Examining eco-efficiency convergence of European Industries.The existence of technological spillovers within a metafrontier framework

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Abstract

European policies regarding global warming have been outspread the last few decades with many initiatives for industrial production process. In this paper we model eco-efficiency performance under a meta-frontier framework for 14 industries from the manufacturing sector from 27 European countries over the 1995-2011 period. The utilization of NOx, SOx, CO2, CH4, N2O, CO, NMVOC and NH3 as undesirable outputs and GVA as the desirable represent the impact of of economic activities on the environment. In the first stage, we estimate eco-efficiency using the conventional Directional Distance Function (DDF) as well as the non-radial DDF approach. In the second stage of analysis, we investigate the existence of conditional and unconditional convergence according to several methodologies. Our eco-efficiency estimates provide a distinct behavior for energy intensive European industries. Moreover, a decline occurs for the majority of them. In addition, our results using distributional dynamics approach and the recent approach of Philips and Sul (2007) supports the non-convergence hypothesis and the creation of distinct clubs. Finally, the establishment of a catch up index indicate an increase in a speed of convergence.

keywords: Eco-efficiency,Non-parametric frontier analyisis, Convergence, Technological heterogeneity,European Industries.

JEL Classifications: C22,C44,D24,Q40,Q52

1 Introduction

Over the 21st century, the atmospheric concentrations of key greenhouse gases escalated due to human activities. As a result, the global average temperature increased rapidly by 0.85°C over the period 1880 to 2012, according to the Intergovernmental Panel on Climate Change (IPCC).[1] Thus, global warming and climate change have evolved into two hot topics in the international community whilst extensive awareness has been devoted to the restrain of the environmental damages in conjunction with the maintenance of economic growth. International institutions such as the United Nations and the International Energy Agency (IEA) attempt to mitigate GHG emissions implementing environmental policies and accomplish the sustainable development's target (IEA 2018; UNEP 2019). In terms of the European Union (EU), countries are required to adhere to the UNFCCC[2] and the Kyoto Protocol[3] emissions obligations (EEA 2017).[4]

Sustainable development and eco-efficiency consist two components for accomplishing these targets. The notion of eco-efficiency describes the ability of an economy to produce the maximum level of economic (desirable) output while causing the minimum environmental damages (undesirable output) and its concept became identical with that of sustainability analysis (Schaltegger and Sturm, 1989; Schmidheiny and Timberlake, 1992). As a measure of assessing the "harmony" between economic and ecological performance, it received enormous attention in the sustainability literature by the World Business Council for Sustainable Development (WBCSD) (Bidwell and Verfaillie, 2000) and OECD (OECD, 1998). The assessment of eco-efficiency establishes a vigorous mechanism in the hands of international organizations and policymakers for the planning and the implementation of environmental policies and the achievement of sustainable development (United Nations, 2009).

Because of its nature, it can be examined from various viewpoints, such as the macro-economy (national level), the meso-economy (regional or industrial level) and micro-economy (company level) (Mickwitz et al., 2006). The first approach for measuring eco-efficiency was focused on

[1] `https://www.ipcc.ch/site/assets/uploads/2018/02/AR5_SYR_FINAL_SPM.pdf`

[2] United Nations Framework Convention on Climate Change

[3] The Kyoto Protocol was adopted in 1997 but came into force in 2005 and sets international binding emission reduction targets for industrialized economies. Countries are also obligated to cohere with the Paris Agreement (2015) mechanism.

[4] The EU members support their commitments to cut down their GHG emissions by 20% below 1990 observed levels by 2020 while the Commission presented a long-term target to reduce emissions to 80-95% below 1990 levels by 2050 (COM/2018/773 final).

the BASF method which evaluated the sustainability through projects with short time and low costs (Saling et al., 2002; Shonnard et al., 2003; Schmidt et al., 2004). Nevertheless, this method had some imperfections that made room for new models to come into play (i.e. Cramer, 1997; Brady et al., 1999; DeSimone and Popoff, 2000; Bleischwitz, 2003; Reith and Guidry, 2003).

Supporting the deficiencies, other researchers paid attention to the ratio approach which computes eco-efficiency as a ratio of (added) value of the production and the (added) environmental impacts (e.g. Glauser and Müller, 1997; Burritt and Schaltegger, 2001; Zhang et al., 2008). However, there are a lot of limitations using this single indicator (Kuosmanen and Kortelainen, 2005; Wang et al., 2011). Besides, as Dahlström and Ekins (2005) pointed out, clear-cut definitions of eco-efficiency do not exist in the literature and the confusion between resource efficiency, resource productivity, resource or pollution intensity and eco-efficiency is quite frequent in studies. The utilization of indicators that consolidate various dimensions with objective weighting are more appropriate for the measure of eco-efficiency (Kuosmanen and Kortelainen, 2005). On the other hand, as Huppes et al. (2007) pointed out, the lack of data, the variations on scales, aspects and desires of each decision making unit could obstruct the proper inquiry of the indicator. In other words, the choice of the indicators also relies on the object that is going to be assessed (product, technology, company or society) (e.g. Saling et al., 2002; Hellweg et al., 2005; Scholz and Wiek, 2005; Managi and Kaneko, 2009).

Whatever the case may be, it is always challenging and crucial to determine the economic and environmental values of products. Dyckhoff and Allen (2001) proposed the Life Cycle Assessment (LCA) technique to prioritize the environmental indicators (Guinée, 2002; de Haes et al., 2002) and it widely utilized by many researchers within a Data Envelopment Analysis (DEA) framework (e.g. Lozano et al., 2009; Iribarren et al., 2011). On the other hand, a variety of studies has used DEA to assess the eco-efficiency (De Koeijer et al., 2002; Korhonen and Luptacik, 2004; Kuosmanen and Kortelainen, 2005; Kortelainen and Kuosmanen, 2007; Zhang et al., 2008; Barba-Gutiérrez et al., 2009; Picazo-Tadeo et al., 2011). However, because in DEA models the undesirable indicators are treated as inputs, the real production process is not reflected (Seiford and Zhu, 2002). The Directional Distance Function (DDF), the alternative approach of DEA, defines a directional vector that seeks for the expansion of good outputs and the reduction of the undesirable ones (Chambers et al., 1998) while it emphasizes on the variety of environmental indicators and indicates the differences that exist between the economic-environmental performance (Picazo-Tadeo et al., 2012; Ramli et al., 2013; Molinos-Senante et al., 2016; Gómez-Calvet et al., 2016).

The joint aspect of previous studies is the ignorance of technological heterogeneity that encompasses differences in economic development, industrial structure, resource endowment and geographical environment and can easily lead to biased estimations (Battese et al., 2004) and the isolation hypothesis (Tsekouras et al., 2016; Kounetas, 2015). Notwithstanding, only a few researchers were involved with the notion of the metafrontier within the DDF (Beltrán-Esteve et al., 2014), the Malmquist index (Munisamy and Arabi, 2015) and LCA approach (Beltrán-Esteve et al., 2017).

The reduction of GHG emissions is considered as the most efficient way to cope with global climate change. However, there must be some kind of convergence of policies to a specific target in order to achieve sustainability (Romero-Ávila, 2008). Economic and political factors could influence asymmetrically each economy in the international agreements for emissions caps (Camarero et al., 2014). In this sense, convergence in climate policies might be difficult to be achieved (Albrecht and Arts, 2005).

The concept of convergence is based on the assumption that different units are initially in disequilibrium. The seminal work of Baumol (1986) introduced the use of (un)conditional β convergence in which a negative relation between the growth rate of the variable of interest and its initial level occurs. Nevertheless, a critical aspect of the regression is that convergence can erroneously be revealed even if it does not really exists (De Long, 1988; Quah, 1993b) while the same rate of convergence is presumed for all units (Quah, 1997). In this sense, σ convergence came into play (Barro and Sala-i Martin, 1990), as an additional approach of β which consists a necessary but not a sufficient condition for σ convergence (Sala-i Martin, 1996). However, as these types of convergence do not allow any information on the intra-distributional dynamics, Quah (1993a; 1993b; 1996a; 1996b) introduced the distribution dynamics method which explores the evolution of the cross-sectional distribution over time adopting stochastic kernels (through Markov chain) to define change in its external shape and the intra-distribution dynamics.[5] On the contrary, in the distribution dynamics approach economies can modify their relative position over time concentrating on the movement from one part of distribution to another instead of the transition of the economy towards a steady state (Magrini, 2004, 2007).

[5] The essential limitation of the regression approach is that the model cannot be evaluated against alternatives and it is likely to exist divergence even if a negative relationship holds between growth rates and initial values (Quah, 1997).

On a macroeconomic point of view, Carlino and Mills (1993) introduced the notion of stochastic convergence through the usage of time - series data and the notions of unit roots and cointegration. Convergence indicates that the shocks in the variable of interest relative to the average of the sample are temporary (Bernard and Durlauf, 1995) whilst the existence of a unit root suggests that the effect of a shock is permanent and consequently will lead to the divergence of the series from the sample mean. From this perspective, the utilization of a catch-up index to examine if there is a catch-up process towards the metafrontier technology was proposed by several researchers (e.g. Kumar and Russell, 2002; Ball et al., 2004; Casu et al., 2016)

A common feature of previous eco - efficiency's convergence studies is that they evaluate eco-efficiency using simple ratios such as per capita to CO_2 emissions (i.e. Strazicich and List, 2003; Aldy, 2006; Romero-Ávila, 2008; Panopoulou and Pantelidis, 2009; Kounetas, 2018) either by focusing on conditional or stochastic convergence. Nonetheless, the ignorance of more environmental indicators suggests that this measure can be considered as a partial index of eco - efficiency. Therefore, the inclusion of a series of compound indicators for environmental performance is of paramount importance. In this direction, Camarero et al. in 2013 and 2014 found a strong evidence of eco-efficiency convergence for 22 OECD and 27 European countries respectively, using the Phillips and Sul approach in conjunction with three air pollutants as the environmental indicators. Phillips and Sul (2007) methodological approach investigates for the existence of convergence clubs across economies. The advantage of this approach is that it can easily identify groups of economies that converge to distinct equilibrium and simultaneously permit individual economies to diverge. In spite of the fact that five and six convergence clubs were initially discovered respectively, in the cases of the distinctive measures of efficiency the number of clubs was fluctuating. On the other hand, Gómez-Calvet et al. (2016) were engaged with eco-efficiency's convergence in EU employing the distribution dynamics approach in order to examine the evolution of the entire distributions over time, while Long et al. (2017) adopted panel unit root tests to investigate the existence of convergence in eco-efficiency of China's cement manufacturers.

The aim of this paper is to contribute in the literature by providing new evidence on eco-efficiency measures and assessing convergence under various approaches using a European industrial sample. More specifically, we employ a fully nonparametric approach to perform benchmarking on eco-efficiency scores across European industries using a conventional and a non-radial slacks Directional Distance Function (DDF) approach. Furthermore, we evaluate specific pollutants' eco-efficiency in order to provide more insight on environmental policies aimed at reducing specific emissions. The existence of heterogeneity among European countries strengthened the necessity for adopting a metafrontier framework in our analysis. This will allow us to reveal any differences that may exist between country's and European's technology framework. In the second part of our analysis, we proceed with a convergence analysis for the eco-efficiency measures and we test for the existence of convergence groups sharing common paths utilizing a variety of methods. Unlike similar studies, the methodology employed in the present research permits the verification of discrete clubs that converge to different equilibrium and the identification of the entities of each club.

The obtained results show that a low level of eco-efficiency exists when the notion of the metafrontier is considered. This indicates that when industries compete each other solely on the boundaries of the national level, their eco-efficiency will be overestimated. Finally, assessing convergence in terms of eco-efficiency under discrete methods adds an interesting insight in the literature and awareness for the policymakers in order to classify the environmental policies more targeted based on the convergence groups and their specific characteristics. Disparities in GDP, the percentage of the manufacturing sector in each economy, the division between heavy and light industries, time horizon that each country became a member of EU and the degree of implementation of the environmental regulations could be some of the main reasons in the formation of the specific clubs.

The remainder of the paper is structured as follows. Section 2 develops the methodology. Section 3 describes the characteristics of European industries and the data, while Section 4 presents and discusses the empirical findings concerning the estimations of eco-efficiency scores and the convergence patterns. Lastly, Section 5 summarizes and concludes.

2 Methodology

Our methodological framework is developed in two stages. In the first part we present the theoretical and methodological underpinnings regarding the estimation of the eco-efficiency scores. At the same time, we discuss expansion in a metafrontier framework presenting the role of heterogeneity in the estimated results. In the second part we discuss if industries experience any convergence or divergence behavior in their economic-ecological relation.

2.1 Eco-Efficiency and DDF approaches

2.1.1 Defining Eco-Efficiency and Directional Distance Function

In the economic-ecological literature, eco-efficiency is defined as the ratio between economic outcome and environmental pressures (Schmidheiny and Zorraquin, 1998). To formalize this concept, we briefly introduce a notation. Consider that we observe the economic performance (desirable output), represented by value added v, of a set of i industries at k countries and their production process causes a series of n damaging environmental pressures (undesirable outputs/pollutants) which are expressed by the vector $\mathbf{p}$=(p_1,...,p_n). According to Kuosmanen and Kortelainen (2005) and Picazo-Tadeo et al. (2011), the pressure generating technology set (PGT) is defined as:

$$PGT = [(v, p)\epsilon R_{+}^{1+N} | \text{value added } v \text{ can be generated with environmental pressures } \mathbf{p}] \quad (1)$$

PGT typifies all feasible combinations of value added and environmental pressures.[6] Following closely Kuosmanen and Kortelainen (2005) eco-efficiency of an industry i that belongs to a country k at time t can be calculated using the following formula:

$$\text{Eco -Efficiency} = \text{ECOE}_{i,t|k} = \frac{\text{Economic value added}}{\text{Environmental pressure}} = \frac{v}{G(\mathbf{p})}, \quad (2)$$

where G symbolizes the function that aggregates the n environmental pressures into a single environmental pressure score.[7]

As Huppes and Ishikawa (2005) pointed out, on a micro-level approach, eco-efficiency improves when economic value added relative to aggregate environmental pressure increases. Adopting the most common approach in the literature, we take a linear weighted average of the particular environmental pressures as an aggregated function and we compute G as:

$$G(p) = \sum_{n=1}^{N} w_n p_n \quad (3)$$

where w_n is the weight assigned to pressure n.

Acting in accordance with the theory of directional distance function proposed by Färe and Grosskopf (2000), the directional technology is defined as:

[6]Some properties are assumed for PGT (Picazo-Tadeo et al., 2012): (a) economic activity unavoidably provokes the generating of some pressures on the environment; (b) it is always possible to produce less value added with the same amount of environmental pressures; (c) pressures can always be increased for any given value added; (d) any convex combination of two or more observed pairs of v and p is also feasible.

[7]Recall that NO_x, SO_x, CO_2, CH_4, N_2O, CO, NMVOC and NH_3 constitute the undesirable outputs used in our study.

$$\overrightarrow{D}[v, \mathbf{p}; \mathbf{d} = (d_v, \mathbf{-d_p})] = sup[\beta|(v + \beta d_v, p - \beta d_p) \in \text{PGT}] \tag{4}$$

with d=($d_v, -d_p$) being the direction vector. Eq. (4)[8], and more particularly β, assesses the proportion by which the value added could be increased, while reducing all environmental pressures at the same proportion, employing the direction vector d= (v, -p).

However, as Gómez-Calvet et al. (2016) pointed out, this model exhibits a drawback since the directional vector that is employed may lead to an equivocal projection on the efficient frontier. Therefore, if a "weakly" efficient frontier point is used as a reference, the efficiency will be overestimated as the slack amount will not be taken under consideration. Consequently, a second analysis is necessary in order to reassure that "strongly" efficiency benchmarks are selected.[9] When the non-radial slacks are determined, a target (desirable value so as to become efficient) for each one of the undesirable outputs can be calculated. This target is expressed as:

$$v_0^* = v_0^g + \beta^* v_0 + s^+ \tag{5}$$

$$\mathbf{p}_0^* = \mathbf{p}_0 - \beta^* \mathbf{p}_0 - s^p$$

where s^+ and s^p represent the non-radial slacks calculated in the second stage of the efficiency analysis and β^* the maximum β from the previous LP program.

An inefficiency measure for the desirable and undesirable outputs can be expressed respectively as:

$$\frac{v_0^* - v_0}{v_0} = \frac{\beta_o^* v_o + S^+}{v_o} = \beta_o^* + \frac{S^+}{v_o}$$

$$\frac{p_0 - p_0^*}{p_0} = \frac{\beta_o^* p_o + S^p}{p_o} = \beta_o^* + \frac{S^p}{p_o}$$

while the efficiency for all cases can be computed as the subtraction of 1 - inefficiency.

2.1.2 A Metafrontier Framework for assessing Eco-Efficiency

As it was established earlier, each industry owns a distinguishing case of technology and its own environmental aspects that fit to a specific country. Moreover, because industrial processes produce a substantial amount of pollution in Europe, regulations concerning industrial emissions abatement has begun to spread all over European countries under a

[8]The corresponding mathematical LP program is introduced in the section of Appendix C.

[9]For space reasons we present the corresponding LP program in Appendix C.

common frame of mind (e.g. IED, 2010).[10] Nevertheless, the existence of heterogeneity (Battese et al., 2004) and the elimination of technological isolation and boundaries (Tsekouras et al., 2016, 2017) among countries has designated the introduction of metafrontier framework essential for the proper estimation of eco-efficiency and the corresponding technology gaps.

In this section we incorporate the concept of a metafrontier technology in the DDF approach of Färe and Grosskopf (2010) in order to expand the indicator of metafrontier eco-efficiency and investigate the notion of heterogeneity across industries and countries (Beltrán-Esteve et al., 2014).
Therefore, adopting their approach we have that:

$$M\vec{D}[v, \mathbf{p}; \mathbf{d} = (d_v, \textbf{-d}_\mathbf{p})] = sup[\beta|(v + \beta d_v, p - \beta d_p) \in \text{PGMT}] \tag{6}$$

where $PGMT = conv\{PGT_1 UPGT_2 UPGT_3 U...UPGT_K\}$ is the convex hull of the jointure of individual pressure generating technologies[11] and d=$(d_v, -d_p)$ being the direction vector.

Metafrontier technology is constructed from all observations for all groups and operates as an envelope of the participated countries (individual technologies). Also, it provides a benchmarking for all industries independently of the group-specific technology to which each industry belongs . The significance and the necessity of metafrontier become apparent as resource endowments, economic infrastructure, other characteristics of the physical, social and economic environment (O'Donnell et al., 2008; Kounetas, 2015) and national, legal and institutional regulations (Halkos and Tzeremes, 2011; Kontolaimou and Tsekouras, 2010) can not be considered with the technology set of a country (group). It should be pointed out that an industry that was efficient with respect to its country frontier, could be inefficient when the European metafrontier comes into play.[12]

We utilize the metatechology ratio based on the recent research studies of Picazo-Tadeo et al. (2012) and Beltrán-Esteve et al. (2014) who extended the approach of O'Donnell et al. (2008) as:

$$\text{Metatechnology ratio}^{i,t|k} = \frac{Metaeco - efficiency^{i,t}}{Eco - efficiency^{i,t|k}} \tag{7}$$

[10]`http://ec.europa.eu/environment/industry/stationary/ied/legislation.htm`

[11]It presents all combinations of environmental pressures p that permit the creation of the value added v (Beltrán-Esteve et al., 2014).

[12]Eco-efficiency estimations with the inclusion of non-radial slacks in the metafrontier approach follow the same logic as before.

Metatechnology ratio disclose how close the technology of country k (group) is to the metatechnology. It is clear that the computed eco-efficiency relative to the technology group frontier will always be equal to or greater that the metaeco-efficiency relative to the metafrontier.

2.2 Convergence Analysis

In the second part of our research we test for the existence of convergence regarding our eco-efficiency estimations. To obtain a more integrated picture we begin from the classical regression and the distribution dynamics approach and we continue with the Phillips and Sul methodology. Finally, a test for the catch-up index is introduced utilizing panel unit roots tests.

2.2.1 The regression approach

The concept of convergence, introduced by Baumol (1986), refers to a negative relation between the growth rate of a variable of interest, in our case eco-efficiency, and its initial level. The traditional neoclassical model of Solow (1956, 1957) was firstly employed to calculate this measure through a regression model. After a while, sigma convergence was established as an additional element of β (Carree and Klomp, 1997). Thus, the measure of unconditional β convergence that expresses the speed of convergence to the steady state[13], is calculated as:

$$y_{it} = a_i + (1 - b_i)y_{i0} + u_i \tag{8}$$

where y_{it} denotes the logarithm of the variable of interest in industry i and period t and y_{i0} is the value in the initial period of examination. Moreover, an additional second parameter is evaluated, the so-called "half-life" as the ratio $\frac{log2}{\beta_i}$, which provides the time that the economy needs to halve the gap between initial and steady state levels.
Carree and Klomp (1997) introduced the extent of the statistical significance of the σ convergence assuming no σ convergence for the sample (null hypothesis) using the following formula:

$$\sigma_{it} = \sqrt{N} \frac{\frac{\hat{\sigma}_{i0}^{2}}{(\hat{\sigma}_{it}^{2} - 1)}}{2\sqrt{1 - (1 - \hat{\beta}_{it})}} \tag{9}$$

As Quah (1993a,b, 1996a,b, 1997)[14] pointed out, the main drawbacks of this method is that convergence is independent from the initial

[13] See Barro and Sala-i Martin (1992) for a more detailed description of growth regression approach.

[14] i.e. Analogy between regressions of growth rates over initial levels and Galton's fallacy of regression towards the mean.

conditions, the steady state[15] to which countries are converging is not the single stable steady state of neoclassical theory and economies may modify their relative position over time.

2.2.2 Distribution dynamics approach

Since Baumol (1986) and Barro and Sala-i Martin (1990) introduced β and σ convergence, a plethora of studies have been applied. However, β and σ approaches have persuasively been criticized for the deficiencies on mobility, stratification and polarization issues (e.g. Quah, 1993a,b; Durlauf and Quah, 1999). Supporting the inadequacies of the regression approach, we proceed on the distribution dynamics approach to study the change in the external shape and the intra-distribution dynamics. As industries can potentially advance between distinct environmental conditions and regimes under the existence of shocks (Fingleton, 1999) and heterogeneity across economies becomes more and more significant (Bimonte, 2009), the examination of dynamics over time results of paramount importance.

We consider the two different types of eco-efficiency[16] scores as a continuous-time stochastic process $\{X(\mathrm{t})\text{: t} \geq 0\}$ where each one is defined as a Markovian chain and F(t) the distribution of X(t). Each $\mathbf{X}$ satisfies the Markovian property $Pr(X_{t+z} \epsilon A | X_j, j \leq t; X_t = x) = S^z(x, A)$ and $A \subseteq E \subseteq R$[17]. As Quah (1997) pointed out, we can assume that $F_{t+z} = \int_E (x, A) F_t dx$ which under certain conditions it can lead to $f_{t+z}(y) = \int_E f_z(y|x) f_t(x) dx$ with $f_t(x)$ and $f_z(y|x)$ being the density functions of F_t and S_z. The joint density function is estimated by the Gaussian kernel method (Fotopoulos, 2006) divided by the implicit marginal distribution as:

$$\hat{f}(y/x) = \frac{\hat{f}(y/x)}{\hat{f}(x)} \tag{10}$$

where
$\hat{f}(x) = \int_{-\infty}^{+\infty} \hat{f}(x, y) dy = \frac{1}{n} \sum_{i=1}^{n} \dfrac{1}{h_x \sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x - x_i}{h_x})^2} \int_{-\infty}^{+\infty} \dfrac{1}{h_y \sqrt{2\pi}} e^{-\frac{1}{2}(\frac{y - y_i}{h_y})^2} dy$
$= \frac{1}{n} \sum_{i=1}^{n} \dfrac{1}{h_x \sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x - x_i}{h_x})^2}$
and $\hat{f}(x, y) = \frac{1}{n} \sum_{i=1}^{n} \dfrac{1}{h_x \sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x - x_i}{h_x})^2} \dfrac{1}{h_y \sqrt{2\pi}} e^{-\frac{1}{2}(\frac{y - y_i}{h_y})^2} =$

[15]See Barro and Sala-i Martin (1992) for a more detailed description of growth regression approach.

[16]Eco-efficiency acts in accordance with the method (conventional, non-radial slack-based approach) and the technology (frontier-metafrontier) employed for each industry i at country k at time t as $\mathrm{ECOE}_{i,t,k|F,MF}^{DDF,NRDDF}$.

[17]E is the state space of X.

$= \frac{1}{n}\sum_{i=1}^{n}\frac{1}{h_x}K\big(\dfrac{x-x_i}{h_x}\big)\frac{1}{h_y}K\big(\dfrac{y-y_i}{h_y}\big)$

Finally, the long run density (Johnson, 2000, 2005) can be estimated as the solution :

$$f_{\infty}(y) = \int_{-\infty}^{+\infty} f_y(y/x) f_{\infty}(x)dx \tag{11}$$

2.2.3 Club Convergence

The main drawback of distribution dynamics analysis is that while Markov analysis allows us to identify the convergence clubs and the spatial distribution of eco-efficiency as a whole, we are not able to determine the economies that can form each one of the clubs. Phillips and Sul (2007) proposed a new methodology for the identification of the economies into clubs where a regression-based test is combined with a clustering procedure.

Consider the ECOE as X_{it} where i=1,2,...,N and t=1,2,...,T are the number of industries at each country k and the number of years respectively. In our study, X_{it} represents the natural logarithm of eco - efficiency. Heterogeneous behavior is captured with a single factor model:

$$X_{it} = \gamma_i \psi_t + u_{it} \tag{12}$$

where γ_i measures the idiosyncratic distance between the common factor ψ_t and the systematic part of X_{it}, ψ_t represents either the aggregated common behavior of X_{it} or any common variable that may influence individual economic behavior and u_{it} the error term.

Phillips and Sul (2007), hereinafter referred to as PS, transformed Eq.(12) in order to allow for γ_i to have a random component that absorbs the error term u_{it} and allows for possible convergence behavior in γ_i over time with reference to the common factor ψ_t. Therefore, the new model[18] is written as follows:

$$X_{it} = \delta_{it}\mu_t \tag{13}$$

PS formulated Eq. (13) and defined the relative transition parameter, h_{it} as

$$h_{it} = \frac{X_{it}}{\frac{1}{N}\sum\limits_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{\frac{1}{N}\sum\limits_{i=1}^{N} \delta_{it}} \tag{14}$$

which measures the loading coefficient δ_{it} in relation to the panel average at time t. Therefore if the factor loading coefficients converge to δ,

[18]Both components, δ_{it} (idiosyncratic) and μ_t (common), are time-varying.

the relative transition parameters h_{it} converge to unity and the cross-sectional variance (H_t) converges to zero as t $\rightarrow \infty$.

$$H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{it}-1)^2 \rightarrow 0, \text{as t} \rightarrow \infty \tag{15}$$

Adopting a semi-parametric model for δ_{it} they obtain:

$$\delta_{it} = \delta_i + \frac{\sigma_i \xi_{it}}{L(t)t^a} \tag{16}$$

where $\xi_{it} \sim$ iid(0,1) across i, a denotes the speed of convergence (the rate at which the cross-sectional variation decays to zero) and L(t) is a slowly varying function such as log(t) for which L(t)$\rightarrow \infty$ as t$\rightarrow \infty$. Hence, δ_{it} converges to δ_i for all positive values of α or when the parameter is zero. The null hypothesis of convergence is:

$$H_0 : \delta_i = \delta \text{ and } \alpha \succeq 0$$

against the alternative hypothesis

$$H_A : \delta_i \neq \delta \text{ for some i and/or } \alpha \prec 0$$

The null hypothesis implies convergence for all economies, while the alternative implies no convergence for some of them.[19] The null hypothesis is tested utilizing the following log t regression:

$$log(H_1/H_t) - 2logL(t) = \hat{c} + \hat{b}logt + u_t, \text{t = [rT],...,T}$$

where L(t)= log(t+1). The coefficient of log t is $\hat{b} = 2\hat{a}$, where α is the estimate of speed convergence in H_0. The null hypothesis is rejected when t-statistic $t_b <$ -1.65. PS suggest starting the regression at point t = [rT], where [rT] is the integer part of rt and r = 0.3. The beta coefficient in the log t regression owns an alternative interpretation than the β coefficient in the standard regression approach used in the literature to test for beta convergence, whilst the higher its value, the faster the rate of convergence. Moreover, when t-statistic suggests that beta is either positive or zero, we deduce that the panel converges. Conversely, if beta is negative, we reject the null hypothesis of convergence. PS using an empirical methodology following a four-step algorithm, they could determine subgroups of economies that converge. [20]

[19]The alternative can include both overall divergence or club convergence, i.e. one or more subsets of the group of economies could comprise convergent groups at different factor loadings.

[20]See Appendix for more details.

3 Data and Variables

In order to examine the arguments encompassing our main research questions, we exploit an exclusive dataset by matching two distinct sources. The dataset allows us to (i) examine eco-efficiency under different technology regimes and methodologies, (ii) evaluate the existence of heterogeneity among DMUs and (iii) test for convergence patterns and technological spillovers. The data used in this paper involve a sample of 14 industries from 27 European countries[21] over a 17 year period, from 1995 to 2011. Hence, our dataset is a balanced panel of 6426 observations in which the decision making units of our analysis are the 14 industries that are in accordance with the International Standard Industrial Classification (ISIC). Another aspect is that the sample period was chosen entirely on the basis that some of the key environmental variables, such as CH_4 and N_2O become unavailable after a certain year.

Concerning the estimation of eco-efficiency through the directional distance functions, we employ a single-desirable output, multi-undesirable output concept. For the measure of eco-efficiency (Kuosmanen and Kortelainen, 2005) the utilization of variables that reflect the economic performance and the environmental pressures are essential. Such being the case, the economic performance is assessed by the gross value added of each industry expressed in million Euros and has been deflated in constant 1995 prices.

On the other hand, the variable of environmental pressures is concentrated on the most harmful pollutants: Nitrogen oxides (NO_x), Sulphur oxides (SO_x), Carbon dioxide (CO_2), Methane (CH_4), Nitrous oxide (N_2O), Carbon monoxide (CO), Non-methane volatile organic compounds (NMVOC) and Ammonia (NH_3). The first two variables along with ammonia are responsible for the acidification of soil and water resources while the following five for the release of GHG into the atmosphere and the climate change. The units of measurement are kilo-tonnes per year for CO_2 emissions and tonnes per year for the rest of the undesirable outputs. Data for Gross Value Added, Nitrogen oxides, Sulphur oxides, Methane, Nitrous oxide, Carbon monoxide, Non-methane volatile organic compounds and Ammonia were collected through the World Input Output Database (WIOD),[22] while data concerning Carbon dioxide from Enerdata Odyssey.[23] Table 2 provides the basic descriptive statistics of the adopted variables of our analysis.

A further review of variables in Table 3 and Fig. 1 discloses some

[21] Table 1 in Appendix A provides a comprehensive representation of the industries and countries participating in our sample.

[22] `http://www.wiod.org/home`

[23] `https://www.enerdata.net/solutions/database-odyssee.html`

additional attractive characteristics. As our decision making units are the industries, the table presents the mean values and the standard deviation for each pair of industry and output. First of all, the industry of Electrical and Optical Equipment (ELO) presents the largest quantities of N_2O, NMVOC and NH_3 on average, while the industry of Machinery and Equipment n.e.c. (MAC) these of CH_4 and SO_x. Regarding the remaining undesirable outputs' variables, the industry of Basic Metals and Fabricated Metal Products (BMF) owns the greatest quantity of CO_2, the Transport Equipment (TRE) of NO_x and the Coke, Refined Petroleum Products (CRP) of CO, on average. From the economic perspective, the industry of Rubber and Plastic Products (RUP) possesses the highest GVA. Moreover, 7 out of 14 industries (50%) significant surpass the total average of GVA and CO_2, 6 out of 14 (42.8%) for CH_4, SO_x and NMVOC, 5 out of 14 (35.7%) for NO_x, 4 out of 14 (28.5%) for N_2O and NH_3 and 3 out of 14 (21.4%) for CO. These clues strengthen the assumption for a more thorough, fully comprehensive analysis and the estimation of an eco-efficiency index for the extraction of more appropriate results and suggestions.

4 Results & Discussion

Implementing the theoretical background outlined in Section 2, we present and discuss the empirical results following a two - part analysis. The industry - specific eco - efficiency scores with respect to the country frontiers along with that of the metafrontier are first presented. Finally, the convergence results of the industrial eco - efficiency are discussed.

4.1 European industries' eco - efficiency

Taking a close look at a country level, it is evident that because of the fact that European countries operate under distinct frontiers where each one has a certain economic, social and environmental structure and properties, the phenomenon of heterogeneity becomes crucial for the differences observed in their eco-efficiency. Table 5 presents the efficiency scores for countries in both conventional and non-radial slack-based DDF approach. Sweden, Finland and Denmark appear to be the most efficient irrespectively the method employed with average scores above 71%, indicating a trend of northern European countries to comply more rapidly on climate norms and environmental requirements of EU. Differences that exist in eco-efficiency scores might be initiated from the environmental awareness, the divergent levels of income and development as well as the orientation of each country in its economic activity(Camarero et al., 2014). This comes to an harmonization with the eco-innovation index

(European Commission,2006)[24] that constitutes a key component in national environmental policy strategies by developing new technologies like bioenergy, technologies for green vehicle, resource management and solar power.[25] The resource scarcity, the discrepancies on climate and the (non)existence of clean energy sources could develop a variety of environmental policies for countries to follow in order to be as eco-efficient as possible.

On the other hand, Table 4 displays the main results of eco-efficiency[26] with respect to the industry specific frontier and metafrontier respectively, highlighting the importance of heterogeneity that exists among European industries. At a first glance, our estimations point out that a high level of eco - inefficiency exists in total when the notion of the metafrontier is considered, whilst on average, scores exhibit lower values than the frontier case regardless of the method employed. Indicatively, the higher values of eco - efficiency belong to industries of Electrical and Optical Equipment, Machinery and Equipment n.e.c. and Transport Equipment that achieved efficiency scores between 26.3% and 42.3% in the conventional method, while in the second method the industry of Rubber and Plastic Products substitutes the latest industry. On the other hand, Coke, Refined Petroleum Products, Other Non-Metallic Mineral Products and Chemicals and Chemical Products are the least eco - efficient, in both methods employed, as they possess the lowest potentials for reduction in environmental pressures and increment in their value added.

Turning our attention to the particular case of the frontiers, eco - efficiency scores tend to be overestimated on the whole, as scores were increased by 3.44% and 4.12% for the two methods respectively. More specifically, Electrical and Optical Equipment, Machinery and Equipment n.e.c. and Transport Equipment, as before, and Textiles and Textile Products own the highest scores on average indicating that they could simultaneously increase their value added and diminish their environmental “damage” by a higher proportion in relation to the rest of the industries. This would suggest that, for example in the first approach, Electrical and Optical Equipment could reduce by 87.5% its environmental pressures and increase at the same time the value added by the same proportion. As eco-efficiency became a synonym for sustainable

[24] `https://ec.europa.eu/environment/ecoap/about-action-plan/objectives-methodology`

[25] `https://ec.europa.eu/environment/ecoap/indicators/index_en`

[26] All efficiency measures were calculated based on a cross - section level separately for each year in the sample, while the estimations have been carried out employing R program.

development (WBCSD,2006)[27], the concept of preventing pollution in manufacturing industries has been transformed to decisions about innovation and competitiveness by maximizing their products, minimizing their emissions, turning their wastes into inputs for other industries and become resource efficient (Huppes and Ishikawa, 2005; Ekins, 2005). The results reflect that 2 out of 3 most efficient industries are considered as heavy indicating that the implementation of stricter environmental regulations, improvements in energy efficiency and participations in voluntary environmental schemes have supported the welfare of society and earth (EEA,2018)[28]. By definition, light industries will require fewer inputs, space and power and will create fewer emissions than heavy ones. Thus, eco-efficiency is heavily conditioned by sectoral idiosyncrasies of products (Camarero et al., 2013) and environmental norms should be directed to industries that emit the highest quantities.

Fig.2 displays the distribution of eco-efficiency with respect to to the frontier for the first period of the sample (1995), the middle (2000) and (2005) and the last (2011). It is obvious that a bimodal behavior exists for both heavy and light industries[29] with similar tails, except for the year 2005 for the light ones. Moreover, the time evolution of the measure, depicted in Fig. 3 and 4, demonstrates a process of continuous and quite significant downward trend for the majority of the industries participated in our sample. Nevertheless, some industries such as Leather and Footwear, Machinery and Equipment n.e.c. and Electrical and Optical Equipment tend to follow a converse path in both approaches in the case of the frontier. On the other hand, Fig.5 illustrates the average meta technology ratio by year between the two categories of industries while Table 6 presents the annual growth of this measure using the two approaches. It is evident that while in the first 7 years the measure was quite high, around 50%, suggesting a smaller distance between the group frontier and the metafrontier, the last years until 2011 it declined greatly for both heavy and light industries.

The above-mentioned results show that the relaxation of the technological isolation (Tsekouras et al., 2016) between European countries could urge to pure technological spillovers that affect eco - efficiency performance and alter the balance between economic and environmental outcome. As eco - efficiency is linked directly with sustainable development, social, economic and environmental characteristics are interconnected with each other. However, while industries intent to increase their

[27]`https://docs.wbcsd.org/2006/08/EfficiencyLearningModule.pdf`

[28]`https://www.eea.europa.eu/themes/industry/intro`

[29]BMF, CHM, CRP, ELO, MAC, TRE and WCP are recognized as heavy, while FBT, LEF, MAN, ONM, PPP, RUP and TXT as light industries.

economic performance as much as possible, the environmental degradation and depletion of natural resources are crowding out and come in second place (European Commission, 1998)[30].

4.1.1 Pressure-specific eco-efficiencies

As carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) emissions constitute the most dangerous and concentrated greenhouse gases, a deeper analysis of these three specific eco-efficiency scores is essential for our study.[31] Figure 6 illustrates the specific efficiencies from a country's angle. It is apparent that European countries operate dissimilarly in every single case. On the whole, the highest values of efficiency scores tend to be concentrated in the middle part of Europe (e.g. France, Germany).

Table 7 displays the average values and the growth rates of CO_2, CH_4 and N_2O efficiency[32] for the total set of the 14 industries. The existence of the technology frontier and metafrontier has contributed to the differences that are observed between these variables. First of all, the average of the eco-efficiency indicators show that the highest score corresponds to CO_2 emissions with respect to the frontier and CH_4 to the metafrontier. For the case of CO_2 efficiency, the industries of Electrical and Optical Equipment, Machinery and Equipment n.e.c. and Textiles and Textile Products present the highest values on average the national frontiers, whilst in the metafrontier the industry of Leather and Footwear replaces the Textiles. Moreover, for CH_4 and N_2O efficiency, on the frontier approach, the above mentioned industries hold their high values while on the metafrontier, the Transport Equipment and Rubber and Plastic Products increase their position in the ranking respectively. The fact that these particular industries are also situated in the overall eco-efficiency index this high can be justified by the fact that those two efficiencies have a strong connection between them.

In general, the lowest values on average belong to the Basic Metals and Fabricated Metal Products, Chemicals and Chemical Products,Coke, Refined Petroleum Products and Other Non-Metallic Mineral Products for the three specific pressures. At this point, it is worth mentioning that 3 out of 4 industries are characterized as heavy. This fact is significant if we consider that heavy industries produce more emissions and waste in the environment because of their larger production and products' lifecycle. However, in the last decade, because of the fact that firms and

[30]`https://www.eea.europa.eu/publications/.../eu_98_uk.pdf`

[31]`https://www.eea.europa.eu/data-and-maps/indicators/atmospheric-greenhouse-gas-concentrations-6/assessment`

[32]The efficiency scores were estimated with the non-radial slack DDF method.

hence industries tend to care for sustainability, the use of Ecolabels[33] and the implementation of policies from EU Commission has led to the decline of the hazardous emissions at a significant extent.

4.2 Do industries among EU countries converge in terms of eco-efficiency?

The differences that exist across European industries in the eco-efficiency scores support the evidence that national and European energy and emission policies should be implemented alternatively. The convergence-divergence pattern that is incorporated in many environmental studies (e.g. Gómez-Calvet et al., 2016; Kounetas, 2018; Kounetas and Zervopoulos, 2019) consists a reciprocal segment with efficiency analysis in order to examine if common policies and measures could actually work. There are several approaches in the literature for the measurement of convergence (e.g. Carree and Klomp, 1997; Quah, 1993a; Durlauf and Quah, 1999).

4.2.1 Beta, Sigma and distribution dynamics convergence

We begin our discussion with the analysis of β-convergence using an ordinary least squares regression. Table 8 reports the estimations of beta indicating the absence of unconditional convergence across EU industries either for the overall eco-efficiency or the specific pressure efficiencies. This points out that industries with lower initial level of eco-efficiency would not acquire higher growth and converge to the best practice frontier, than industries with higher initial levels of efficiency. In conjunction with β convergence, Table 9 presents the standard estimation and the coefficient of the two series of the efficiencies (σ-convergence), whilst we additionally test the null hypothesis of equal variances proposed by Carree and Klomp (1997) where the results show a statistically significant variance increase. Therefore, a first unequivocal evidence of divergence indeed exist between EU industries and an increase in the cross-sectional dispersion is observed for our variables of interest. The particular findings appear to challenge the works of Moutinho et al. (2014) and Strazicich and List (2003) who found significant evidence of convergence for industries.

As many specialists pinpointed, the regression approach fails to reveal the dynamics of the entire cross- sectional distribution. The distribution dynamics approach that studies the "time horizon" of the distribution explains both the change in its external shape and intra-distribution dynamics.

[33] http://ec.europa.eu/environment/ecolabel/index_en.htm

Figures 7 and 8 display how the cross-sectoral metafrontier eco-efficiency in 1995 evolves into 2011. From the three-dimensional surface plot in the left parts of the figures it is observed the presence of two peaks with a light dip in between them. Thus, considering a constant point in x-axis, the distribution of eco-efficiency in 2011 relative to its initial 1995 level shows two local maxima in high and middle eco-efficiency parts where each one demonstrates the transitions from a particular part of the distribution to another. This supports the absence of convergence for European industries and the formation of two main clubs. A possible explanation of the divergence pattern can be associated with the different structures and size of the industries engaged in our sample. The differentiations that exist among industries in economic and environmental aspects such as the energy consumption, emission abatements and economic development could not create consistent paths for the whole set of industries since their characteristics differ significantly (Dahlström and Ekins, 2005). Moreover, over the 17-year horizon, a large portion of the probability mass is concentrated along the 45^o diagonal, as indicated in the contour plots, suggesting a limited degree of mobility. The structural and technological differences in in conjunction with the unbalanced industrial environment and output inequalities among the industries of each country do not allow for the establishment of one steady state of convergence. A potential cause of the divergence phenomenon is that the selection and learning processes are much slower in the traditional industries pointing directly to consumers than in the case of two technologically progressive industries (Lotti and Santarelli, 2004; Cheong and Wu, 2018).

The probabilities of the transition from one distribution to another for the specific pressure efficiencies are depicted in Figures 9, 10 and 11. As far as CO_2 efficiency is concerned, it exhibits two local maxima in both high and middle efficiency parts and an absence of a lower part. Analogous path for the CH_4 efficiency is noticed where two local maxima are established with the only difference from the previous pollutant being the closeness of the twin peaks. On the other hand, three local maxima appear to be formed in high and middle efficiency parts of N_2O. In all cases, the stochastic kernels reveal the existence of specific clubs whilst the contour plots reinforce the fact that most European industries in 2011 had the same relative efficiency they had in 1995 since a large proportion of the probability mass remains clustered around the main diagonal. The prices of fuel mix such as gasoline and differences in temperature may be substantial factors for the increase of emissions. As Strazicich and List (2003) described, the price of gasoline and temperature have a negative relationship with emissions. Therefore, countries with colder climate will experience higher growth rates of emissions.

The corresponding ergodic distribution for each efficiency measure, depicted in the inferior part of the figures, was estimated by iteration of the stochastic kernels. The specific pressure efficiency's distributions, namely CO_2, CH_4 and N_2O, point out a long run prediction for the creation of one club. However, when all undesirable outputs are taken under consideration as pressures in the estimation of the eco-efficiency measure, the ergodic distribution connotes a bimodal, two peaked pattern. This implies that convergence patterns of eco-efficiency is influenced by all specific pressures of the sample as the contribution of each pollutant is confronted differently from the authorities. Therefore, the economic and the environmental dimension of industries should be examined more thoroughly to prevent climate change, implement effectively the relevant environmental regulations and supervene sustainability for industries and economies.

4.2.2 Econometric Convergence Tests

As mentioned before, the main drawback of distribution dynamics approach is that although it recognizes the number of convergence clubs, it does not allow to determine the economies that form each club. Phillips and Sul (2007) closed this gap focusing on the "economic transition", heterogeneity and divergence patterns in growth from an econometric perspective.

Tables 10 shows that the estimated value for b of conventional and non-radial slack-based eco-efficiency is -0.517 and -0.508 respectively and in both cases the t-statistic indicates that parameter is significantly less than zero suggesting divergence for the full group of industries. The specific finding acts in accordance with the previous results indicating that in the future eco-efficiency will present a full panel divergence path. Nevertheless, convergence can still exist since subgroups of industries and countries could form discrete clubs and converge to different steady states with diverse convergence speed. Putting into action the algorithm of Phillips and Sul we examine whether there are subgroups of industries over the period 1995-2011 that eventually converge. Table 11 presents the results for the case of the conventional approach which initially implies the existence of 6 subgroups, 5 of them converge while there is evidence of entities that diverge. The first group has a fitted coefficient that is significantly negative suggesting a rejection of convergence and revealing evidence of divergence. Although the estimate γ is negative for club 2, the t-statistic indicate that is not statistically different from zero suggesting convergence among the members of this club. The middle panel reports the tests conducted to determine whether any of the original subgroups can be merged to form larger convergence clubs. The results show evidence of convergence only between clubs two and three. Therefore, there is no evidence to support mergers of the original groupings, with the only exception of 2 and 3. The whole set of the initial clubs will constitute separate clubs apart from the aggregate of 2 and 3 that will form one convergence club. The right panel of Table gives the final empirical classification from this clustering analysis into four growth convergence clubs and one divergent subgroup of entities.

On the contrary, Table 12 initially indicate the existence of 4 subgroups, 3 of these converge while there is evidence of entities that diverge. The first group has a fitted coefficient that is significantly negative revealing evidence of divergence. However, as before, the t-statistic indicate that is not statistically different from zero suggesting convergence among the members of this club. The middle panel show evidence of divergence for all aggregate clubs. Therefore, there is no evidence to support merges of the original groupings and the whole set of the initial clubs will constitute separate clubs with different steady states. Finally, for the case of the specific pressure efficiencies, the results indicate discrete steady states since various convergence clubs are generated throughout the full panel.[34]

Figures 12, 13, 14, 15 and 16 display the industry-country combination for each of the convergence clubs and divergent groups that are created. In most cases, the first convergence club consists of 4 observations with the only exception of N_2O efficiency. As someone could argue, the main identical element in the construction of the clubs is that they "attract" the same countries instead of industries. This suggests that a club is more likely to assemble more observations of the same country than of the same industry.

4.2.3 Catch-up Index and panel unit root tests

The utilization of the metafrontier is a useful way to discuss the problem of technological heterogeneity (Battese et al., 2004). However, the convergence analysis towards a metatechnology is new as in most of previous studies an average technology set was usually employed. Therefore, in order to assess whether industries converge toward the same technology we additionally utilize a catch-up index to measure the speed by which industries catch up tho the best technology. The only difference from the aforementioned approaches is that in this case our variable of interest turns into the catch-up index. Following closely Casu et al. (2016), we exploit panel unit root tests to determine whether there are any technical spillovers between the metafrontier and the (national) frontiers.

[34]For more details See Tables 13,14,15 and 16 in Appendix A.

Employing the catch up index defined as the ratio of eco-efficiency of the metafrontier to that of the country frontier we test for the presence of convergence between the manufacturing industries given that

$$lnECOE_{t,k} = \mu^k + \rho ln\left(\frac{ECOE^{MF}_{t-1,k}}{ECO_{t-1,k}}\right) + lnECOE_{t-1,k} + \varepsilon_{t,k} \tag{17}$$

and
$$lnECOE^{MF}_{t,k} = \mu^{MF} + lnECOE^{MF}_{t-1,k} + \eta_{t,k} \tag{18}$$

Combining Eq.17 and 18 we have:

$$ln\left(\frac{ECOE_{t,k}}{ECOE^{MF}_{t,k}}\right) = \mu + (1-\rho) ln\left(\frac{ECOE_{t-1,k}}{ECO^{MF}_{t-1,k}}\right) + \psi_{t,k} \tag{19}$$

where $\mu = (\mu^k - \mu^{MF})$. The existence of a unit root in (19) would suggest no catching up in terms of eco-efficiency and divergence to wards the best technology.

Table 17 reports the catch-up index of countries in different time periods. Time periods were selected based on the most important global environmental agreement, known as the Kyoto Protocol. Its significance is a milestone in global efforts to combat climate change, it has a great impact on development policy and constitutes a new component in the world economic order. Its ratification on behalf of the European Union occurred on 31 May 2002.[35] Therefore, the division of the whole sample time period into two separate (1995-2002 and 2003-2011) was conducted onto this date. As it is observed, most of the countries display a decline in the catch-up index after 2003, with the exceptions of Bulgaria, Finland, Italy, Poland and Sweden.The phenomenon of the reduced catch-up index consists an indication of a gradual increase in the speed of convergence after the implementation of the environmental norms and policies of the Protocol and the significance of the notions of eco-efficiency and sustainability for European countries. Moreover, the increasing speed of convergence comes into agreement with the fact that industries play a crucial role for the economic development and sustainability and the integration of the environmental rules since the Kyoto Protocol has become of paramount importance on national levels (EEA,2015).[36]

Moving on in our analysis, Table 18 and 19 present the results of the panel unit root tests for convergence using both conventional and non radial slack DDF approach. We perform three discrete tests that examine the presence of a unit root in the series. The Levin et al. (2002) and the Fisher-type test following Choi (2001) own the same null hypothesis of non-stationarity. However, they possess different alternatives as

[35] `https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32002D0358`

[36] `https://www.eea.europa.eu/soer-2015/europe/industry`

the Fisher type allows for different autoregressive coefficients, while the Levin-Lin-Chu test requires the same one. Finally, the Hadri (2000) test works under the null hypothesis of (trend) stationarity for all series against the alternative that some of the panels have a unit root.[37]

Table 18 reports the results for the convergence based on the conventional approach for the whole time period as well as the two separate time periods. When referring to this case, we can denote that for the entire time period and the 2003-2011 period the null hypothesis in the Levin-Lin-Chu test is rejected. Therefore, we find stationarity and hence convergence with a level of significance at 1%. On the contrary for the 1995-2002 period we do not reject the null hypothesis and as a result we find the existence of divergence. Likewise to the LLC test, the Fisher-type test does not reject the null hypothesis of non-stationarity and we find divergence between units in all time periods. On the contrary, utilizing the Hadri test we strongly reject the null hypothesis that all panels' series are stationary in favor of the alternative that at least one of them contains a unit root. This means that convergence is taking place, but not across all countries or in the same way. Overall, these results suggest that divergence takes place among industries of the sample.

Concentrating on the second DDF approach, as shown in Table 19, the same results apply for the full time period. Nevertheless, for the two 1995-2002 period the LLC and the Fisher-type tests suggest convergence towards the metafrontier. On the other hand, the Hadri test for the specific time period indicates that stationarity does not occur for the whole set of series as we reject the null hypothesis at a significance level of 1%. The same results apply for the case of 2003-2011 period with the only difference being on Fisher-type test.

5 Conclusions

The intentions of EU members to comply with the Commission's environmental initiatives, although multitudinous, provide antipodal results concerning emissions abatement, energy consumption reduction, resource protection and renewable diffusion. More specifically, when greenhouse gases and natural resources are considered, the objectives of sustainable development and eco - efficiency become more apparent and significant. In this sense, a detailed analysis is more than essential for European industries of the manufacturing sector in order to evaluate and reconsider their environmental actions, norms and standards.

[37]In all cases, we allowed for country fixed effects and an exclusion of time trend when possible (Baltagi, 2008).

This paper contributes to the previous literature of eco-efficiency in numerous respects. Firstly, we investigate eco-efficiency on a deeper level for both aggregate GHG emissions and the three most hazardous pollutants, namely, carbon dioxide, methane and nitrous oxide using European industries of the manufacturing sector as the examined entities. The methodological framework that we follow distinguishes between the conventional and the non-radial slack-based DDF approach. The utilization of two approaches let us examine the weak and strong efficient frontier and the levels of the underestimated inefficiency. Moreover, convergence analysis has been implemented using different approaches to provide a more integrated picture compared to previous studies. Possible convergence environmental policies and measures could be implemented in European industries and countries if convergence clubs do exist. Thirdly, a catch-up index is adopted as an indicator of the differences in the speed of convergence towards the metafrontier between industrial eco-efficiency.

Our results specify distinct paths for eco-efficiency considering the approach and the regime employed. First of all, high eco-inefficiency scores are observed among industries when we acknowledge the barrier of technological isolation and include in the study a metafrontier framework. Furthermore, the three most efficient industries are recognized as heavy, suggesting that the necessity for sustainability and a balance between ecological and economic prosperity are more apparent and intense for this group of industries. On the other hand, when industries compete each other inside their national boundaries, scores tend to be overestimated. The fact that some industries that produce a large quantity of contaminating products and face higher amounts of binding policies could choose to import a part of these goods from more polluting countries consists an essential strategy in sustainability analysis. Taking into consideration the time evolution, the majority of industries display a downward trend through time which suggests that, on average, European industrial eco-efficiency declines while the establishment of a catch-up index indicate an increase in the speed of convergence. From a dynamic point of view, convergence behavior of aggregate eco-efficiency and the three particular pressure efficiencies is subject to each specific convergence approach. Overall, our results support the hypothesis of non-convergence for all examined variables across the 14 European industries from 1995 to 2011 on a common steady state. However, the analysis point to 3 to 5 convergence clubs depending on the particular efficiency case.

One possible explanation for these discrepancies in the convergence clubs could be the income and the production levels of countries and industries respectively in terms of the economic factors. Other factors, such as technological improvements, cap and trade openness and energy mix changes could help policymakers to create an homogeneous frame for EU. The development of new technologies and practices and the possibility of technological interaction between European countries justifies the fact that industries, and the economy in general, can benefit from the creation of value added and the implementation of "common", proven policies for the environment and natural resources.

Finally, we would like to highlight that our research focuses on eco-efficiency of European industries of the manufacturing sector presenting a novelty in the literature. This paper could be a reliable tool for policy makers to propose better environmental policies, governments and firms to understand the notion of eco-efficiency and its benefits and the techniques to improve it. Exploring further assumptions of the scale properties could be an interesting line of future research. The construction of composite indicators of environmental pressures with non-linear structures (see,for example, Zhou et al. (2010)) and the examination of various directional scenarios or investigating the factors that could affect industrial eco-efficiency and its convergence patterns might be interesting topics for future research.

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Appendix A

Table 1: List of European Countries and Manufacturing industries

Country (Code)		Code	Industry name
Austria (AUT)	Latvia (LVA)	BMF	Basic Metals and Fabricated Metal Products
Belgium (BEL)	Lithuania (LTU)	CHM	Chemicals and Chemical Products
Bulgaria (BGR)	Luxembourg (LUX)	CRP	Coke, Refined Petroleum Products
Cyprus (CYP)	Malta (MLT)	ELO	Electrical and Optical Equipment
Czech Republic (CZE)	Netherlands (NLD)	FBT	Food, Beverages and Tobacco
Denmark (DNK)	Poland (POL)	LEF	Leather and Footwear
Estonia (EST)	Portugal (PRT)	MAC	Machinery and Equipment n.e.c.
Finland (FIN)	Romania (ROU)	MAN	Manufacturing and Recycling
France (FRA)	Slovakia (SVK)	ONM	Other Non-Metallic Mineral Products
Germany (DEU)	Slovenia (SVN)	PPP	Pulp Paper, Paper, Printing and Publishing
Greece (GRC)	Spain (ESP)	RUP	Rubber and Plastic Products
Hungary (HUN)	Sweden (SWE)	TXT	Textiles and Textile Products
Ireland (IRL)	United Kingdom (GBR)	TRE	Transport Equipment
Italy (ITA)		WCP	Wood and Wood and Cork Products

Table 2: Summary Statistics of economic performance and environmental regulations of European Manufacturing Sector (1995-2011)

Variables	Mean	Std. Dev.	Min	Max
Desirable Output				
GVA	4052.217	9211.258	0.066	125754.300
Undesirable Outputs				
CO_2	2819.412	6871.769	0.020	67864.280
CH_4	2490.926	16856.270	0.008	421821.500
N_2O	583.219	3853.644	0.007	87629.890
NO_X	5710.239	13258.580	0.090	123951.100
SO_X	6650.100	18509.210	0.001	230874.300
CO	19095.990	109577.900	0.013	1874829.000
NMVOC	8480.078	30355.370	0.003	543802.900
NH_3	209.296	1173.157	0.000	20774.880

Table 3: Mean values of sample variables by industry from 1995 to 2011

Industry	GVA	CO_2	CH_4	N_2O	NO_X	SO_X	CO	NMVOC	NH_3
BMF	4280.493	3070.836	2652.837	384.945	6249.753	7043.917	26703.240	8543.103	182.945
	(8922.078)	(7040.207)	(16924.550)	(2024.577)	(13990.450)	(17617.540)	(134430.000)	(25611.760)	(970.433)
CHM	4039.468	2986.933	2600.184	377.392	5852.222	6562.927	26964.710	7917.525	159.116
	(8906.142)	(7226.078)	(16466.540)	(2105.488)	(13646.840)	(16457.890)	(133240.800)	(25737.640)	(922.089)
CRP	3993.345	2895.205	2472.149	312.303	5399.843	6097.875	27112.550	7898.997	144.048
	(9195.071)	(7237.102)	(15312.550)	(1788.514)	(12906.530)	(15397.450)	(139196.800)	(25659.790)	(815.750)
ELO	3839.670	2722.856	2453.146	1050.313	5534.737	6888.217	17401.810	9788.112	309.634
	(8694.496)	(6787.881)	(14615.310)	(6493.773)	(13117.980)	(17805.310)	(105746.400)	(37744.090)	(1605.431)
FBT	4204.067	2741.813	2397.434	1034.763	5550.550	6312.065	17113.890	9498.401	305.490
	(9323.629)	(6753.063)	(13736.060)	(6475.068)	(12860.860)	(15917.220)	(101213.200)	(35681.610)	(1560.216)
LEF	4298.810	2803.924	2504.762	999.365	5598.385	6165.354	17359.190	8878.202	302.970
	(9640.945)	(6856.138)	(13809.800)	(6210.300)	(12673.240)	(14879.620)	(103587.500)	(34590.500)	(1516.520)
MAC	4061.845	2767.434	3095.772	645.165	5497.931	7994.375	16361.860	8175.677	220.148
	(9733.508)	(6746.432)	(23125.860)	(4415.895)	(12363.000)	(23314.210)	(95564.590)	(31739.890)	(1299.845)
MAN	3788.902	2762.386	3029.874	503.784	5470.196	7453.557	16700.110	8243.949	201.097
	(9308.081)	(6751.558)	(22837.910)	(3039.065)	(12314.980)	(22063.730)	(102385.000)	(30352.130)	(1222.477)
ONM	3919.579	2826.749	2857.497	515.863	5425.280	7142.391	16363.710	9102.027	190.978
	(9320.230)	(6824.095)	(19597.070)	(2969.893)	(12114.580)	(21211.540)	(97384.300)	(32987.260)	(1122.888)
PPP	4151.913	2478.749	2131.346	508.225	4867.315	6081.702	17010.260	8570.104	182.336
	(9305.819)	(6387.081)	(16065.110)	(3010.322)	(10978.040)	(20123.070)	(108723.400)	(31672.430)	(1077.144)
RUP	4335.627	2836.491	2066.178	457.207	6244.085	6764.737	17329.580	8282.985	188.181
	(10083.650)	(6823.807)	(15074.920)	(2631.106)	(15029.970)	(20539.300)	(102916.200)	(30445.370)	(1025.416)
TXT	4120.423	2902.599	2153.470	461.532	6167.792	6196.617	17435.250	7696.413	160.489
	(10113.670)	(7203.504)	(15236.700)	(2614.701)	(15060.080)	(17851.460)	(98474.910)	(27720.720)	(924.838)
TRE	3777.569	3056.921	2235.523	471.433	6388.662	6383.144	17258.950	7956.925	196.970
	(8030.935)	(7257.447)	(14910.980)	(2604.591)	(14692.420)	(17268.670)	(100415.300)	(26306.900)	(995.664)
WCP	3919.332	2618.876	2222.787	442.769	5696.594	6014.516	16228.720	8168.675	185.748
	(8219.274)	(6298.372)	(14806.170)	(2436.876)	(13293.680)	(16349.850)	(97760.850)	(25353.390)	(997.255)
TOTAL	4052.217	2819.412	2490.926	583.219	5710.239	6650.100	19095.990	8480.078	209.296
	(9211.258)	(6871.769)	(16856.270)	(3853.644)	(13258.580)	(18509.210)	(109577.900)	(30355.370)	(1173.157)

Note: Standard deviation in parentheses

Table 4: Industries' Eco - Efficiency estimations

	Conventional		With slacks			Conventional		With slacks	
Industry	F_{eco}	MF_{eco}	F_{eco}	MF_{eco}	Industry	F_{eco}	MF_{eco}	F_{eco}	MF_{eco}
BMF	0.456	0.103	0.259	0.056	ONM	0.500	0.070	0.274	0.037
	(0.246)	(0.125)	(0.189)	(0.070)		(0.319)	(0.105)	(0.255)	(0.054)
CHM	0.536	0.089	0.390	0.052	PPP	0.657	0.158	0.492	0.099
	(0.364)	(0.169)	(0.386)	(0.125)		(0.303)	(0.203)	(0.334)	(0.148)
CRP	0.433	0.059	0.305	0.028	RUP	0.695	0.260	0.560	0.172
	(0.393)	(0.106)	(0.391)	(0.046)		(0.268)	(0.276)	(0.285)	(0.223)
ELO	0.875	0.423	0.850	0.328	TXT	0.798	0.253	0.684	0.161
	(0.277)	(0.375)	(0.310)	(0.357)		(0.259)	(0.255)	(0.322)	(0.201)
FBT	0.640	0.131	0.465	0.082	TRE	0.773	0.265	0.617	0.168
	(0.293)	(0.150)	(0.322)	(0.107)		(0.263)	(0.264)	(0.323)	(0.185)
LEF	0.739	0.238	0.604	0.158	WCP	0.562	0.134	0.421	0.079
	(0.296)	(0.254)	(0.339)	(0.210)		(0.299)	(0.164)	(0.303)	(0.100)
MAC	0.734	0.263	0.657	0.180	Total	0.648	0.188	0.507	0.123
	(0.329)	(0.298)	(0.352)	(0.231)		(0.329)	(0.245)	(0.359)	(0.194)
MAN	0.677	0.186	0.523	0.121					
	(0.291)	(0.222)	(0.310)	(0.167)					

Note: Standard deviation in parentheses

Table 5: Countries' Eco - efficiency estimations under the two approaches

Country	Eco_c	Eco_s	Country	Eco_c	Eco_s
AUT	0.624	0.625	LVA	0.405	0.369
	(0.299)	(0.352)		(0.258)	(0.344)
BEL	0.588	0.469	LTU	0.377	0.312
	(0.315)	(0.370)		(0.281)	(0.321)
BGR	0.306	0.277	LUX	0.784	0.598
	(0.340)	(0.382)		(0.286)	(0.355)
CYP	0.464	0.415	MLT	0.567	0.548
	(0.347)	(0.363)		(0.323)	(0.356)
CZE	0.521	0.421	NLD	0.702	0.550
	(0.271)	(0.294)		(0.318)	(0.370)
DNK	0.796	0.746	POL	0.809	0.619
	(0.276)	(0.283)		(0.227)	(0.328)
EST	0.330	0.333	PRT	0.490	0.316
	(0.314)	(0.333)		(0.330)	(0.322)
FIN	0.786	0.742	ROU	0.338	0.326
	(0.365)	(0.325)		(0.238)	(0.309)
FRA	0.696	0.568	SVK	0.330	0.230
	(0.335)	(0.371)		(0.293)	(0.360)
DEU	0.731	0.670	SVL	0.599	0.500
	(0.296)	(0.340)		(0.277)	(0.330)
GRC	0.485	0.430	ESP	0.624	0.462
	(0.283)	(0.289)		(0.273)	(0.306)
HUN	0.421	0.328	SWE	0.737	0.712
	(0.348)	(0.336)		(0.289)	(0.263)
IRL	0.573	0.467	GBR	0.659	0.620
	(0.314)	(0.332)		(0.272)	(0.333)
ITA	0.734	0.685			
	(0.239)	(0.302)			

Note: Standard deviation in parentheses

Table 6: Growth of Eco-Efficiency with respect to the MTR

Periods	Conventional	Slack-based
1995-1996	1.004	1.008
	(0.106)	(0.148)
1996-1997	0.997	0.995
	(0.089)	(0.132)
1997-1998	0.981	0.980
	(0.092)	(0.155)
1998-1999	0.985	1.003
	(0.084)	(0.122)
1999-2000	0.999	1.004
	(0.170)	(0.183)
2000-2001	1.000	0.997
	(0.118)	(0.134)
2001-2002	0.937	0.920
	(0.122)	(0.160)
2002-2003	0.969	0.984
	(0.156)	(0.172)
2003-2004	0.991	0.978
	(0.106)	(0.104)
2004-2005	0.966	0.986
	(0.075)	(0.068)
2005-2006	0.999	0.992
	(0.097)	(0.103)
2006-2007	0.950	0.939
	(0.123)	(0.155)
2007-2008	0.992	0.993
	(0.032)	(0.029)
2008-2009	1.002	0.998
	(0.026)	(0.031)
2009-2010	1.039	1.058
	(0.171)	(0.177)
2010-2011	0.974	0.958
	(0.172)	(0.171)

Note: Standard deviation in parentheses

Table 7: Scores and growth rates of pressure specific Eco-efficiency

	Frontier			Metafrontier			Growth rates w.r.t. MF		
Industry	CO_2	CH_4	N_2O	CO_2	CH_4	N_2O	CO_2	CH_4	N_2O
BMF	0.164	0.160	0.276	0.030	0.042	0.050	-0.001	-0.001	-0.002
	(0.216)	(0.214)	(0.243)	(0.056)	(0.073)	(0.076)	(0.045)	(0.045)	(0.059)
CHM	0.373	0.306	0.297	0.050	0.035	0.029	-0.004	-0.003	-0.002
	(0.402)	(0.432)	(0.440)	(0.137)	(0.124)	(0.119)	(0.067)	(0.076)	(0.067)
CRP	0.252	0.246	0.298	0.015	0.020	0.017	-0.002	0.001	-0.001
	(0.413)	(0.417)	(0.412)	(0.054)	(0.061)	(0.040)	(0.048)	(0.019)	(0.027)
ELO	0.840	0.848	0.843	0.292	0.328	0.286	-0.020	-0.019	-0.021
	(0.330)	(0.316)	(0.324)	(0.369)	(0.383)	(0.381)	(0.157)	(0.165)	(0.166)
FBT	0.388	0.384	0.419	0.059	0.062	0.073	-0.003	-0.003	-0.004
	(0.366)	(0.375)	(0.374)	(0.108)	(0.112)	(0.115)	(0.091)	(0.098)	(0.100)
LEF	0.604	0.550	0.558	0.137	0.143	0.126	-0.015	-0.012	-0.016
	(0.346)	(0.402)	(0.383)	(0.222)	(0.238)	(0.220)	(0.111)	(0.114)	(0.127)
MAC	0.626	0.651	0.621	0.145	0.184	0.135	-0.012	-0.008	-0.011
	(0.382)	(0.371)	(0.383)	(0.227)	(0.256)	(0.224)	(0.154)	(0.136)	(0.143)
MAN	0.531	0.466	0.411	0.104	0.108	0.083	-0.013	-0.011	-0.011
	(0.361)	(0.370)	(0.365)	(0.162)	(0.187)	(0.163)	(0.135)	(0.129)	(0.133)
ONM	0.131	0.264	0.238	0.014	0.030	0.027	-0.002	-0.002	-0.002
	(0.267)	(0.317)	(0.292)	(0.047)	(0.051)	(0.048)	(0.028)	(0.028)	(0.033)
PPP	0.455	0.407	0.433	0.080	0.080	0.070	-0.006	-0.006	-0.006
	(0.363)	(0.383)	(0.384)	(0.145)	(0.154)	(0.143)	(0.135)	(0.134)	(0.137)
RUP	0.521	0.537	0.516	0.131	0.173	0.144	-0.011	-0.008	-0.011
	(0.326)	(0.321)	(0.340)	(0.230)	(0.249)	(0.242)	(0.163)	(0.161)	(0.149)
TXT	0.639	0.630	0.673	0.122	0.139	0.133	-0.013	-0.008	-0.016
	(0.376)	(0.377)	(0.353)	(0.203)	(0.229)	(0.217)	(0.140)	(0.157)	(0.155)
TRE	0.577	0.590	0.560	0.127	0.185	0.117	-0.008	-0.005	-0.009
	(0.363)	(0.367)	(0.399)	(0.173)	(0.226)	(0.187)	(0.152)	(0.149)	(0.145)
WCP	0.448	0.380	0.326	0.066	0.085	0.043	-0.006	-0.006	-0.004
	(0.313)	(0.359)	(0.349)	(0.084)	(0.134)	(0.073)	(0.069)	(0.063)	(0.051)
Total	0.468	0.458	0.462	0.098	0.115	0.095	-0.008	-0.007	-0.008
	(0.396)	(0.405)	(0.400)	(0.193)	(0.214)	(0.196)	(0.116)	(0.116)	(0.117)

Note: Standard deviation in parentheses

Table 8: Estimated results for β-convergence with respect to the metafrontier

Explanatory Variable		Metafrontier DDF	Metafrontier NRDDF
ECOE	α	-0.090***	-0.110***
	β	0.085***	0.028***
	Weighted Statistics		
	R^2	0.591	0.685
	Half-life	9.468	7.662
CO_2E	α		-0.001***
	β		0.112***
	Weighted Statistics		
	R^2		0.752
	Half-life		6.138
CH_4E	α		-0.002***
	β		0.080***
	Weighted Statistics		
	R^2		0.576
	Half-life		8.656
N_2OE	α		-0.001***
	β		0.105***
	Weighted Statistics		
	R^2		0.732
	Half-life		6.573

Table 9: Estimated Results for σ-convergence with respect to the metafrontier

Explanatory Variable	Standard deviation 1995	Standard deviation 2011	Variation coefficient 1995	Variation coefficient 2011	T3 test t-statistic	T3 test Prob.
$ECOE^{DDF}$	0.298	0.196	1.019	1.659	77.530	0.000
$ECOE^{NRDDF}$	0.251	0.144	1.233	2.186	125.410	0.000
CO_2E	0.263	0.134	1.507	3.146	169.520	0.000
CH_4E	0.272	0.187	1.390	2.042	59.430	0.000
N_2OE	0.249	0.132	1.696	3.489	154.660	0.000

Note: The null hypothesis examines no convergence.

Note: T_2 and T_3 statistics are distributed as a χ^2 and N(0,1) respectively.

Note: Results are the same for T_2 statistic.

Table 10: Full convergence tests for Eco-Efficiency

log(t)	Coeff.	SE	T-stat.
$ECOE^{DDF}$	-0.517	0.005	-102.383
$ECOE^{NRDDF}$	-0.508	0.008	-58.310

Table 11: Convergence club classification :14 industries from 27 countries from 1995 to 2011 for $ECOE_{MF}^{DDF}$

Initial classification $\hat{\gamma}$ (SE of $\hat{\gamma}$)		**Tests of club converging** $\hat{\gamma}$ (SE of $\hat{\gamma}$)					**Final classification** $\hat{\gamma}$ (SE of $\hat{\gamma}$)	
Club 1 [4]	-0.840*	Club 1+2					Club 1 [4]	-0.840*
	(0.016)	-0.400*						(0.016)
Club 2 [6]	-0.040	(0.052)	Club 2+3				Club 2 [81]	0.826
	(0.088)		0.8265					(0.08)
Club 3 [75]	1.193		(0.080)	Club 3+4			Club 3 [186]	0.004
	(0.113)			-0.171*				(0.114)
Club 4 [106]	0.004			(0.0124)	Club 4+5		Club 4 [130]	0.536
	(0.014)				-0.086*			(0.021)
Club 5 [130]	0.536				(0.011)	Club 5+6	Club 5 [57]	0.155
	(0.021)					-0.0739*		(0.055)
Club 6 [57]	0.155					(0.0076)		
	(0.055)							

Note[1]: *Reject the null hypothesis of convergence at 5% level.
Note[2]: Number in brackets stand for the number of decision making units in a group.
The tests of club merging have as a null hypothesis that club i and Club j can be considered as a joint convergence club. The test is distributed as a one-sided t statistic with a 5% critical value of -1.65.

Table 12: Convergence club classification :14 industries from 27 countries from 1995 to 2011 for $ECOE_{MF}^{NRDDF}$

Initial classification $\hat{\gamma}$ (SE of $\hat{\gamma}$)		**Tests of club converging** **Final classification** $\hat{\gamma}$ (SE of $\hat{\gamma}$)		
Club 1 [4]	-0.840*	Club 1+2		
	(0.016)	-0.383*		
Club 2 [18]	0.587	(0.0249)	Club 2+3	
	(0.096)		-0.247*	
Club 3 [185]	-0.007		(0.009)	Club 3+4
	(0.015)			-0.409*
Club 4 [171]	0.086			(0.0093)
	(0.020)			

Note[1]: *Reject the null hypothesis of convergence at 5% level.
Note[2]: Number in brackets stand for the number of decision making units in a group.
The tests of club merging have as a null hypothesis that club i and Club j can be considered as a joint convergence club. The test is distributed as a one-sided t statistic with a 5% critical value of -1.65.
No clubs can be merged in the Final classification .

Table 13: Full convergence tests for the specific pressure efficiencies

Efficiency	Coeff.	SE	T-stat.
$\log(t)^{CO2}$	-0.358	0.02	-12.399
$\log(t)^{CH4}$	-0.352	0.013	-26.902
$\log(t)^{N2O}$	-0.351	0.017	-20.223

Table 14: Convergence club classification :14 industries from 27 countries from 1995 to 2011 for $CO_2^{NRDDF,MF}$

Initial classification		**Tests of club converging**						**Final classification**	
$\hat{\gamma}$ (SE of $\hat{\gamma}$)		$\hat{\gamma}$ (SE of $\hat{\gamma}$)						$\hat{\gamma}$ (SE of $\hat{\gamma}$)	
Club 1 [4]	-0.840*	Club 1+2						Club 1 [4]	-0.840*
	(0.016)	-0.5755*							(0.309)
Club 2 [7]	0.064	(0.050)	Club 2+3					Club 2 [7]	0.064
	(0.110)		-0.213*						(0.110)
Club 3 [140]	-0.004		(0.010)	Club 3+4				Club 3 [149]	0.048
	(0.007)			0.048					(0.011)
Club 4 [9]	0.640			(0.0114)	Club 4+5			Club 4 [195]	0.213
	(0.020)				0.625				(0.045)
Club 5 [142]	0.888				(0.040)	Club 5+6		Club 5 [23]	0.309
	(0.049)					0.213			(0.017)
Club 6 [53]	0.469					(0.045)	Club 6+7		
	(0.049)						-0.062*		
Club 7 [23]	0.309						(0.017)		
	(0.017)								

Note[1]: *Reject the null hypothesis of convergence at 5% level.
Note[2]: Number in brackets stand for the number of decision making units in a group.
The tests of club merging have as a null hypothesis that club i and Club j can be considered
as a joint convergence club. The test is distributed as a one-sided t statistic with a 5% critical value of -1.65.

Table 15: Convergence club classification :14 industries from 27 countries from 1995 to 2011 for $CH_4^{NRDDF,MF}$

Initial classification		**Tests of club converging**				**Final classification**	
$\hat{\gamma}$ (SE of $\hat{\gamma}$)		$\hat{\gamma}$ (SE of $\hat{\gamma}$)				$\hat{\gamma}$ (SE of $\hat{\gamma}$)	
Club 1 [4]	-0.840*	Club 1+2				Club 1 [4]	-0.840*
	(0.016)	-0.950*					(0.016)
Club 2 [4]	1.559	(0.067)	Club 2+3			Club 2 [12]	1.615
	(1.375)		1.614				(0.177)
Club 3 [8]	1.956		(0.177)	Club 3+4		Club 3 [277]	-0.022
	(0.184)			-0.0732*			(0.014)
Club 4 [277]	-0.022			(0.014)	Club 4+5	Club 4 [85]	0.238
	(0.014)				-0.299*		(0.023)
Club 5 [85]	0.238				(0.0130)		
	(0.023)						

Note[1]: *Reject the null hypothesis of convergence at 5% level.
Note[2]: Number in brackets stand for the number of decision making units in a group.
The tests of club merging have as a null hypothesis that club i and Club j can be considered
as a joint convergence club. The test is distributed as a one-sided t statistic with a 5% critical value of -1.65.

Table 16: Convergence club classification :14 industries from 27 countries from 1995 to 2011 for $N_2O^{NRDDF,MF}$

Initial classification		**Tests of club converging**			**Final classification**	
$\hat{\gamma}$ (SE of $\hat{\gamma}$)		$\hat{\gamma}$ (SE of $\hat{\gamma}$)			$\hat{\gamma}$ (SE of $\hat{\gamma}$)	
Club 1 [4]	-0.840*	Club 1+2			Club 1 [25]	0.209
	(0.016)	0.209				(0.079)
Club 2 [21]	0.657	(0.079)	Club 2+3		Club 2 [217]	-0.051
	(0.124)		-0.163*			(0.039)
Club 3 [217]	-0.051		(0.0321)	Club 3+4	Club 3 [136]	0.076
	(0.039)			-0.250*		(0.035)
Club 4 [136]	0.076			(0.021)		
	(0.035)					

Note[1]: *Reject the null hypothesis of convergence at 5% level.

Note[2]: Number in brackets stand for the number of decision making units in a group.

The tests of club merging have as a null hypothesis that club i and Club j can be considered as a joint convergence club. The test is distributed as a one-sided t statistic with a 5% critical value of -1.65.

Table 17: Catch-up indexes of Eco-Efficiency

Country	1995-2002 (a)	2003-2011 (b)	change (a) to (b)
AUT	0.609	0.136	↓
BEL	0.471	0.386	↓
BGR	0.007	0.010	↑
CYP	0.216	0.036	↓
CZE	0.052	0.019	↓
DNK	0.304	0.070	↓
EST	0.246	0.082	↓
FIN	0.639	0.831	↑
FRA	0.549	0.300	↓
DEU	0.516	0.183	↓
GRC	0.258	0.110	↓
HUN	0.754	0.324	↓
IRL	0.441	0.148	↓
ITA	0.245	0.487	↑
LVA	0.050	0.015	↓
LTU	0.459	0.373	↓
LUX	0.361	0.107	↓
MLT	0.723	0.256	↓
NLD	0.616	0.209	↓
POL	0.097	0.104	↑
PRT	0.443	0.214	↓
ROU	0.047	0.018	↓
SVK	0.245	0.189	↓
SVL	0.557	0.263	↓
ESP	0.833	0.674	↓
SWE	0.849	0.869	↑
GBR	0.242	0.110	↓

Table 18: Panel unit root tests for $ECOE_{MF}^{DDF}$ convergence

Test	Specification	Statistic	p-value
		1995-2002	
Levin-Lin-Chu	1 lag, no time trend	Adj t*: 2.432	0.990
Fisher-type	1 lag, panel, no time trend	Inv. X^2: 630.178	0.999
		Inv. Norm Z: 10.907	1.000
		Inv. Logit L*: 9.858	1.000
		Mod. Inv. X^2: -3.235	0.999
Hardi LM	No time trend, het. Robust	Z: 36.488	0.000
		2003-2011	
Levin-Lin-Chu	1 lag, no time trend	Adj t*: -18.928	0.000
Fisher-type	1 lag, panel, no time trend	Inv. X^2: 934.187	0.000
		Inv. Norm Z: -3.564	0.000
		Inv. Logit L*: -3.518	0.000
		Mod. Inv. X^2: 4.582	0.000
Hardi LM	No time trend, het. Robust	Z: 33.480	0.000
		1995-2011	
Levin-Lin-Chu	1 lag, no time trend	Adj t*: -6.605	0.000
Fisher-type	1 lag, panel, no time trend	Inv. X^2: 617.812	0.999
		Inv. Norm Z: 5.369	1.000
		Inv. Logit L*:5.368	1.000
		Mod. Inv. X^2:-3.553	0.999
Hardi LM	No time trend, het. Robust	Z: 120.246	0.000

Table 19: Panel unit root tests for $ECOE_{MF}^{NRDDF}$ convergence

Test	Specification	Statistic	p-value
		1995-2002	
Levin-Lin-Chu	1 lag, no time trend	Adj t*: -1.2e+02	0.000
Fisher-type	1 lag, panel, no time trend	Inv. X^2: 1949.121	0.000
		Inv. Norm Z: -0.424	0.335
		Inv. Logit L*: -10.264	0.000
		Mod. Inv. X^2: 30.683	0.000
Hardi LM	No time trend, het. Robust	Z: 32.681	0.000
		2003-2011	
Levin-Lin-Chu	1 lag, no time trend	Adj t*: -18.052	0.000
Fisher-type	1 lag, panel, no time trend	Inv. X^2: 805.144	0.104
		Inv. Norm Z: -2.430	0.007
		Inv. Logit L*: -2.623	0.004
		Mod. Inv. X^2: 1.263	0.103
Hardi LM	No time trend, het. Robust	Z: 31.321	0.000
		1995-2011	
Levin-Lin-Chu	1 lag, no time trend	Adj t*: -11.048	0.000
Fisher-type	1 lag, panel, no time trend	Inv. X^2: 687.363	0.964
		Inv. Norm Z:1.674	0.953
		Inv. Logit L*: 1.443	0.925
		Mod. Inv. X^2: -1.765	0.961
Hardi LM	No time trend, het. Robust	Z: 113.421	0.000

Appendix B

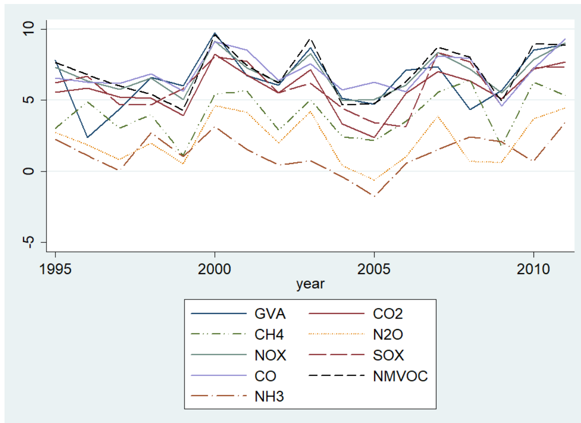

Figure 1: Mean values of sample variables (logarithmic form) through time

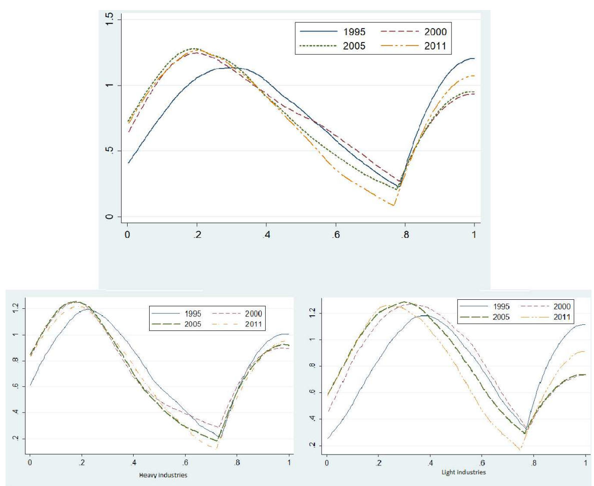

Figure 2: Kernel densities of $ECOE_F^{NRDDF}$ in 1995, 2000, 2005 & 20011 for heavy and light industries.

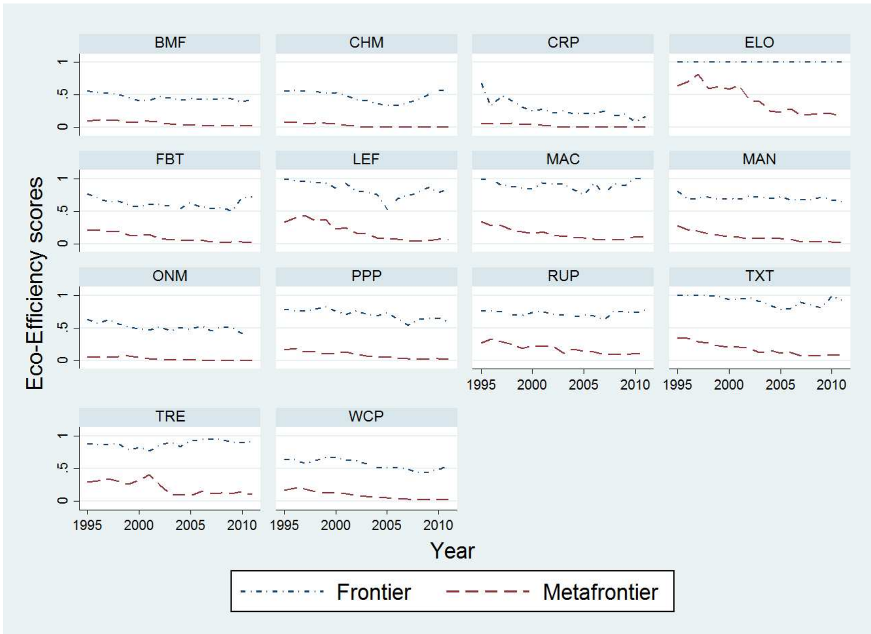

Figure 3: $ECOE^{DDF}$ tendency of European Industries in 1995-2011

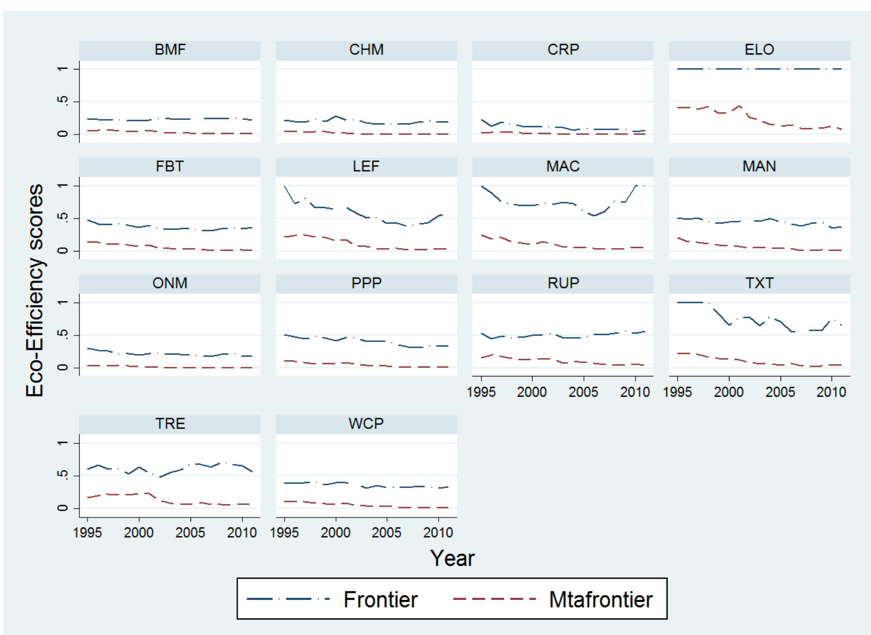

Figure 4: $ECOE_{MF}^{NRDDF}$ tendency of European Industries in 1995-2011

Figure 5: MTR of heavy vs light industries by year

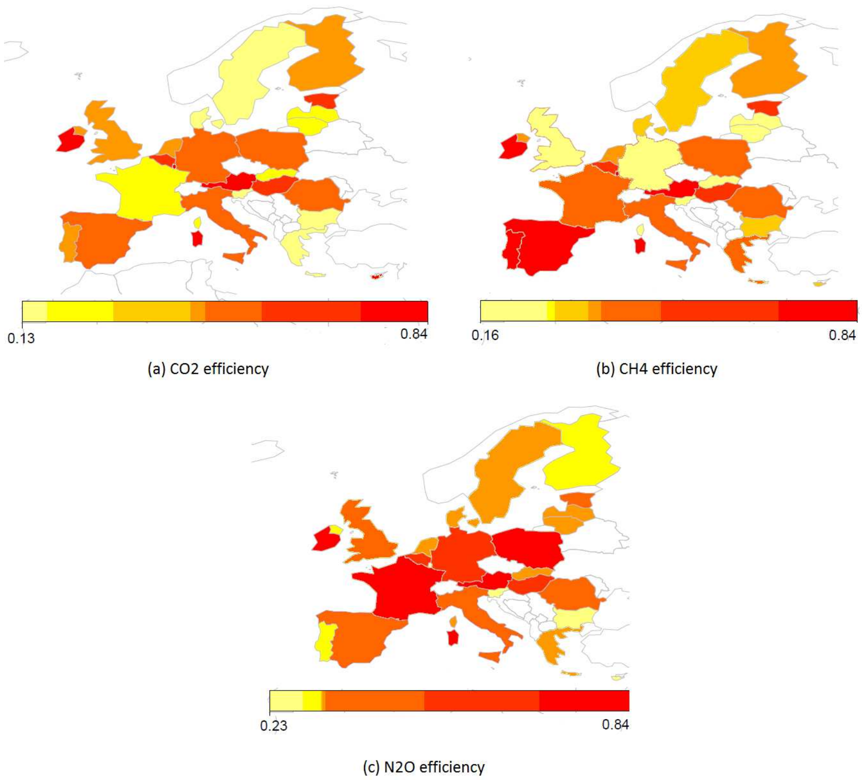

Figure 6: CO_2, CH_4 and N_2O efficiency in Europe

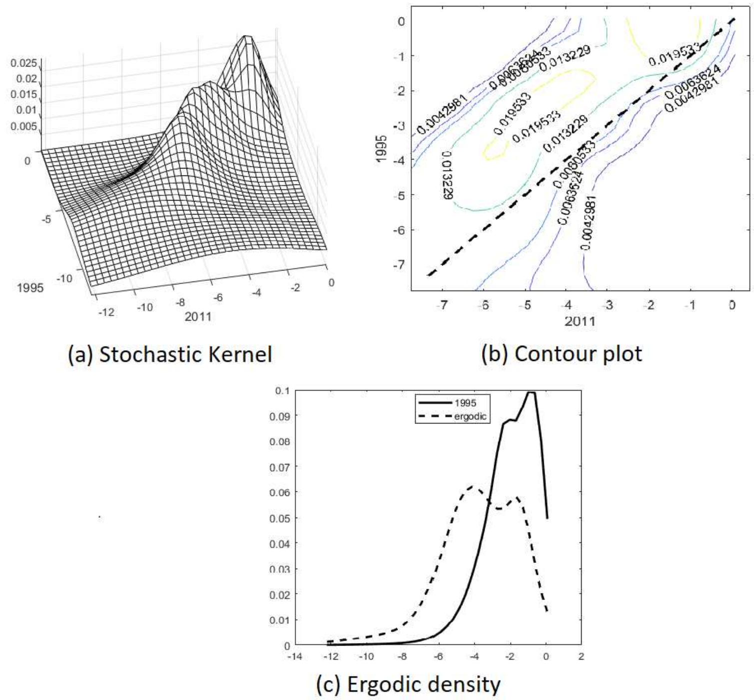

Figure 7: Stochastic kernel, Contour plot and Ergodic distribution of the distribution of $ECOE_{MF}^{DDF}$

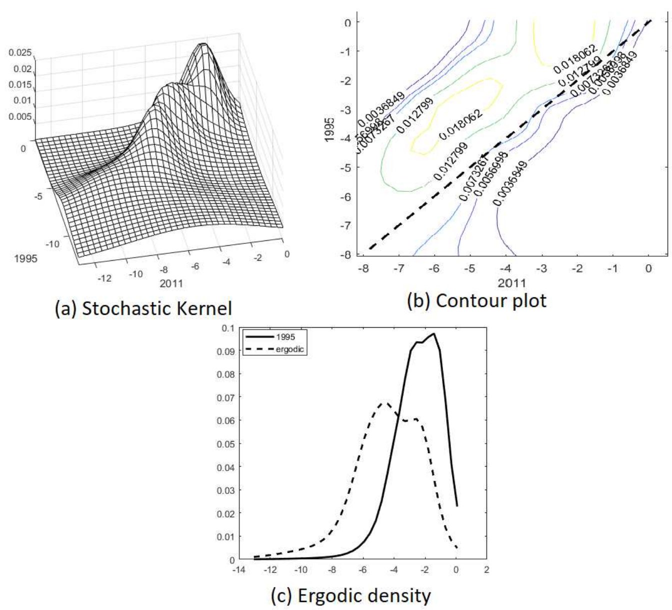

Figure 8: Stochastic kernel, Contour plot and Ergodic distribution of the distribution of $ECOE_{MF}^{NRDDF}$

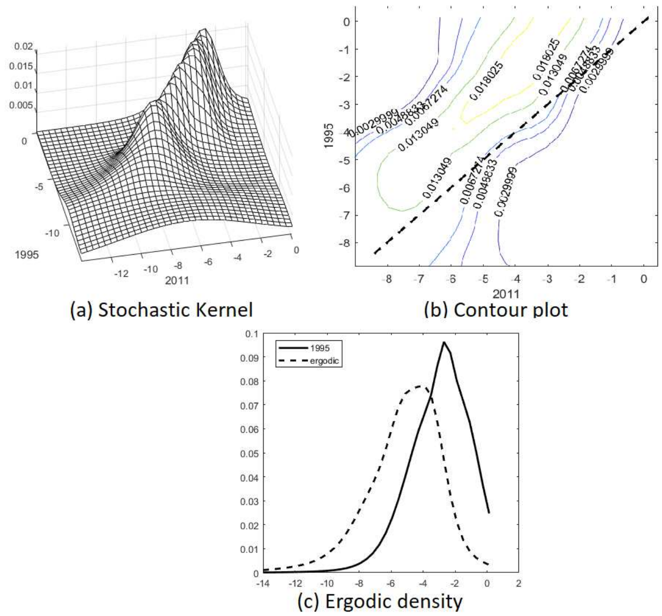

Figure 9: Stochastic kernel, Contour plot and Ergodic distribution of the distribution of $CO_2E_{MF}^{NRDDF}$

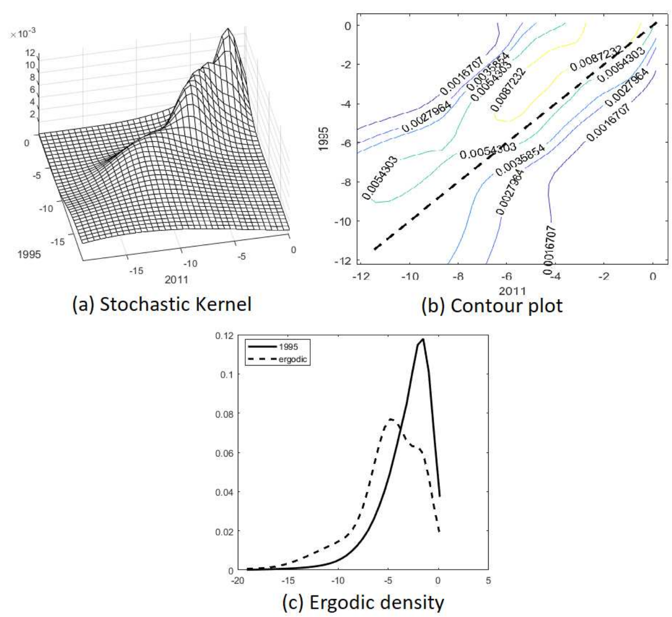

Figure 10: Stochastic kernel, Contour plot and Ergodic distribution of the distribution of $CH_4E_{MF}^{NRDDF}$

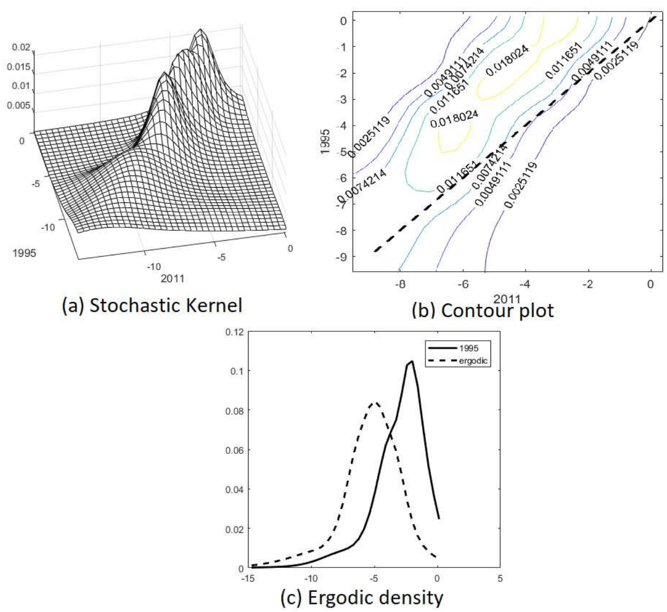

Figure 11: Stochastic kernel, Contour plot and Ergodic distribution of the distribution of $N_2OE_{MF}^{NRDDF}$

Club 1: (4)

ELO (FIN, ESP, SWE), TRE (ESP)

Club 2: (81)

MAC (FIN, FRA, DEU, HUN, ITA, BEL, LTU, NLD, POL, SVN, ESP), RUP (FIN, AUT, DEU, HUN, ITA, LUX, BEL, NLD, POL, SVK, ESP, SWE), BMF (FRA, ITA, ESP, GBR), ELO (FRA, DEU, HUN, BEL, ITA, LTU, MLT, NLD, POL, PRT, SVK, SVN, AUT), LEF (FRA, HUN, ITA, BEL, POL, ESP), PPP (FRA, ITA, LTU, MLT, ESP), TXT (FRA, ITA, LTU, MLT, BEL, POL, ESP), WCP (FRA, ITA, SVK, ESP), CRP (GRC, LUX), MAN (HUN, ITA, LTU, BEL, MLT, SVK, ESP), CHM (IRL), FBT (ITA, ESP), TRE (ITA, LTU, BEL, PRT, SVK, SWE, GBR)

Club 3: (106)

CRP (FIN, FRA, IRL, LTU, POL, PRT, SWE, DNK), FBT (FIN, IRL, LTU, POL, SVK), MAN (FIN, FRA, DEU, MLT, NLD, POL, PRT, GBR), TXT (FIN, AUT, DEU, GRC, HUN, LUX, NLD, SVK, SVN, SWE, GBR), TRE (FIN, FRA, AUT, DEU, GRC, HUN, LUX, MLT, NLD, POL, SVN, CYP), RUP (FRA, LTU, MLT, PRT, GBR), LEF (DEU, GRC, LTU, NLD, PRT, SVK, SVN, SWE, GBR, AUT, CZE), BMF (GRC, HUN, LTU, LUX, SVN, CZE, EST, FIN), ONM (GRC, HUN, LTU, LUX, MLT, POL, ROU, ESP, CYP, CZE), WCP (HUN, LTU, LUX, NLD, BEL, POL, EST), ELO (IRL, LUX, GBR, DNK) , PPP (IRL, NLD, PRT, SVK), CHM (LVA, LTU, LUX, MLT, NLD, DNK), MAC (LUX, PRT, SVK, SWE, GBR, AUT)

Club 4: (130)

BMF (AUT, DEU, BEL, IRL, LVA, MLT, NLD, POL, PRT, SVK, SWE, CYP, DNK), PPP (AUT, FIN, DEU, GRC, HUN, LVA, LUX, BEL, ROU, SVN, GBR, CYP, CZE, DNK, EST), LEF (FIN, IRL, LVA, MLT, ROU, CYP, DNK, EST), ONM (FIN, DEU, IRL, SVK, SVN, EST), WCP (FIN, AUT, DEU, GRC, IRL, MLT, PRT, SVN, SWE, GBR, CYP, CZE, DNK), FBT (FRA, DEU, GRC, HUN, BEL, LUX, NLD, PRT, ROU, SVN, SWE, GBR, CYP, AUT, DNK, EST), CHM (DEU, GRC, BEL, ITA, AUT, SWE, CYP), ELO (GRC, LVA, ROU, CZE, EST), MAC (GRC, IRL, LVA, MLT, CZE, DNK, EST), MAN (GRC, IRL, LVA, LUX, ROU, SVN, SWE, CYP, CZE, DNK, AUT, EST), RUP (GRC, IRL, LVA, SVN, CYP, CZE, DNK, EST), CRP (BEL, ITA, AUT, CYP, EST), TXT (IRL, LVA, PRT, ROU, BGR, CYP, CZE, DNK, EST), TRE (IRL, LVA, CZE, DNK, EST)

Club 5: (57)

CHM (FIN, FRA, HUN, POL, PRT, ROU, BGR, SVK, SVN, ESP, GBR, CYP, EST), ONM (FRA, ITA, LVA, BEL, NLD, PRT, SWE, GBR, BGR, DNK, AUT), CRP (DEU, HUN, LVA, MLT, NLD, ROU, BGR, SVK, SVN, ESP, GBR, CZE), FBT (LVA, BGR, CZE), WCP (LVA, ROU, BGR), PPP (POL, SWE, BGR), BMF (BGR, ROU), MAC (ROU, BGR, CYP), TRE (ROU, BGR), ELO (BGR, CYP), LEF (BGR), MAN (BGR), RUP (BGR)

Figure 12: Clustering analysis and final convergence clubs of $ECOE_{MF}^{DDF}$

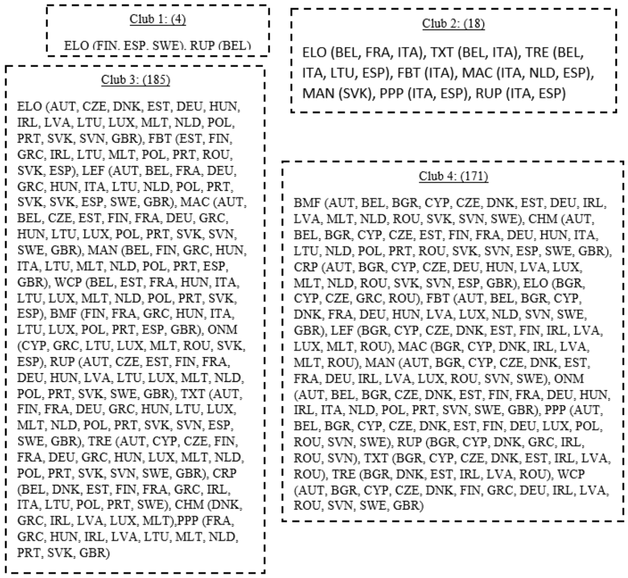

Figure 13: Clustering analysis and final convergence clubs of ECOE_{MF}^{NRDDF}

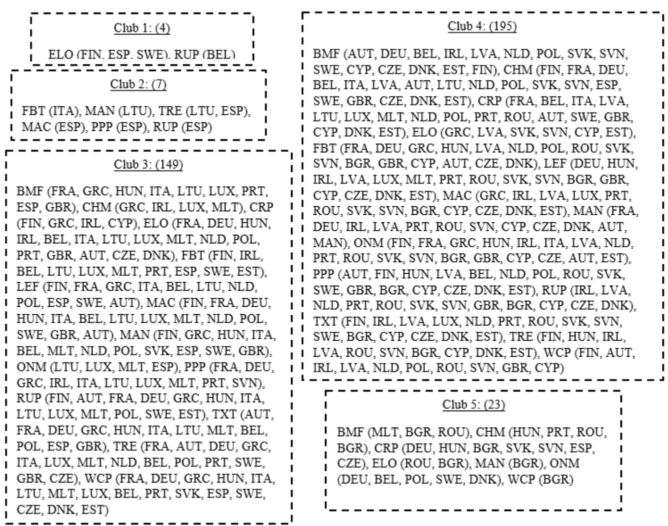

Figure 14: Clustering analysis and final convergence clubs of $\text{CO}_2\text{E}_{MF}^{NRDDF}$

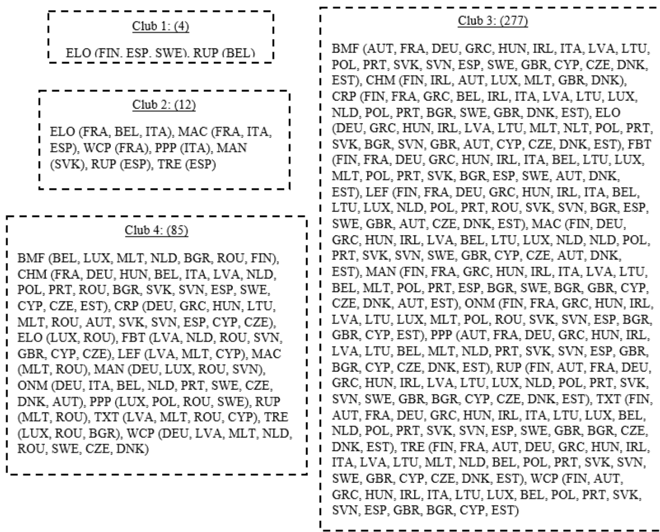

Figure 15: Clustering analysis and final convergence clubs of $CH_4E_{MF}^{NRDDF}$

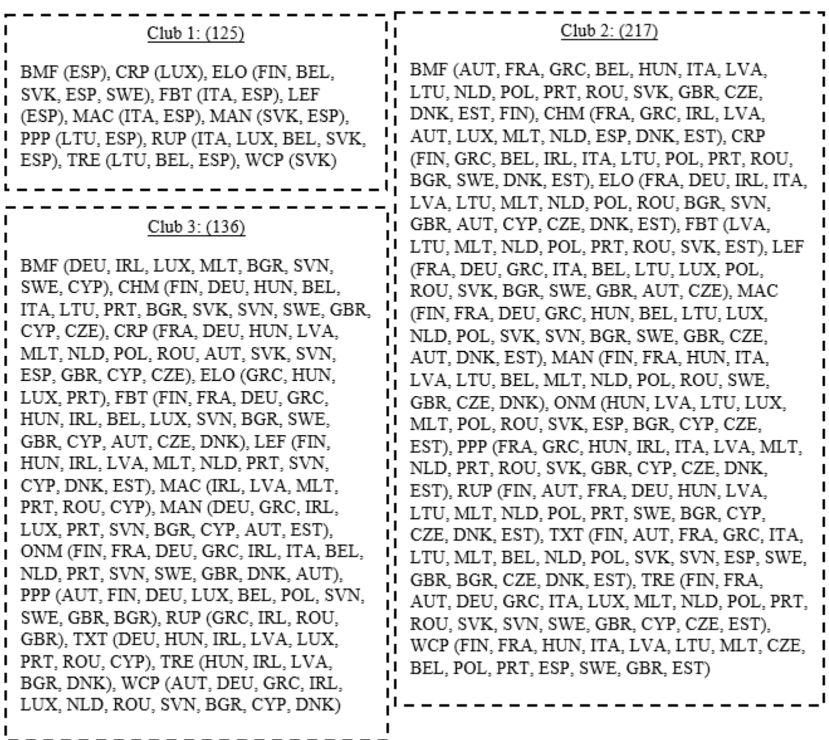

Figure 16: Clustering analysis and final convergence clubs of $N_2OE_{MF}^{NRDDF}$

Appendix C

8 Conventional and non-radial slack-based DDF approach

8.1 Conventional DDF approach

As in Picazo-Tadeo et al. (2011), Gómez-Calvet et al. (2016) and Camarero et al. (2013), eco-efficiency is assessed using a non-parametric approach. Formally, the indicator of eco-efficiency for each European industry i is computed using the DDF technique:

$$\beta^* = max\beta$$

subject to:

$$\mathbf{v}\lambda \geq v_0(1+\beta)$$
$$\mathbf{p}\lambda \leq \mathbf{p}_0(1-\beta)$$
$$\lambda \geq 0$$

λ being a variable representing the weighting of decision-making unit i in the composition of the eco-efficient frontier. The parameter β^* which is the solution of the above-mentioned program, indicates the score of inefficiency and assesses how much value added is increased while environmental pressures are silmuntaneously decreased by the same proportion.

8.2 Second stage analysis (Non-radial slacks):

In this stage we proceed by incorporating in our analysis non-radial slacks as proposed by Gómez-Calvet et al. (2016). For this case, the problem is transformed as follows:

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

subject to:

$$\mathbf{v}\lambda - s^+ = v_0(1+\beta^*)$$
$$\mathbf{p}\lambda + \mathbf{s}^p = \mathbf{p}_0(1-\beta^*)$$
$$\lambda \geq 0, s^+ \geq 0,\ \mathbf{s}^p \geq 0$$

9 Convergence Analysis

9.1 Empirical algorithm of Phillips and Sul (2007)

In this section of Appendix we present the algorithm of Phillips and Sul convergence.

- Step 1 (Ordering): Order the panel members according to the last observation. This step is important as evidence of convergence will be most apparent in the recent years. In cases of high volatility, the ordering is based on the average of the final observations.

- Step 2 (Core Group Formation): In this step we identify the core groups of economies that converge. We calculate the t-statistic t_k for sequential log t regressions based on the highest k highest members (Step 1) with $2 \leq k \leq N$. The maximum t_k with $t_k >$ -1.65 will determine the size of the group. The maximum value of t_k will secure the low false inclusion rate.

- Step 3 (Club membership): Through this step we appraise each individual economy that is not included in the core convergence group (Step 2) for membership in this group. Adding one economy at a time and calculating t-statistic from the beginning. If t-statistic is greater than a chosen critical value c*,[38] then the new economy satisfies the membership condition and is included in the group. Finally, we examine if the whole new group satisfies $t_k >$ -1.65 for convergence.

- Step 4 (Recursion and Stopping): Economies that were not selected in Step 3, will form a supplementary group. We run t_k for these economies and if the results show convergence, then this group of economies will become a second convergence club. If not, Steps 1 to 3 will be repeated to detect subgroups of convergence. If no core group is found in Step 2 then the whole sample will display divergent behavior.

[38] PS set c = 0. This ensures a high confidence of accuracy with respect to the inclusion into convergence clubs.

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