we compute a specific environmental pressure indicator.

As introduced above, the *direction vector* $\mathbf{g}=(g_v, -\mathbf{g_p})$, determines a reference point in the frontier that will serve as a benchmark for efficiency (or more properly inefficiency) measurement. In the literature, we can find several alternatives. The first one is an arbitrary direction based on expert prescription, a second choice is the alternative proposed by Briec (1997) and its version with undesirable outputs from Chung et al. (1997). In this case, the vector of observed variables for each DMU determines the direction for optimisacion. More sophisticated alternatives are the Multi-directional Efficiency Analysis (MEA) proposed by Bogetoft and Hougaard (1999) or the Range Directional Model (RDM) by Silva Portela et al. (2004) which is particularly convenient in the presence of negative data.

In our analysis we apply the DDF model using Briec's (1997) improvement vector, which, as mentioned above, is defined by the observed variables for each individual DMU, but reversing for the undesirable outputs, that is: $\overrightarrow{g}_0 = (v_0, -\mathbf{p_0})$. This approach has been followed by Chung et al. (1997), Blancard et al. (2006), Lee et al. (2002), Färe and Grosskopf (2000), Watanabe and Tanaka (2007), Picazo-Tadeo and Prior (2009), among others. The mathematical program for our particular problem is:

$$\begin{aligned} &\beta^* = \max \beta \\ &\text{s.t.} \quad \mathbf{v}\boldsymbol{\lambda} \quad \geq v_0 + \beta v_0 \\ &\qquad\;\; \mathbf{p}\boldsymbol{\lambda} \quad \leq \mathbf{p}_0 - \beta \mathbf{p}_0 \\ &e\boldsymbol{\lambda} \geq 0\,, \beta \text{ free} \end{aligned} \tag{7}$$

We may rearrange the right hand side of the constraints:

$$\begin{aligned} &\beta^* = \max \beta \\ &\text{s.t.} \quad \mathbf{v}\boldsymbol{\lambda} \quad \geq v_0\,(1+\beta) \\ &\qquad\;\; \mathbf{p}\boldsymbol{\lambda} \quad \leq \mathbf{p}_0\,(1-\beta) \\ &e\boldsymbol{\lambda} \geq 0\,, \beta \text{ free} \end{aligned} \tag{8}$$

This program provides an inefficiency score in the $[0, 1)$ range, where 0 is the benchmark for efficient units. Conversely, we may define an efficiency index by subtracting from one the inefficiency score obtained. This is the first stage of the analysis and provides a first inefficiency measure.

Nevertheless, this model has a drawback due to the *lack of indication*,[4] as the projection determined by the directional vector may not belong to the strongly efficient frontier. Consequently, if a weakly efficient frontier point is used as reference, the true amount of slack (compared to the strongly efficient frontier) will not be considered and the inefficiency will be under estimated.

When dealing with small size samples relative to the number of input and output dimensions, the extent of inefficiency cannot be fully assessed by computing only the first stage inefficiency measure, but also slacks need to be considered in order to provide a *comprehensive* performance measure (as slacks may be hiding an important part of potential environmental pressure reduction; Picazo-Tadeo et al., 2009).

Assuring that only strongly efficiency benchmarks are selected, the application of a second stage to account for non-directional slacks is required. For this complementary stage, we propose a new mathematical program that finds the non-directional slacks and computes a new inefficiency measure (δ) based on the inefficiency obtained in the first stage (β) plus an average mean of the relative non-directional

[4] In the Operations Research literature (e.g. Cooper et al., 1999) an index satisfying the property of *indication* of efficiency (an efficiency index is equal to one if and only if the input vector is efficient in the sense of Koopmans, 1951) is said to be *comprehensive*.

slacks:

$$\delta^* = \max\left[\beta^* + \frac{1}{1+s}\left(\frac{S_v^+}{v_{r0}^+} + \sum_{r=1}^{s}\frac{S_r^p}{p_{r0}}\right)\right]$$

$$\begin{aligned} \text{s.t.} \quad \mathbf{v}\boldsymbol{\lambda} - \mathrm{S}^+ &= v_0\,(1+\beta^*) \\ \mathbf{p}\boldsymbol{\lambda} + \mathbf{S}^p &= \mathbf{p}_0\,(1-\beta^*) \\ e\boldsymbol{\lambda} \geq 0\,, \mathrm{S}^+ \geq 0\,, \mathbf{S}^p \geq 0 & \end{aligned} \tag{9}$$

Once the weak efficiency is determined (β^* from the first stage) and the non directional slacks are determined (S^+ and $\mathbf{S}^p$ in the second stage), it is not difficult to establish a target for each variable and DMU. This target represents the desired value in order to become a strong efficient unit, and can be expressed as:

$$\begin{aligned} v_0^* &= v_0^g + \beta^* v_0 + S^+ \\ \mathbf{p}_0^* &= \mathbf{p}_0 - \beta^* \mathbf{p}_0 - \mathbf{S}^p \end{aligned} \tag{10}$$

Also, we can express an inefficiency measure, in the interval [0,1), for each variable in the following way:

$$\begin{aligned} &\text{For the desirable output:} && \frac{v_0^* - v_0}{v_0} = \frac{\beta_0^* v_0 + S^+}{v_0} = \beta_0^* + \frac{S^+}{v_0} \\ &\text{For each undesirable output:} && \frac{p_0 - p_0^*}{p_0} = \frac{\beta_0^* p_0 + S^p}{p_0} = \beta_0^* + \frac{S^p}{p_0} \end{aligned} \tag{11}$$

In summary, the quotient between the absolute improvement quantity and the observed variable can be understood as the specific pollutant pressure indicator. This approach has also been followed by Camarero et al. (2013a) in the context of a radial model when analysing pressure specific eco-efficiency indicators for the most important pollutants in the OECD countries.

In our particular context, pollutant specific pressures are established based on this inefficiency score defined in (11). For each pollutant, a score in the [0,1) interval shows that the larger it is, the larger the extent of inefficiency and the greater abatement opportunity. Conversely, we may define an efficiency score by subtracting from one the inefficiency score. For convenience, we will use efficiency scores in the empirical application.

3. On the dynamics of the indicators of interest

We now present a model which captures the dynamics of the indicators under analysis, i.e. not only eco-efficiency but also CO_2e, NO_x and SO_2, based on the analysis of the evolution of their distributions. One of the main advantages of the method (based on previous contributions in the field of empirical growth and convergence analysis) is an ability to shed light on the movement of countries' performance within the cross-sectional distribution of the variable of interest—in our case either eco-efficiency, CO_2e, NO_x or SO_2.[5] This implies that it we will ultimately find out whether either eco-efficiency (or the specific pollutant pressure being investigated improves steadily over time), if countries' positions in the ranking

[5]For a review on the different approaches to convergence analysis see, for instance, Islam (2003).

vary, or if there is the tendency for countries is to become more alike (i.e. to converge) or disparate (i.e. to diverge) in their pollution abatement characteristics—either towards the best or worst practice.

Our approach to analysing dynamics, which we may refer to as a *model of explicit distribution dynamics*, can be decomposed into three stages. In the first one we analyze the cross section distribution of the variables at different points in time through the nonparametric estimation of density functions. In the second one we model the *law* governing the motion of such a distribution (i.e., its *law of motion* or how it evolves over time). Finally, we identify its long-run characterisation, which we will refer to indistinctly as ergodic or stationary distribution. The joint consideration of these three components provides a complete picture of the dynamics of the indicators of interest, not based on some summary statistics only (i.e. mean and standard deviation) but rather on the evolution of the *entire* distributions.

3.1. The evolution of the external shape of the distributions (densities)

In the first stage of the model, we evaluate the evolution over time of the shape of the distributions of pollutant pressure indicators (i.e. of their densities). They will indicate whether the tendency is to become more alike (converge), disparate (diverge), or to remain stagnant. The first two scenarios would be revealed by probability mass becoming either tighter (convergence) or more spread (divergence), although there is a wide range of possibilities. For instance, if several modes emerged this would unveil the existence of inefficient behaviours, or the possibility that some countries are achieving the objectives, whereas others are not.

The methods considered in this stage will be based on estimating nonparametrically density functions via kernel smoothing, for which a kernel estimator for each pollutant pressure indicator, as well as the eco-efficiency indicator, are considered, namely, $\widehat{f}(x) = 1/(Nh) \sum_{i=1}^{N} K\Big(\|x - X_i\|_x/h\Big)$. In this equation, x is the point of evaluation, X is the indicator of interest (eco-efficiency or pollutant pressure), N is the number of observations (countries), h is the bandwidth, $\|\cdot\|_x$ is a distance metric on the space of X, and $K(x)$ is a kernel function (see Härdle and Linton, 1994). As for the choice of $K(x)$, which may be defined in terms of univariate and unimodal probability density functions, we considered the Gaussian kernel, which is a reasonable choice in many settings (Silverman, 1986).

3.2. Law of motion of the distributions: transtion probability matrices

In the second stage, our model evaluates the *law* governing the evolution of the distributions of the variables of interest. The rationale for considering a second stage deals with the hidden characteristics of the evolution of the densities, since there could exist a remarkable amount of changes in countries' relative positions—i.e. intra-distribution mobility or *churning*—regardless of whether convergence, divergence, or stagnancy is taking place. Should this type of mobility exist, it could occur that an *a priori* static distribution concealed high intra-distribution mobility. In this scenario, a mere analysis of the evolution over time of the densities of interest would be misleading—we might conclude that no tendencies existed, but the implications of this high intra-distribution mobility would be relevant, as we shall see.

We will refer to $s_{i,t}$ as country i's indicator of interest (eco-efficiency, as well as CO_2e, NO_x and SO_2) in period t, whereas $F_t(s)$ refers to the cumulative distribution of $s_{i,t}$ across countries and, corresponding to $F_t(s)$, we can define a probability measure $\lambda_t((-\infty, s]) = F_t(s),\ \forall s \in \mathbb{R}$, which would be the probability density function for each indicator in period t. The model would then analyze the dynamics of λ_t, i.e. the dynamics of the cross-section distribution of either eco-efficiency or any of the pollutant pressure indicators of interest, for which we will consider a stochastic difference equation:

$$\lambda_t = P^*(\lambda_{t-1}, u_t), \text{ integer } t, \tag{12}$$

where $\{u_t : \text{integer } t\}$ is the sequence of disturbances of the entire distribution, and P^* is the operator mapping disturbances and probability measures into probability measures. Hence, P^* would unveil information on how the distribution of any of the indicators considered at time $t-1$ transforms into a different one at time t. We may assume that the stochastic difference equation is first order and that operator P^* is time invariant. Therefore, setting null values to disturbances, and iterating in (12) we obtain the future evolution of the distribution (Redding, 2002):

$$\lambda_{t+\tau} = (P^* \cdot P^* \cdot \ldots \cdot P^*)\lambda_t = (P^*)^\tau \lambda_t \tag{13}$$

By discretizing the set of possible values of s into a finite number of cells $k \in \{1, \ldots, K\}$, P^* would become a transition probability matrix

$$\lambda_{t+1} = P^* \cdot \lambda_t \tag{14}$$

where λ_t is now a $K \times 1$ vector of probabilities, according to which an indicator for a particular country is located in a given grid at time t. In our case, the discretization implies dividing the space of possible F_t values into several grid cells (also labelled as states, or classes), i.e., e_k, $k = 1, \ldots, K$. Then, after classifying each country-year observation into one of the K classes, we construct a 5×5 matrix whose p_{kl} entries indicate the probability that a country initially in state k will move to state l over the period considered (T). Each row of the matrix would constitute a vector of transition probabilities, adding up to unity.[6]

The transition probability matrices therefore enable measurement of the probability that a given country moves to a higher (or lower) position (in the particular rankings of our indicators of interest). For calculating the transition matrices, we start discretizing the observations into a certain number of states e_k. This implies that state $e_k = (0.2, 0.4)$ would include countries with given values for these indicators between 0.2 and 0.4. The value for each entry in the matrix reports the probability that a given country will transit out during the period considered—from its initial class to other classes. We can estimate the transitions by counting the number of transitions out of and into each cell, i.e., for each p_{kl} cell, $p_{kl} = \frac{1}{T-1}\sum_{t=1}^{T-1}\frac{n_{kl}^t}{n_k^t}$, where T is the number of years or periods, n_{kl}^t is the number of countries moving during one period from class k to class l, and n_k^t is the total number of countries that started the period in class l.

[6]The boundaries between grid cells are chosen such that country-year observations are equally divided across cells, and each cell corresponds to one fifth of the distribution of each indicator of interest—considering a pool of all years. For instance, in the case of eco-efficiency, observations in the first state refer to countries with the lowest value corresponding to this indicator. This criterion has been followed extensively (see, for instance Redding, 2002); however, other criteria are also valid (Kremer et al., 2001; Quah, 1993). An alternative strategy to avoid the discretization problem is to consider stochastic kernels (Quah, 1996; Bashtannyk and Hyndman, 2001).

3.3. Ergodic distributions

In the final (third stage), our model aims to characterise the hypothetical ergodic (stationary) distribution, for which we use the information offered by the transition probability matrices. In this respect, several results (scenarios) might arise. For instance, on the one hand we might find a distribution with the probability mass concentrated mainly in the central class or classes (indicative of convergence towards the mean). On the other hand, we might find a more polarised distribution, or one with the probability mass distributed in either the upper or lower states of the distribution. In sum, the ergodic distribution helps us to uncover the degree to which the countries in our dataset present a tendency to convergence, diverge, to polarise, or for other different scenarios, for any of the indicators considered—eco-efficiency as well as CO_2e, NO_x and SO_2.

This ergodic (stationary) distribution, formally, corresponds to the eigenvector associated with the largest eigenvalue of the transition probability matrix. If $\{X_n\}$ is a Markov chain with transition probability matrix P, and there is a probability vector $V = (v_1, v_2, \ldots)$ (i.e., $v_i \in [0, 1]$, $\sum v_i = 1$) such that $VP = V$, then V is called the ergodic (stationary) distribution for the Markov chain $\{X_n\}$. Furthermore, for a finite and irreducible Markov chain with probability matrix P, a unique ergodic distribution exists, i.e. there exists V (a probability vector) such that $VP = V,\ Ve = 1,\ e = (1, 1, \ldots)$.

We may compute ergodic distributions following more straightforwardly. The only non-zero estimated transition probabilities are those between adjacent groups, and we will assume that the true transition probabilities satisfy this condition, what is referred to as the triple diagonal condition (Kremer et al., 2001). In a wide variety of scenarios (which also affects ours) this assumption is reasonable (the indicators do not halve or double in a single year). If the triple diagonal condition is then satisfied, the ergodic probabilities (π_j) maintain a relatively simple relation to the probability of transition between groups i and j, denoted p_{ij}:

$$\frac{\pi_1}{\pi_2} = \frac{p_{21}}{p_{12}}, \frac{\pi_2}{\pi_3} = \frac{p_{32}}{p_{23}}, \frac{\pi_3}{\pi_4} = \frac{p_{43}}{p_{34}}, \frac{\pi_4}{\pi_5} = \frac{p_{54}}{p_{45}}$$

4. Data and sources

Pollutants data for this analysis have been obtained from the Eurostat database, section "Environment and Energy", that compiles this information from the European Environment Agency (EEA). Though the most harmful pollutants have been considered, data availability (just for the period from 1993 to 2010) has been an important constraint in this study.

Regarding the pollutants that exert pressure on the environment, we propose the inclusion of three of them:[7] two are harmful pollutants, Nitrous Oxides (NO_x) and Sulphur Dioxide (SO_2) responsible for acidification of soil and water resources, and the third one is the release into the atmosphere of GHG, which are commonly measured in Carbon Dioxide equivalent (CO_2e) units. These three variables are included in the model as *undesirable* outputs on the input side. In the literature, many authors have considered pollutants like CO_2 in efficiency analysis (Zhou et al., 2008b; Arcelus and Arocena, 2005; Zofio and Prieto, 2001; Ezcurra, 2007; Camarero et al., 2013a) or SO_2 (Yaisawarng and Klein, 1994; Barla and

[7]Besides data availability, another important reason for this decision has been the risk of dimensionality, or the risk of losing discriminatory power of the DEA method when the balance between the amount of variables and decision units is not appropriate. As a rule of thumb, it is recommended that in order to achieve a satisfactory balance between efficient and non-efficient DMUs, the number of decision making entities should be three times as large as the sum of inputs and outputs (Nunamaker, 1985).

Perelman, 2005). The Unit of measurement are tonnes for NO_x and SO_2 and million tonnes for CO_2e. As a *desirable* output, we account for the Gross Domestic Product (GDP) as a proxy of the activity of a country. A brief summary of the data is presented in Table 1.

The evolution of the aggregate data for each variable has been depicted in Figure 1. There are remarkable differences in observed reduction among the three pollutants during the evaluated period. On the left vertical axis of Figure 1, independent scales for each pollutant have been depicted using zero emissions as the lowest range value. In particular, observed reduction in the SO_2 emissions are close to 75%, whereas CO_2e accounts for the worst abatement (about 5%) both of them under the evaluated period (1993–2010).

5. Results

For each sample year during the 1993–2010 period, and for each country (EU27), we have computed four environmental performance indicators, namely eco-efficiency and three pollutant specific efficiencies. This has resulted in the evaluation of 27 countries during 18 years and 4 indicators: eco-efficiency, CO_2e, SO_2 and NO_x efficiencies. All these indicators represent a total amount of 1,944 efficiency scores. A summary of the eco-efficiency scores, grouped in different enlargements, has been reported in Table 2 and plotted in Figures 2 and 3 for the unweighted and weighted averages, respectively.[8]

We begin our study describing the time path of the eco-efficiency indicator for each EU enlargement. In Table 2 and Figures 2 and 3 we present a summary of the eco-efficiency results (first indicator), there we show that eco-efficiency has improved regardless of the country aggregated selected. Nonetheless, this improvement has differed both between and within enlargements. When comparing results from the unweighted and weighted averages plotted in Figures 2 and 3 respectively, we observe that both averages differ, showing the presence of differences between country sizes. This is the case of the EU25 enlargement which took place in 2004 which presents better performance for the unweighted rather than the weighted average. For this group of countries, it seems that small countries performed better than larger ones. Conversely, the rest of enlargement follows an opposite trend. It is also relevant to note that the EU15 enlargement has been setting the benchmark, or reference, for the rest of countries during all periods, showing an almost steady efficiency average.

These summary statistics (unweighted and weighted mean) represent a first approximation to the dynamics of efficiency distributions. However, these dynamics can be much more complex to be summarised into only two summary statistics. Standard deviation, also reported in Table 2 helps in shedding some light about this dispersion, but it hardly informs us on the (likely) existence of multi-modality, for instance. The inclusion of higher moments of distribution may help in overcoming these limitations, but it does not fully inform on the evolution of the *entire* distribution of efficiency scores.

In order to achieve a fuller view of the dynamics, we have applied the model of explicit distribution dynamics considered in Section 3 to the evolution of the indicators of interest during the 1993–2010 period. In the first state of this approach, described in Section 3.1, we proposed to examine the evolution of the external shapes of the distributions of the variables of interest. The results for the eco-efficiency indicator are provided in Figure 4 for every other sample year, in order to save space. Unlike previous

[8] Weighted averages have been obtained using GDP as a weighting factor.

contributions such as, for instance, Ezcurra (2007), we do not normalise the efficiency indicators dividing by the corresponding year average, since the values are already bounded in the $)0,1]$ interval.

The results plotted in Figure 4 indicate that the shape of the distribution has remained almost invariant during the first half of the period. Conversely, from 2000 and onwards, there is a clear trend towards an increase of the probability mass on the right side of the distribution. Moreover, from 2002 to 2008 there is evidence of bi-modality in the distribution that vanishes in 2010 in favour of a unimodal distribution, with higher efficiency levels—although given the low number of observations, this tendency could be driven by some anomalous behaviour. In summary, regarding the eco-efficiency, the second half of the period has been characterised by a generalized efficiency improvement, but the emergence of multi-modality in the upper tail of the distribution indicates that this seems to be driven by only some of the countries. This period in which bi-modality seems to emerge is coincidental with the establishment of important milestones related to the energy sector and environmental protection, such us the Kyoto Protocol negotiations and signature, the Renewable Energy Directives, the Energy Efficiency Action Plan, and the establishment of the EU Emission Trading System (Phase 1 and 2).

Analogously, the densities for the pollutant specific efficiencies have been plotted in Figure 5 for the same sample of years as above. For the sake of brevity, each figure includes densities for the three pollutants. The solid line represents the CO_2e efficiency, the dotted line the NO_x efficiency, and the dashed line the SO_2 efficiency. Some interesting points emerge for these plots. Firstly, the shape of the densities is similar for CO_2e and NO_x but completely different for SO_2. In particular for the first two pollutants, there is a trend for probability mass to concentrate towards upper efficiency values, whereas for SO_2 the distribution is almost uniform along all evaluated periods. It seems that despite the remarkable observed SO_2 abatement achieved during the last two decades, there are still a set of countries with low efficiencies for this particular pollutant, which would therefore present further pollution abatement opportunities. Secondly, the densities for the other two pollutants (CO_2e and NO_x) show similar patterns, with slightly better performance for the NO_x in some periods (2002 to 2008). It should also be pointed out that NO_x efficiency has shown a steady positive evolution (probability mass shifting to the right), whereas for CO_2e efficiency this trend is partially blurred. More specifically, during the 2004–2006 period there has been a positive evolution followed by a decline in 2008 and improvement in the last analysed period (2010).

Although the information conveyed by the evolution of the densities is relevant, there are some specific trends they cannot capture. Specifically, regardless of the tendency which might have existed for the evolution of the densities, they cannot disclose the likely existence of intra-distribution mobility (or *churning*) of efficiency scores. The densities described in the previous paragraphs provide detailed information on how the external shape of the whole set of efficiencies evolves over time, but they do not inform on whether changes in the relative positions among countries are actually taking place. In other words, although the external shape of the densities might be unaffected, changes in countries' relative positions could be taking place, which would require further analysis.

Therefore, in the second stage of the analysis we propose an analysis of the *law of motion* of the cross-section distribution of efficiencies, in order to detect whether this type of mobility is actually taking place. According to the methodology described in Section 3, the second stage in this analysis is the estimation of transition probability matrices between selected periods. Specifically, our analysis will focus on how distributions in t turn into other distributions in $t+1$, $t+5$ and $t+17$, i.e. we consider annual, quinquennial, and 17-year transitions.

The results are reported in Tables 3–6. The upper limits for each table correspond to the quintiles of the total amount of observations (country-year) considered for each variable of interest, which is a usual criterion. In the first column in each table ("# observations") we report the number of observations starting in each state of relative efficiency during the first period (t). Regarding the interpretation of each entry of the matrix, they correspond to the probability of a given country with a certain level of efficiency to either remain in the same state, or move to another state of efficiency—either better or worse. For instance, the entry a_{11} in the first matrix of Table 3 indicates that, in the following period ($t+1$ in this particular case), 92.6% out of the 95 observations remained in the same state of efficiency, whereas entry a_{12} indicates that 7.4% of the 95 observations starting in state 1 in period t moved to the following state of higher efficiency—whose upper limit is 0.565. Note that, since these are probability matrices, the entries in each row sum to one.

In the extreme case of full persistence, the transition matrix would be the identity matrix—i.e. probability mass fully concentrated along the main diagonal. In contrast, if the diagonal values were close to zero it would be indicating that intra-distribution mobility is quite high.

The probability mass concentrated in the main diagonal of the transition matrices (Tables 3–6) is lower for large transition and in fact, there are some cases in which probability mass completely abandons some entries of the main diagonal. This result is to be expected, since movements are more likely to occur over long time periods. This is the case for the SO_2 efficiency for the 1993–2010 transition that presents three out of the five stages in the main diagonal with almost zero probability mass concentrated on the entries on the right.

Another important point that can be deduced from the transition matrices is the persistence of the set of efficient countries. Almost all efficient countries present high persistence for all periods as can be inferred from the high values (high probability) in the main diagonal. Only those matrices related to the CO_2e efficiency present lower probabilities compared with the rest. This specific pollutant presents certain particularities which differ from the rest; in particular, we observe that the initial density distribution is mainly skewed to the right and, more interestingly, the final distribution has moved further to the top with lower dispersion.

A deeper analysis of the tendencies observed in the matrices contained in Tables 3–6 indicate that intra-distribution mobility differs across both the indicators and transitions considered. Regarding the annual transitions, displayed in the upper matrix in each table, the highest persistence correspond to the eco-efficiency indicator (Table 3) and the SO_2 indicator (Table 5), whose respective entries on the main diagonal correspond to 0.84 and 0.87, respectively. In contrast, both CO_2e and NO_x show more mobility, since the averages in the main diagonal are 0.753 and 0.787 (Tables 4 and 6). This ranking is virtually unchanged when considering quinquennial transitions. In this case, the highest mobility still corresponds to CO_2e, as indicated by the middle panel in Table 4—whose entries in the main diagonal average to 0.523.

These rankings are more volatile when considering 17-year transitions. However, this result was to be expected due to the relatively low number of observations (compared to the number of states). Of special note is the a_{55} entry found in all matrices with the only exception being for CO_2e. As shown in the lower panel in Tables 3, 5 and 6, probability mass collapses in those entries. This merely indicates that the countries which were in those states in 1993 remained in that state in 2010—i.e. there has been no *leaking* of probability to other states of less efficiency; in contrast, there are several countries which have moved to this state of highest efficiency.

Only for CO_2e (lower panel in Table 4) do we observe that some probability abandoned the state of highest efficiency, as indicated by $a_{55} = 0.500$. Since only 4 observations started in that class of highest efficiency in 1993 (see the first column in the lower panel of Table 4), this would imply that only 2 countries of those 4 who were initially in that state remained there in 2010, whereas the other two moved to state 4—as shown by $a_{54} = 0.500$. We will elaborate further on this below.

The last stage of the model of explicit distribution dynamics corresponds to the analysis of the ergodic, or stationary, distribution. Having constructed the five states considering probability uniformly distributed (20%) across states, it indicates which would be the long-run distribution according to these states *if the tendencies observed during the analysed period persisted*, i.e. under current trends.

The results corroborate with what was found for the intra-distribution mobility analysis. The more favourable future scenario, in terms of efficiency, corresponds to both eco-efficiency and, more especially, SO_2, for which the probability mass tends to concentrate in the highest states of relative efficiency, regardless of the transitions considered (see Tables 3 and 5). However, in the case of NO_x and, very especially, CO_2e (see Tables 6 and 4) the distribution of the probability is closer to the initial state. This is especially the case for CO_2e, for which, regardless of whether we consider yearly or quinquennial transitions, a substantial amount of probability mass remain in the three states of lowest efficiency.

6. Conclusions

In this research we have proposed a two-stage evaluation of the evolution of environmental performance in the context of the European Union (EU27). In the first stage we constructed four environmental performance indicators (namely, eco-efficiency and three pollutant specific indicators: CO_2e, SO_2 and NO_x), and the second stage was devoted to analysing their dynamics during the 1993–2010 period.

The environmental performance indicators have been developed using nonparametric frontier techniques based on a directional distance function accounting for non-radial slacks, whereas the analysis of the evolution has been evaluated considering a model of explicit distribution dynamics which attempts to unveil questions such as how the distribution of the environmental performance indicators evolves (estimating density functions using kernel methods), to analyse whether there have been changes in countries' relative positions over time, and also to ascertain which the long-run (ergodic distribution) of these indicators might be, under current trends.

The results of the study reveal some improvements for some of the four proposed environmental performance indicators. The results obtained for these indicators suggest that there are still opportunities for further improvements in pollutants like SO_2, and to a lesser extent for the rest of the indicators. Our results also reveal that the convergence process between 1993 and 2010 has not been a continuous process, which is a consideration for policymakers and decision makers when designing future plans to preserve the environment. More specifically, although the general tendency is an improvement in several of the indicators considered, the underlying dynamics are complex, and they reveal that the degree of fulfillment of the objectives pursued is heterogeneous. Some of the opposite tendencies which affect the different EU countries are ultimately jeopardising the process of convergence in different key areas developed by the EU climate policies.

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Table 1: Data summary from 1993 to 2010

Country	GDP 1000 Million (bn) PPS		CO_2e Thousands tonnes		SO_2 Tonnes		NO_x Tonnes	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Belgium	251.528	43.991	143,351.333	7,166.482	177,647.222	69,480.216	310,890.111	56,089.206
Bulgaria	53.877	16.816	69,831.500	7,368.098	892,339.889	276,889.286	140,126.611	12,468.586
Czech Republic	157.487	35.433	146,159.500	5,854.310	492,100.000	427,505.614	365,754.167	106,608.320
Denmark	135.485	24.324	71,325.222	7,023.580	61,364.556	53,410.564	208,553.556	49,373.523
Germany	1,935.326	294.070	1039,143.444	65,206.609	972,268.500	686,510.405	1808,475.611	312,756.365
Estonia	14.379	5.495	19,199.333	1,633.156	98,346.222	25,875.760	38,479.167	2,908.424
Ireland	103.343	35.944	64,809.667	4,321.501	109,154.778	52,135.053	121,031.056	15,307.136
Greece	191.653	46.370	123,549.333	9,289.796	504,675.222	67,341.606	373,610.222	29,483.862
Spain	830.291	233.684	369,770.000	46,888.551	1387,512.000	445,058.951	1304,079.778	115,567.938
France	1,370.114	253.205	554,799.000	16,974.248	634,090.056	260,061.646	1505,771.944	216,709.362
Italy	1,281.220	181.937	541,515.556	25,452.160	740,343.111	411,097.771	1432,070.889	325,869.362
Cyprus	13.035	4.035	10,356.000	,945.426	38,049.278	9,145.939	20,392.778	,995.047
Latvia	20.020	6.893	11,849.000	1,320.647	24,234.944	22,395.345	38,048.833	2,983.812
Lithuania	32.560	10.918	22,227.556	1,649.153	59,635.167	29,327.188	61,103.278	9,424.616
Luxembourg	22.174	7.107	11,171.667	1,440.426	4,925.778	3,948.557	45,940.944	7,420.292
Hungary	118.438	30.128	77,270.278	3,975.632	397,873.111	250,439.147	184,805.111	14,840.548
Malta	6.321	1.300	2,758.111	,258.621	20,249.944	8,237.711	9,074.278	,375.809
Netherlands	414.459	94.587	215,061.444	8,080.514	82,786.444	33,793.183	385,195.056	67,006.495
Austria	206.915	36.367	84,160.111	5,046.274	33,148.389	9,958.641	206,648.167	17,556.354
Poland	382.051	110.961	404,112.111	22,580.944	1636,821.000	570,652.518	929,789.944	129,277.905
Portugal	162.402	33.923	77,307.944	7,083.909	216,449.111	79,535.559	248,779.056	24,896.802
Romania	151.877	53.106	152,809.556	17,376.410	583,359.167	94,204.475	337,400.111	43,954.357
Slovenia	32.877	8.315	19,447.444	1,001.114	75,455.167	54,446.733	51,923.611	5,237.389
Slovakia	62.159	21.211	50,982.000	2,458.946	145,378.611	75,143.110	117,719.167	30,057.642
Finland	117.378	26.360	73,954.000	4,703.708	89,013.944	17,397.825	223,759.944	49,896.423
Sweden	220.617	44.004	69,887.111	4,384.907	47,769.000	16,467.380	200,192.111	32,993.736
United Kingdom	1,386.221	288.161	666,219.833	41,672.585	1285,202.056	781,741.981	1776,851.444	404,216.272

Table 2: Eco-efficiency enlargement averages

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
EU27																		
Simple Average	0.585	0.591	0.596	0.603	0.606	0.618	0.622	0.615	0.625	0.641	0.637	0.627	0.646	0.670	0.662	0.658	0.690	0.711
Weighted Average	0.686	0.696	0.695	0.710	0.709	0.715	0.707	0.706	0.720	0.728	0.726	0.704	0.722	0.752	0.742	0.721	0.772	0.791
Standard Deviation	0.194	0.192	0.188	0.187	0.187	0.182	0.189	0.199	0.196	0.205	0.204	0.199	0.203	0.195	0.199	0.199	0.180	0.194
EU12 enlargement																		
Simple Average	0.669	0.677	0.680	0.692	0.697	0.704	0.711	0.706	0.719	0.745	0.743	0.720	0.742	0.766	0.757	0.747	0.781	0.819
Weighted Average	0.706	0.716	0.715	0.731	0.732	0.735	0.724	0.724	0.741	0.750	0.750	0.725	0.745	0.779	0.770	0.746	0.802	0.824
Standard Deviation	0.087	0.088	0.085	0.089	0.090	0.101	0.136	0.144	0.144	0.161	0.154	0.151	0.169	0.159	0.167	0.163	0.138	0.143
Accession date: 1-1-1986																		
EU15 enlargement																		
Simple Average	0.862	0.862	0.867	0.857	0.859	0.867	0.862	0.872	0.864	0.866	0.847	0.855	0.874	0.858	0.855	0.862	0.870	0.863
Weighted Average	0.917	0.917	0.920	0.914	0.912	0.915	0.911	0.917	0.910	0.912	0.902	0.905	0.917	0.907	0.903	0.907	0.914	0.911
Standard Deviation	0.239	0.240	0.230	0.247	0.244	0.230	0.239	0.222	0.235	0.232	0.265	0.252	0.219	0.246	0.252	0.239	0.225	0.238
Accession date: 1-1-1995																		
EU25 enlargement																		
Simple Average	0.448	0.455	0.463	0.473	0.476	0.491	0.492	0.481	0.496	0.507	0.506	0.503	0.518	0.551	0.541	0.539	0.568	0.585
Weighted Average	0.379	0.396	0.404	0.418	0.419	0.446	0.450	0.436	0.456	0.468	0.462	0.456	0.464	0.488	0.481	0.472	0.509	0.522
Standard Deviation	0.133	0.128	0.122	0.108	0.101	0.092	0.085	0.093	0.087	0.087	0.091	0.094	0.093	0.098	0.102	0.123	0.101	0.131
Accession date: 1-5-2004																		
EU27 enlargement																		
Simple Average	0.348	0.353	0.354	0.342	0.332	0.362	0.385	0.347	0.354	0.350	0.346	0.348	0.368	0.403	0.406	0.413	0.481	0.475
Weighted Average	0.356	0.362	0.367	0.366	0.350	0.373	0.395	0.351	0.361	0.358	0.354	0.361	0.385	0.427	0.426	0.442	0.512	0.501
Standard Deviation	0.028	0.029	0.038	0.062	0.049	0.033	0.031	0.013	0.024	0.025	0.025	0.038	0.052	0.071	0.056	0.084	0.086	0.072
Accession date: 1-1-2007																		

Table 3: Transition probability matrices and ergodic distributions for eco-efficiency (1-year, 5-year and 17-year transitions)

		Upper limit				
$(t, t+1)$	# observations	0.464	0.565	0.658	0.794	1.000
	95	0.926	0.074	0.000	0.000	0.000
	91	0.022	0.835	0.143	0.000	0.000
	93	0.000	0.086	0.753	0.161	0.000
	92	0.000	0.000	0.087	0.750	0.163
	88	0.000	0.000	0.000	0.080	0.920
Ergodic distribution	**459**	**0.024**	**0.081**	**0.134**	**0.249**	**0.511**
		Upper limit				
$(t, t+5)$	# observations	0.464	0.565	0.656	0.794	1.000
	79	0.759	0.228	0.013	0.000	0.000
	68	0.044	0.632	0.265	0.059	0.000
	71	0.000	0.141	0.507	0.296	0.056
	74	0.000	0.000	0.189	0.473	0.338
	59	0.000	0.000	0.000	0.102	0.898
Ergodic distribution	**351**	**0.007**	**0.040**	**0.094**	**0.187**	**0.672**
		Upper limit				
(1993,2010)	# observations	0.485	0.588	0.691	0.807	1.000
	8	0.375	0.375	0.125	0.125	0.000
	5	0.000	0.400	0.200	0.400	0.000
	7	0.000	0.143	0.000	0.429	0.429
	4	0.000	0.000	0.250	0.250	0.500
	3	0.000	0.000	0.000	0.000	1.000
Ergodic distribution	**27**	**0.000**	**0.000**	**0.000**	**0.000**	**1.000**

Table 4: Transition probability matrices and ergodic distributions for CO_2e efficiency (1-year, 5-year and 17-year transitions)

		Upper limit				
$(t, t+1)$	# observations	0.552	0.659	0.759	0.892	1.000
	95	0.853	0.105	0.042	0.000	0.000
	92	0.087	0.674	0.152	0.043	0.043
	92	0.011	0.130	0.685	0.130	0.043
	90	0.000	0.044	0.122	0.722	0.111
	90	0.000	0.022	0.000	0.144	0.833
Ergodic distribution	**459**	**0.114**	**0.168**	**0.196**	**0.257**	**0.266**
		Upper limit				
$(t, t+5)$	# observations	0.531	0.657	0.757	0.883	1.000
	78	0.654	0.205	0.128	0.013	0.000
	69	0.174	0.406	0.232	0.072	0.116
	72	0.000	0.292	0.403	0.181	0.125
	65	0.000	0.092	0.200	0.508	0.200
	67	0.000	0.000	0.015	0.343	0.642
Ergodic distribution	**351**	**0.083**	**0.164**	**0.185**	**0.289**	**0.279**
		Upper limit				
$(1993, 2010)$	# observations	0.573	0.701	0.787	0.929	1.000
	8	0.375	0.250	0.125	0.250	0.000
	5	0.000	0.400	0.400	0.000	0.200
	7	0.000	0.286	0.000	0.286	0.429
	3	0.000	0.000	0.000	0.667	0.333
	4	0.000	0.000	0.000	0.500	0.500
Ergodic distribution	**27**	**0.000**	**0.000**	**0.000**	**0.600**	**0.400**

Table 5: Transition probability matrices and ergodic distributions for SO_2 efficiency (1-year, 5-year and 17-year transitions)

		Upper limit				
$(t, t+1)$	# observations	0.073	0.141	0.312	0.612	1.000
	94	0.915	0.085	0.000	0.000	0.000
	93	0.043	0.806	0.151	0.000	0.000
	93	0.000	0.075	0.785	0.129	0.011
	91	0.000	0.000	0.044	0.868	0.088
	88	0.000	0.000	0.000	0.023	0.977
Ergodic distribution	**459**	**0.014**	**0.028**	**0.056**	**0.180**	**0.721**
		Upper limit				
$(t, t+5)$	# observations	0.072	0.139	0.312	0.612	1.000
	80	0.650	0.275	0.075	0.000	0.000
	78	0.115	0.410	0.410	0.064	0.000
	68	0.000	0.132	0.426	0.382	0.059
	64	0.000	0.000	0.063	0.688	0.250
	61	0.000	0.000	0.000	0.033	0.967
Ergodic distribution	**351**	**0.001**	**0.004**	**0.015**	**0.110**	**0.869**
		Upper limit				
1993 - 2010	# observations	0.094	0.153	0.370	0.728	1.000
	9	0.222	0.444	0.111	0.222	0.000
	6	0.000	0.167	0.667	0.000	0.167
	4	0.000	0.000	0.000	1.000	0.000
	5	0.000	0.000	0.200	0.000	0.800
	3	0.000	0.000	0.000	0.000	1.000
Ergodic distribution	**27**	**0.000**	**0.000**	**0.000**	**0.000**	**1.000**

Table 6: Transition probability matrices and ergodic distributions for NO_x efficiency (1-year, 5-year and 17-year transitions)

		Upper limit				
$(t, t+1)$	# observations	0.565	0.667	0.746	0.900	1.000
	95	0.842	0.126	0.000	0.000	0.032
	92	0.087	0.652	0.250	0.011	0.000
	91	0.000	0.198	0.692	0.110	0.000
	93	0.000	0.011	0.065	0.817	0.108
	88	0.023	0.000	0.000	0.045	0.932
Ergodic distribution	**459**	**0.133**	**0.144**	**0.158**	**0.196**	**0.370**
		Upper limit				
$(t, t+5)$	# observations	0.565	0.666	0.749	0.902	1.000
	78	0.603	0.282	0.051	0.013	0.051
	66	0.227	0.318	0.364	0.091	0.000
	72	0.000	0.403	0.458	0.125	0.014
	73	0.000	0.027	0.096	0.589	0.288
	62	0.016	0.000	0.000	0.145	0.839
Ergodic distribution	**351**	**0.087**	**0.122**	**0.130**	**0.224**	**0.438**
		Upper limit				
(1993,2010)	# observations	0.562	0.683	0.753	0.920	1.000
	8	0.375	0.500	0.000	0.125	0.000
	5	0.000	0.200	0.200	0.200	0.400
	5	0.000	0.200	0.400	0.200	0.200
	6	0.000	0.000	0.333	0.333	0.333
	3	0.000	0.000	0.000	0.000	1.000
Ergodic distribution	**27**	**0.000**	**0.000**	**0.000**	**0.000**	**1.000**

Figure 1: EU27 aggregated pollutant and GDP evolution.

Source: Authors. Data: European Environmental Agency and Eurostat

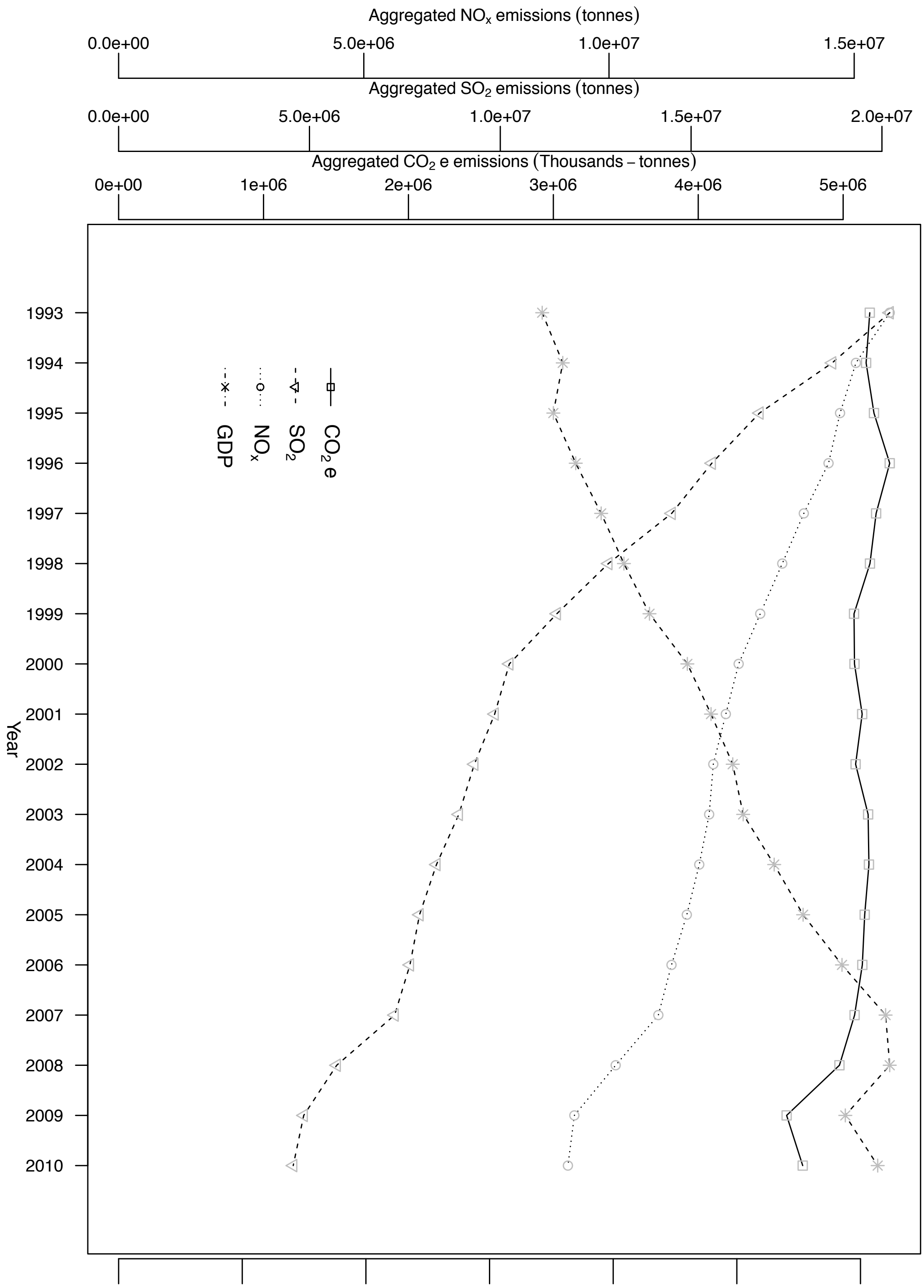

Figure 2: Eco-efficiency simple averages for each enlargement set of countries

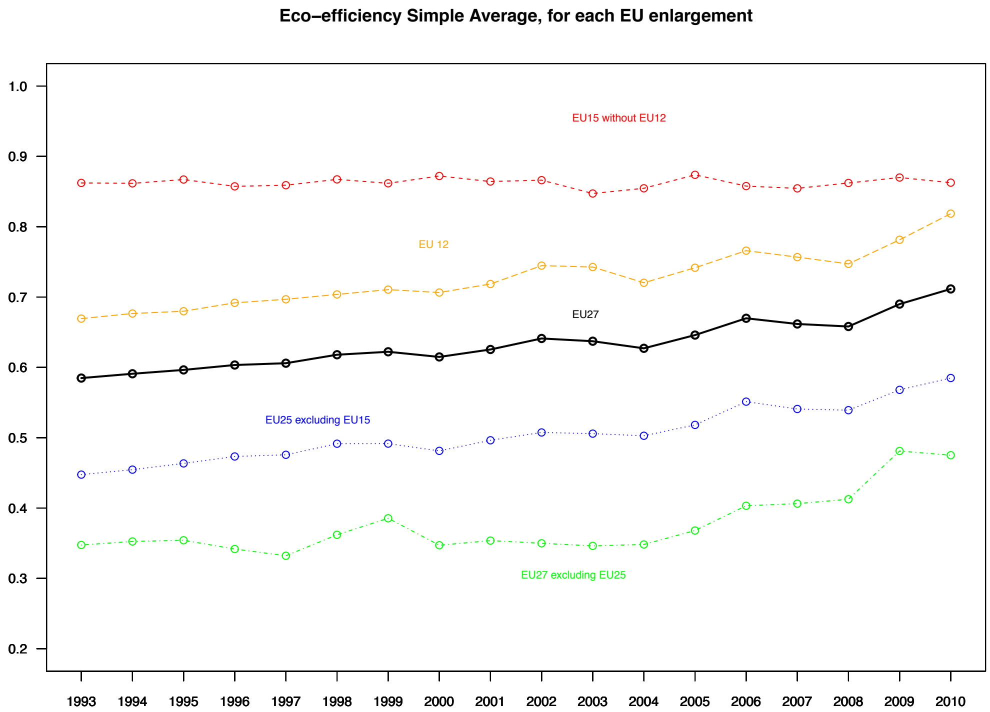

Figure 3: Eco-efficiency weighted averages for each enlargement set of countries

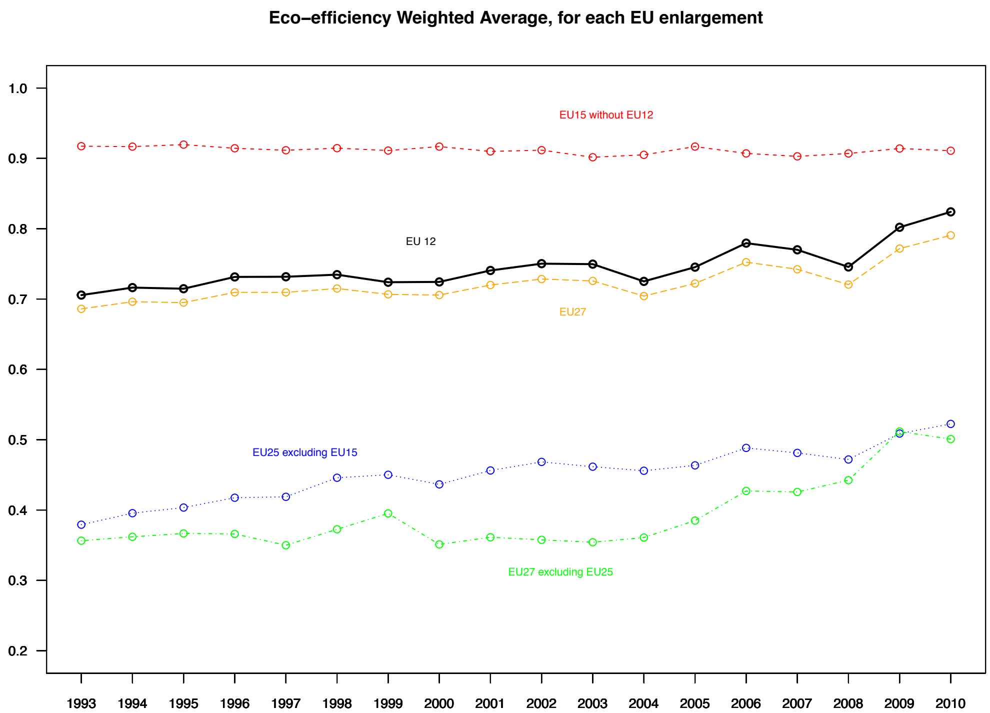

Figure 4: Evolution of eco-efficiency density in EU27

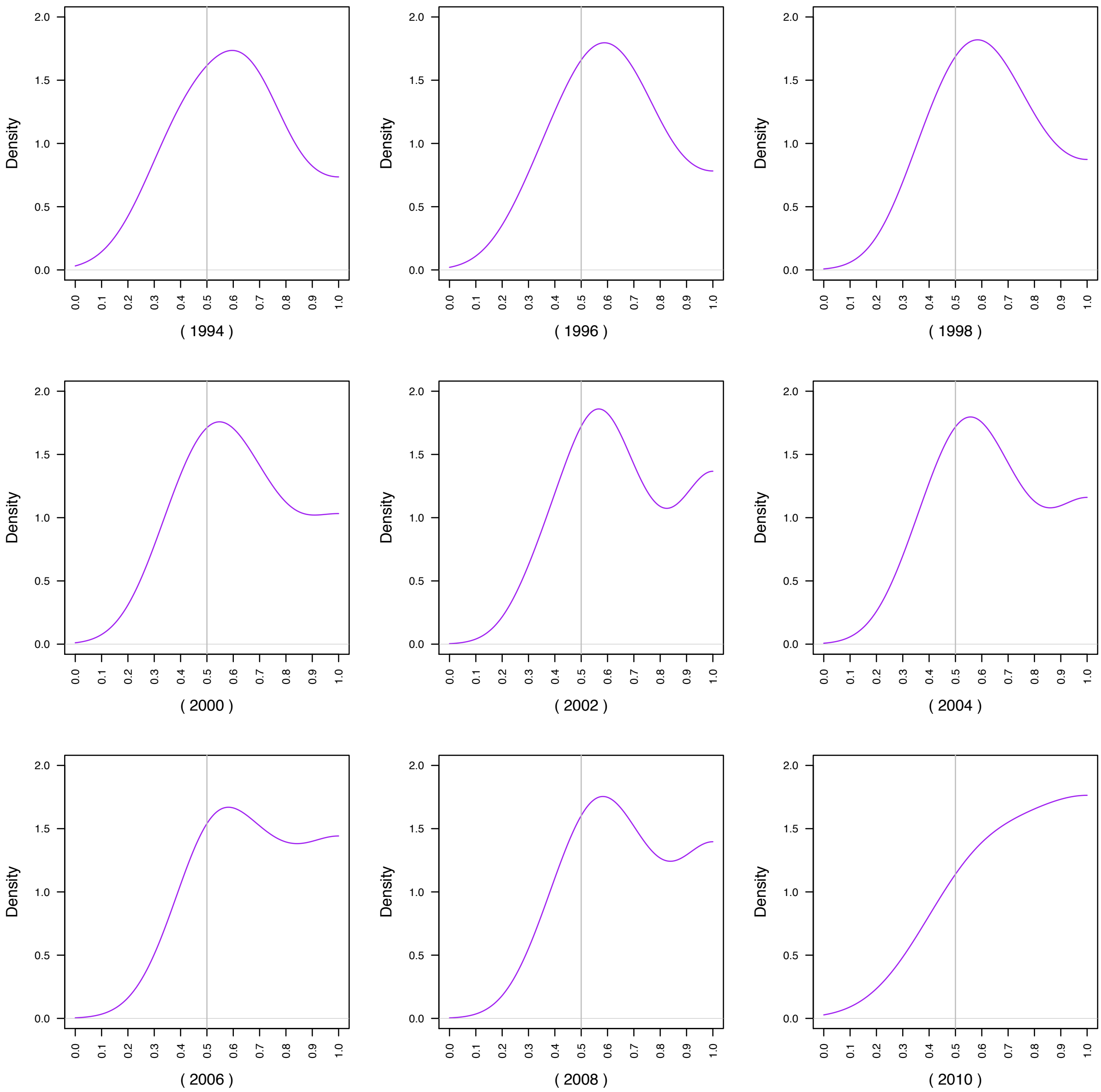

Figure 5: Evolution of pollutant efficiency densities in EU27.

Solid line: CO_2e efficiency.

Dotted line: NO_x efficiency.

Dashed line: SO_2 efficiency