European industrial eco-efficiency under different pollutants' scenarios and heterogeneity structures. Is there a definite direction? there a de nite direction?

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4 February 2020

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Abstract

Eco-efficiency has intensified the attention of policymakers in the last decades as the ability to create more goods and services with less impact on the environment consists an instrument towards sustainability. In this paper we utilize data of 14 industries from 27 European countries from 1995 to 2011 to estimate distinct objectives of economic and ecological performance by utilizing directional distance functions under a metafrontier framework. Our results reveal that the existence of a unified technology set causes large differences in the industrial eco-efficiency levels while energy intensive industries can be characterized as the most eco-inefficient. Although the speed of eco-efficiency convergence increases throughout the years, the case of CO_2 emissions presents an erratic behavior compared to the other pollutants. Thus, a decomposition of industrial CO_2 emissions can be considered as a further subject of research in our study in order to identify the drivers of this change through time.

keywords: Eco-efficiency, Metafrontier, Spillovers, Catch-up, Kaya Identity, European Industries.

JEL Classifications: D29, L23, L60, Q57

1 Introduction and motivation

As the concept of sustainability becomes more deeply entrenched in the society, there has been increasing attention to the development and estimation of eco-efficiency in political, academic and business circles. Eco-efficiency was introduced in the World Commission on Environment and Development (Brundtland et al., 1987) and is considered as a substantial instrument to promote sustainability as it contains both concepts of economic performance and environmental well-being.[1] Defined by the World Business Council for Sustainable Development (WBCSD) at the 1992 Earth Summit, eco-efficiency relates to the creation of more economic value that satisfies human needs and improves quality of life while progressively aims on the reduction of ecological impacts and resource intensity (Madden et al., 2005). In other words, its notion explains the ability of an entity (i.e firm, industry, country) to produce the maximum level of economic output while causing the minimum environmental damages (Schaltegger and Sturm, 1989; Schmidheiny and Timberlake, 1992). Despite the growing number of studies assessing eco-efficiency at country level, there is substantial empirical evidence regarding different types of pollutants at industrial level. Meanwhile, the result of the industrial process contains not only the products, but also some pressures on the environment such as air and water pollution, waste generation and consumption of natural resources (EEA, 2018)[2]. In this regard, since European pollution from industrial activities comprise a significant share of total emissions (EEA, 2017)[3] the demand of an integrated and comprehensive research is needed.

Undoubtedly, industrial greenhouse gases activities play such an important role in sustainability. This paper deals with economic and ecological performance of the European industries from the manufacturing sector at European level. Following closely the seminal work of Kuosmanen and Kortelainen (2005) who defined the measure of eco-efficiency, we build indicators for assessing the economical and ecological performance. More specifically, distinct scenarios of directional vectors are utilized, as (Picazo-Tadeo et al., 2012) proposed, in order to examine different objectives of economic and ecological performance of industries using different industrial pollutants. As far as we aware, diverse scenarios have not been

[1]BASF was the initial approach for the measurement of sustainability and eco-efficiency through projects with short time and low costs (Saling et al., 2002; Schmidt et al., 2004).

[2]`https://www.eea.europa.eu/downloads/f6f0fc15c9de4d1c8de3d21469f12b91/1574178275/industrial-pollution-in-europe.pdf`.

[3]`https://www.eea.europa.eu/data-and-maps/indicators/industrial-pollution-in-europe-3/assessment`

used before to evaluate eco-efficiency of European industries as we do in this paper. At the same time, as industries are not isolated at their country productive frontier, they deal with asymmetric technological opportunities and may exploit knowledge and technological spillovers. As a result, heterogeneity exists creating discrepancies among industries that belong to different European countries (Tsekouras et al., 2016, 2017). The estimation of eco-efficiency under a metafrontier framework allows us also to examine possible spillover effects in terms of absorptive capacity and innovative capabilities generated at the European level (Cohen and Levinthal, 1990). Hence, the second research question of this paper focus on the speed that each industry at its national frontier (technology) catch-up to the metafrontier (metatechnology) with respect to the different pollutants behavior.

Eco-efficiency was firstly determined as the ratio of GDP to CO_2 emissions (e.g. Glauser and Müller, 1997; Burritt and Schaltegger, 2001; Zhang et al., 2008).[4] Despite its easiness and straightforwardness, it entirely ignored the diverse dimensions of the undesirable outputs that could be produced from the production process (Kuosmanen and Kortelainen, 2005; Wang et al., 2011). Recently, the benchmarking techniques, such as the Data Envelopment Analysis (DEA) or the Directional Distance Function (DDF), for the assessment of eco-efficiency gained ground (Korhonen and Luptacik, 2004; Kuosmanen and Kortelainen, 2005). Nevertheless, the choice of the indicators could depend on the entity that we want to review (Saling et al., 2002; Hellweg et al., 2005; Scholz and Wiek, 2005.; Huppes and Ishikawa, 2007; Managi and Kaneko, 2009). To deal with these shortcomings, many authors employ a DEA framework (e.g. Lozano et al., 2009; Iribarren et al., 2011; Fan et al., 2017; Gómez et al., 2018; Shao et al., 2019) [5]. On the other hand, the DDF approach highlights the variety of environmental indicators and points out the disrepancies of economic and environmental performance by treating pollutants as outputs, and not as inputs like the DEA method (e.g. Picazo-Tadeo et al., 2012; Gómez-Calvet et al., 2016).

Summarizing, as the number of policies and regulations is increasing in the last decades towards energy and environment, the importance of indexes that measure both economic and environmental outcomes be-

[4]There were several times that its definition was confused with resource efficiency, resource productivity, resource or pollution intensity Dahlström and Ekins (2005).

[5]Dyckhoff and Allen (2001) proposed Life Cycle Assessment (LCA) technique to prioritize the environmental indicators (Guinée, 2002; de Haes et al., 2002) and many authors used it into DEA to assess eco-efficiency (De Koeijer, 2002; Korhonen and Luptacik, 2004; Kuosmanen and Kortelainen, 2005; Kortelainen and Kuosmanen, 2007; Zhang et al., 2008; Picazo-Tadeo et al., 2011).

comes more intense. The contribution of this study differs in two, so far, important dimensions. Firstly, we include in our analysis a wider spectrum of pollutants scenarios aiming at a more integrated picture regarding industrial eco-efficiency performance. To our knowledge, the eco-efficiency scenarios have not been used previously to assess it on an industrial level of European countries. Secondly, our methodological approach allows the interaction between national technologies (frontiers) and European metatechnology (metafrontier) and provide us not only with eco-efficiency results at both levels, but also with the examination of the catch-up hypothesis. This provides policymakers and managers the opportunity for more insight in the potential improvements of the industrial economic and ecological performance. Several regulations concerning the mitigation of the pollutants have been developed from the United Nations (UN) and the International Energy Agency (IEA). In Europe, the Kyoto protocol obligations about emissions have to be taken into consideration by all countries.[6] However, the results from these policies could not be considered successful for the whole set of countries.

Our results support the evidence of eco-efficiency differences with respect to technology structure and economic - environmental pressures perspective. Moreover, energy intensive industries appear to be more eco-efficient while countries present the lowest level of catching-up in the case of CO_2 emissions. The specific finding led to the creation of an additional research question and a further contribution. Thus, the examination of the drivers of industrial CO_2 emissions per capita was originated as a potential research issue. Hence, employing the Kaya identity we determine the role of industries in the mitigation of CO_2 emissions in three distinct time periods in which economic and environmental events took place. All these environmental policies that EU tries to implement was an outcome of the rapid economic growth of European countries and the simultaneous increase of carbon emissions mostly. In this direction, understanding the driving forces of industrial emissions would benefit policy formulations to quantify changes in predetermined factors of interest in order to limit global warming to 1.5^oC.

We considered the above-mentioned topics to be very relevant and deserving of investigation because the balance between economic growth and environmental quality is crucial for the sustainability conditions in Europe. The increasing emissions per capita of some European countries have attracted researchers to get involved with the decomposition of the driving forces of their change. The Kaya (1990) identity under the

[6] The EU members have committed to cut down their GHG emissions by 20% below 1990 observed levels by 2020. Moreover, the Commission's longterm target is to reduce emissions to 80-95% below 1990 levels by 2050 (COM/2018/773 final).

application of the log mean Divisia Index (LMDI) is the most popular technique because of some desirable properties such as consistency in aggregation or path independence (e.g. Ang and Pandiyan, 1997; Jung et al., 2012; O'Mahony, 2013; Li et al., 2014; Štreimikienė and Balezentis, 2016; Ma and Cai, 2018). Hence, if countries could prevent or control as much as possible the pollution from the manufacturing sector, then the notion of sustainability will gain traction again in the European agenda in the near future.

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, convergence patterns and the determinants of emissions per capita. Lastly, Section 5 summarizes and concludes.

2 Methodology

Our methodological framework is developed in three parts as follows. In the first part we present the theoretical and methodological frameworks regarding the estimation of eco-efficiency scores and the distinct directional vectors that are adopted. At the same time, we consider a metafrontier approach in order to emphasize on the role of heterogeneity in the estimated results. In the second part we discuss the underpinnings of a catch-up index that examines if industries converge in terms of eco-efficiency. Finally, in the third part we present Kaya identity.

2.1 Directional Distance Function and Eco-efficiency Assessment

As mentioned in the introduction, we define eco-efficiency as the ratio between economic value and environmental pressures (Schmidheiny and Zorraquin, 1998). Eco-efficiency can be improved when (a) value added increases as environmental pressures are maintained on the same level, (b) environmental pressures decrease as value added is maintained on the same level and (c) value added increases with a simultaneous decrease of environmental pressures.

Thus, let us assume that we observe the economic value added v, generated in the production process by a set of i = 1,...,I decision-making units (industries) at k = 1,...,K countries, Their production process causes a series of n = 1,....,N damaging environmental pressures which are expressed by the vector $\mathbf{p}$ = (p1,...,pn). In this sense, Kuosmanen and Kortelainen (2005) and Picazo-Tadeo et al. (2011) pointed out that all feasible combinations of value added v (desirable output) and environmental pressures **p** (undesirable outputs/pollutants) are described through the pressure generating technology set[7] (PGT) as:

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

At this point, it is worth noting that in literature there are various ways for treating the undesirable outputs (Dyckhoff and Allen, 2001; Seiford and Zhu, 2002). Adopting the regular definition of eco-efficiency in the ecological literature, proposed by Kuosmanen and Kortelainen (2005), we describe eco-efficiency as the following ratio:

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

where G symbolizes the function that aggregates the n environmental pressures into a single environmental pressure score. In this formulation it is well known that environmental pressures are complex in their computation due to the absence of market prices. Thus, we adopt the most common approach in the literature for the computation of the aggregate environmental pressure score as a linearly weighted average of the particular pressures with weights w_n:

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

where w_n is the weight assigned to pressure n Kuosmanen and Kortelainen (2005).

Utilizing the theoretical framework of Chambers et al. (1998) and Färe and Grosskopf (2000) for directional distance function, the pressure generating technology can be expressed as:

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

with d=$(d_v, -d_p)$ being the direction vector. Eq.(4) allows for the simultaneous increase of value added and decrease of environmental pressures according to the directional vector that the researcher employs.

The various directional distance functions, as displayed in Figure 1, give us the advantage to examine the ecological and environmental relationship from different perspectives and help policymakers, managers and researchers in the evaluation of eco-efficiency.

[7]We assume some properties 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.

2.1.1 Assessing the role of pressures on the environment

In this paper we consider that we want to examine the magnitude of reducing the environmental pressures of our European industries without altering the level of their economic performance. To do so, we employ the following directional vector:

$$\mathbf{d} = (d_v, \text{-}\mathbf{d_p}) = (0, \text{-}\mathbf{p}) \tag{5}$$

and the directional distance function:

$$\text{ECOE}^1_{i,t|k} = \overrightarrow{D}[v, \mathbf{p}; \mathbf{d} = (0, \text{-}\mathbf{p})] = sup\{\beta^1 | [(v, (1-\beta^1)\mathbf{p}] \in \text{PGT}\} \tag{6}$$

where β^1 assesses the proportion by which all environmental pressures could be decreased while preserving the same observed level of value added[8]. Solving the following mathematical program we compute the eco-efficiency score for each European industry i′:

$$\begin{aligned}
&\max_{\beta^1_{i'}, \lambda_i} ECOE^1_{i'} = \beta^1_{i'} \\
&\text{s.t.:} \quad v_{i'} \leq \sum_{i=1}^{I} \lambda_i v_i \qquad (i) \\
&(1-\beta^1_{i'}) p^n_{i'} \geq \sum_{i=1}^{I} \lambda_i p^n_i \quad \text{n} = 1,....,\text{N} \qquad (ii) \\
&\lambda_i \geq 0 \qquad i = 1, ..., I \quad (iii)
\end{aligned} \tag{7}$$

where λ_i represents the weighting of the DMU i in the construction of the eco-efficient frontier. The parameter $\beta^1_{i'}$ consists the solution of the above-mentioned program. A score of zero would indicate a benchmarking for eco-efficiency and in this case there would be no peer that causes lesser pressures with the same amount of value added. Therefore, the larger it is, the greater will be the extent of inefficiency. For convenience in our empirical analysis, we will use efficiency scores.

2.1.1.1 Pressure-specific eco-efficiency

Each environmental pressure might have different impact on the environment. For example, an industry that generates more waste than emissions would be interested to reduce the undesirable outputs that are responsible for the specific type of environmental pressure. A special case of the previous directional vector is the possibility of an industry to reduce a specific pressure or group of pressures without affecting their

[8] It is worth mentioning that in this case the directional distance function becomes identical with the conventional Shephard's input distance function and the Farrell-Debreu (Farrell, 1957) input-oriented measure of technical efficiency (Färe and Lovell, 1978)

economic performance. The directional vector for this scenario is expressed as follows:
$$\mathbf{d} = [d_v, -(\mathbf{d}_{\mathbf{p}_m}, \mathbf{d}_{\mathbf{p}_{-m}})] = [0, (\text{-}\mathbf{p}_m, 0)] \tag{8}$$

where m being the specific environmental pressure that is reduced and -m the remaining pressures and the directional distance function:

$$\mathrm{ECOE}^2_{i,t|k} = \overrightarrow{D}\{v, \mathbf{p}; \mathbf{d} = [0, (\text{-}\mathbf{p}_m, 0)]\} = sup\{\beta^2 | [(v, (1-\beta^2)\mathbf{p}_m, \mathbf{p}_{-m}] \in \mathrm{PGT}\} \tag{9}$$

where β^2 assesses the maximum possible decrease in environmental pressure or group of pressures m without increasing the remaining pressures (-m) and maintaining the level of value added. Solving the following program we estimate eco-efficiency as:

$$\max_{\beta^2_{i'}, \lambda_i} ECOE^2_{i'} = \beta^2_{i'}$$
$$\text{s.t.:} \quad v_{i'} \leq \sum_{i=1}^{I} \lambda_i v_i \qquad (i)$$
$$(1-\beta^2_{i'})p^m_{i'} \geq \sum_{i=1}^{I} \lambda_i p^m_i \quad \text{m} \in \text{n and m} \notin -m \qquad (ii) \tag{10}$$
$$p^{-m}_{i'} \geq \sum_{i=1}^{I} \lambda_i p^{-m}_i \quad -m \in n \quad (iii) \tag{11}$$
$$\lambda_i \geq 0 \quad i = 1, ..., I \quad (iv)$$

2.1.2 Highlighting the role of economic performance

On the other hand, if industries tend to concentrate more on their economic performance then, an alternative directional vector should be employed. In this case, the directional vector is expressed as:
$$\mathbf{d} = (d_v, \text{-}\mathbf{d}_\mathbf{p}) = (v, 0) \tag{12}$$

and the directional distance function:

$$\mathrm{ECOE}^3_{i,t|k} = \overrightarrow{D}[v, \mathbf{p}; \mathbf{d} = (v, \mathbf{0})] = sup\{\beta^3 | [(v, (1+\beta^3)v, \mathbf{p}] \in \mathrm{PGT}\} \tag{13}$$

The directional distance function, parameter β^3 estimates the proportion by which value added could be increased without changing the level of environmental pressures within the pressure generating technology set[9]. As before, β^3 has a lower bound of zero. In this scenario, the eco-efficiency is assessed by utilizing the following program:

$$\max_{\beta^3_{i'}, \lambda_i} ECOE^3_{i'} = \beta^3_{i'}$$
$$\text{s.t.:} \quad (1+\beta^3_{i'})v_{i'} \leq \sum_{i=1}^{I} \lambda_i v_i \qquad (i)$$
$$p^n_{i'} \geq \sum_{i=1}^{I} \lambda_i p^n_i \quad n = 1, ..., N \quad (ii) \tag{14}$$
$$\lambda_i \geq 0 \quad i = 1, ..., I \quad (iii)$$

[9]In this case, eco-efficiency is equivalent with the conventional Farrell-Dereu output-oriented measure of thechnical efficiency (Färe and Lovell, 1978)

2.1.3 Balancing between economic and ecological performance

An ultimate scenario that industries and policymakers might need to clarify is the simultaneous increase of value added and reduction of environmental pressures. This objective can be monitored as:

$$\mathbf{d} = [d_v, -\mathbf{d_p}] = (v, \text{-}\mathbf{p}) \tag{15}$$

and the corresponding directional distance function:

$$\text{ECOE}^4_{i,t|k} = \overrightarrow{D}[v, \mathbf{p}; \mathbf{d} = (v, \text{-}\mathbf{p})] = sup\{\beta^4 | [(1+\beta^4)v, (1-\beta^4)\mathbf{p}] \in PGT\} \tag{16}$$

where β^4 assesses the proportion by which value added can be increased with a simultaneous reduction of environmental pressures by the same volume. In this case, eco-efficiency is computed utilizing the program:

$$\begin{aligned}
&\max_{\beta^4_{i'}, \lambda_i} ECOE^4_{i'} = \beta^4_{i'} \\
&\text{s.t.:} \quad (1 + b^4_{i'})v_{i'} \leq \sum_{i=1}^{I} \lambda_i v_i \quad (i) \\
&(1 - \beta^4_{i'})p^n_{i'} \geq \sum_{i=1}^{I} \lambda_i p^n_i \quad n = 1, ..., N \quad (ii) \\
&\lambda_i \geq 0 \qquad i = 1, ..., I \quad (iii)
\end{aligned} \tag{17}$$

2.2 Eco-Efficiency under the Metafrontier (European) Technology

In the literature, the assessment of eco-efficiency has mostly been investigated assuming that entities share the same production technology (e.g. Picazo-Tadeo et al., 2012). However, this hypothesis is unsuitable if an industry confronts different technological restrictions. Eco-efficiency scores under the frontier framework are not comparable across groups, in our case countries, as they are estimated against distinct technological frontiers. The common environmental regulations[10] across industries and countries, the existence of heterogeneity (Battese et al., 2004) and the effacement of the technological isolation and boundaries (Tsekouras et al., 2016, 2017) among countries have originated the introduction of the metafrontier framework that is fundamental for the possibility of technological spillovers between industries. The utilization of a metafrontier framework will guarantee that differences that exist due to different geographical, technological, structural, administrative, regulatory, social and operational regimes as well as relocations of industries could be annihilated. In addition, when a common technology frontier is utilized,

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

industries could "absorb" some of the knowledge or the technology that is transferred across European industries improving their eco-efficiency performance.

Therefore, incorporating the concept of a metafrontier (European) technology (Beltrán-Esteve et al., 2014) the directional distance function is expressed as follows:

$$M\vec{D}[v, \mathbf{p}; \mathbf{d} = (d_v, \textbf{-d}_\mathbf{p})] = sup[\beta|(v + \beta d_v, p - \beta d_p) \in \text{PGMT}] \quad (18)$$

where $PGMT = conv\{PGT_1 U PGT_2 U PGT_3 U ... U PGT_K\}$ is the convex hull of the jointure of individual pressure generating technologies[11] and d=$(d_v, -d_p)$ being, as already mentioned, the direction vector.

The major benefit of the metafrontier directional distance function (MDDF)[12] is the fact that it operates as an envelope of the individual technologies (countries). As a consequence, it becomes a benchmarking for all entities (industries) independently of the specific technology in which each industry belongs to. In this sense, it is reasonable to think that an industry that is efficient with respect to its country frontier might be inefficient when European metafrontier is employed. Resource endowments, economic infrastructure, other characteristics of the physical, social and economic environment (O'Donnell, 2008; Kounetas, 2015) and national, legal and institutional regulations (Kontolaimou and Tsekouras, 2010.; Halkos and Tzeremes, 2011) cannot be considered within the technology set of a country. Therefore, differences in the eco-efficiency scores under the frontier and the metafrontier framework will exist.

2.3 A Catch-up Index for eco-efficiency measures

The introduction of a metafrontier technology is linked to the industry's ability to receive technological flows from the European metatechnology. Thus, one of the motivation of this paper is to examine how eco-efficiency technology transfer occurs and catch-up do happens. Under this logic, we now turn our attention on the calculation of a catch-up index to measure the speed at which industries catch-up to the best technology. The catch-up hypothesis states that industries that lag furthest behind from the technology leaders would present higher rates of eco-efficiency growth and benefit the most from the diffusion of technical knowledge. Moreover, following Abramovitz (1986) and Nelson and Phelps (1966)

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

[12] The MDDF is modified accordingly to the directional vector that is applied in each case. Once again, we take into consideration four distinct scenarios regarding the economic and environmental performance of the entities.

the opportunity for rapid growth is taken by the industry who possesses specific technological competencies and its ability to absorb, mobilize resources and transform the existing knowledge.

In order to test whether there are any technology spillovers between the metafrontier and the frontier technology, we use means of panel unit root tests (Casu et al., 2016). The catch-up index is defined as the ratio of eco-efficiency of the metafrontier to that of the country frontier[13]. Then, we determine the existence of convergence given that:

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

and

$$lnECOE^{MF}_{t,k} = \mu^{MF} + lnECOE^{MF}_{t-1,k} + \eta_{t,k} \tag{20}$$

Combining both equations we have:

$$ln\left(\frac{ECOE_{t,k}}{ECOE^{MF}_{t,k}}\right) = \mu + (1-\rho)ln\left(\frac{ECOE_{t-1,k}}{ECO^{MF}_{t-1,k}}\right) + \psi_{t,k} \tag{21}$$

where $\mu = (\mu^k - \mu^{MF})$. The existence of a unit root in Eq.(22) would suggest no catching up in terms of eco-efficiency and, hence, divergence towards the best technology.

2.4 Decomposition of carbon emissions

The analysis of the decomposition by defining a governing function that can relate the aggregate and the decomposed factors which are predefined. As a quite flexible, parsimonious and easy to use, the Kaya identity (Kaya, 1990) decomposition analysis for the CO_2 emissions has been adopted implying that:

$$C = \sum_i C_i = \sum_i (\frac{E_i}{E})\cdot(\frac{C_i}{E_i})\cdot(\frac{E}{Y})\cdot(\frac{Y}{P})\cdot P = \sum_i EC_i \cdot FM_i \cdot EI \cdot PC \cdot P \tag{22}$$

where E is the total energy consumption (TEC) of all fuel types, E_i the TEC of fuel type i, C the total CO_2 emissions from all fuel types, C_i the CO_2 emissions form fuel type i, Y the total output and P population.

Therefore, as Table 1 displays, CO_2 emissions are decomposed into the EC_i that represents the emission coefficient for fuel type i, FM_i the share of fuel consumed, or in other words the fuel mix, EI the energy intensity, PC the income per capita and P the population. In this sense,

[13] We have to note that for the computation of the catch-up index we average across industries for each country k at time t.

i denotes each type the fuel type that is used (solid, petroleum, gas)[14] In order to make the per capita CO_2 emissions (CPC) we divide each term with P. Therefore,

$$CPC = \frac{C}{P} = \sum_i EC_i \cdot FM_i \cdot EI \cdot PC \tag{23}$$

An observed change from time t-1 to time t in the aggregate CPC (ΔCPC) will be described as:

$$\Delta CPC = \Delta EC + \Delta FM + \Delta EI + \Delta PC \tag{24}$$

where Δ is the impact associated with the change of each factor. A variety of techniques have been developed with reference to the IDA with the Log Mean Divisia Index (LMDI) being the most popular (Ang et al., 2003; Ang, 2004, 2015).[15]

3 Data and Variables

As it has been already mentioned, the economic and the environmental performance are jointly utilized to formulate our eco-efficiency index. In order to determine the most appropriate set of variables, we take into account the existing literature. This study considers fourteen industries[16] of the manufacturing sector, from twenty seven European countries[17] while the observation period covers seventeen years, from 1995 to 2011. Thereby, our dataset is comprised of 6426 observations in a panel dimension and refers to an aggregate level for each industry.

The proposed approach analyzed in this study to assess eco-efficiency is based on the measure of Kuosmanen and Kortelainen by employing a single-desirable output, multi-undesirable output concept. Hence, the numerator that focuses on the economic performance is assessed by the Gross Value Added (GVA) of each industry expressed in millions Euro while it has been deflated in constant 1995 prices.

Concerning the ecological performance and the most harmful pollutants that exert pressures on the environment, we include the following ones: Carbon dioxide (CO_2), Methane (CH4), Nitrous oxide

[14]The fuels that were utilized in this study were limited as data for the other ones such as renewable were not available.

[15]See Appendix for more information.

[16]Data on 2-digit manufacturing industries have been employed according to the International Standard Industrial Classification (ISIC).

[17]Table 2 provides a comprehensive representation of the fourteen industries and twenty seven countries participating in our sample.

(N2O), Nitrogen oxides (NOx), Sulphur oxides (SOx), Carbon monoxide (CO), Non-methane volatile organic compounds (NMVOC) and Ammonia (NH3). The units of measurement are kilo-tonnes per year for CO_2 emissions[18] and tonnes per year for the rest of the pollutants. Data for Carbon dioxide were collected from Enerdata Odyssey[19] while data for the rest of the variables through the World Input Output Database (WIOD).[20]

Table 3 and Figure 2 present some basic descriptive statistics and the relationship between the employed variables. Moreover, Table 4 and Figure 3 display the mean growth rates across industries and the time evolution respectively. Overall, it is observed that all undesirable outputs present reductions over the 1995 to 2011 period while the economic output exhibits a positive change in total. More specifically, the highest reduction in terms of CO_2 belongs to the industry of BMF while the same industry possesses the highest change in CO. On the other hand, the industry of CHM display the greatest decreases, on average, in N_2O, NMVOC and NH_3 in absolute terms while the industry of CRP in terms of CH_4 and SO_x. Lastly, the ONM owns the largest shift in the quantity of NO_x for our sample period. However, it is worth mentioning that, on average, the pollutant of SO_x demonstrates the greatest decline for the industries of the manufacturing sector over the period 1995-2011.

4 Results and Discussion

Based on the theoretical background outlined in Section 3, we examine the European industrial relative level of environmental pressures in relation to the economic activity volume. In this section we present the empirical findings utilizing a three-part analysis. Firstly, we obtain and compare eco-efficiency results taking into account the existence of technological heterogeneity. Secondly, we assess the magnitude of convergence as a result of technological spillovers employing a catch-up index. Thirdly, we incorporate the Kaya Identity analysis to assess the decomposition changes of CO_2 emissions.

4.1 Eco-efficiency under distinct directional vectors

The utilization of various directional vectors gives us the opportunity to evaluate eco-efficiency under different points of view representing a wide range of objectives and purposes for the relationship of economic and

[18] 21We are fully aware that CO_2 emissions are presented in line with UNFCCC accounting rules and IPCC reporting guidelines, which do not often readily capture changes in fuel and the sectoral mix of energy use both upstream (Kounetas, 2018).

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

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

ecological performance.

Therefore, for each one of the industries with respect to a specific country at a time, we have computed the eco-efficiency indicators by solving the respective linear programs for each year during the 1995-2011 period. We begin our analysis with a representation of the main descriptive statistics,[21] as shown in Table 5. At first glance, our results point out to a high level of eco-efficiency with respect to the frontier and a low level to the metafrontier. More specifically, the scores for the indicators $ECOE^1_{MF}$, $ECOE^3_{MF}$, $ECOE^4_{MF}$ and $ECOE^2_{CO_2|MF}$ own considerably low levels of eco-efficiency. On the other hand, under the frontier approach, eco-efficiency presents, on average, scores above 60%. This finding strengthens the concept of technological heterogeneity among industries and its existence originates huge variations on the estimated scores. As industries in different countries have to deal with distinct production opportunities and employ separate feasible input-output combinations, it is evident that a divergence behavior will occur. However, comparing the performance of industries under a common unrestricted technology set augments the role of technological spillovers that may appear among them and the broadness of the production environment. Hence, the diffusion of technological knowledge could influence either positive or negative the eco-efficiency scores of the individual industries.

Tables 6 and 7 present thoroughly the eco-efficiency estimations under the distinct scenarios. Our estimations point out that, on average, the highest values of eco-efficiency were attained under the specific-pressures $ECO^3_{CH_4}$ and the $ECO^3_{NO_x}$ scenarios while the lowest under the ECO^4 with respect to the metafrontier. This points out that industries could become more eco-efficient when they concentrate on the reduction of specific undesirable outputs rather than on the simultaneous increase of their value added and the decrease of their pollutants at the same rate. For example, for the case of ELO, the industry could reduce by 57.7% its environmental pressures and increase at the same time its value added by the same proportion. Indicatively, the higher values of eco-efficiency belong to industries of LEF, ONM, ELO, BMF and CRP. However, the industry of ONM and CRP in conjunction with WCP, CHM and MAN possess at the same time the lowest values in some cases. The processes of chemical reactions and fossil fuel combustion that is used to provide intensive heat in order to convert raw materials into industrial products result at an increasing number of manufacturing CO_2 emissions. In-

[21] The $ECOE^2_{F,MF}$ indicator is referred to the specific pressure reduction each time while the remaining pressures and value added are maintained at the same observed level.

dustries that include production of chemicals and petrochemicals, iron and steel, cement, pulp and paper, and aluminum, account for most of the sector's energy and emission consumption in many countries (IPCC, 2010)[22]. Hence, European countries try to mitigate their industrial emissions giving emphasis on the above-mentioned industries by developing policies for the EU Emissions Trading SYSTEM (ETS) or becoming as eco-efficient as possible. As sustainable development and the well-being of Europe have a substantial impact on the environment, the Industrial Emissions Directive (IED) aims to protect the environment and the human health by reducing all harmful industrial emissions across the EU through strict policies and fines[23].Innovation through new technologies, investments on planning, technical experience, management and administration and diffusion of knowledge could make an industry transpose from eco-inefficient to an eco-efficient one.

On the other hand, Tables 8 and 9 display the main results of eco-efficiency highlighting the importance of heterogeneity that exists among European countries. The EU-15 has a common emission target that needs to be jointly achieved. However, the Kyoto protocol agreement sets distinct emission limitation and reduction targets for each member country.[24] As such,the proportion of eco-efficient countries is relatively high in pressure specific indicators whilst in the rest of the scenarios they own low levels of eco-efficiency. As Schmalensee et al. (1998) indicated, high-income countries, such as DEU, FRA, SWE, NLD and the GBR have started to reduce per capita GHG emissions, while others in the same area, like ESP, POR and ITA have increased emissions. Additionally, some Eastern European countries, such as the CZE, HUN, POL and SVK, have reduced GHG emissions even more than the richest EU countries. Comparing with our results, it is evident that countries such as ESP, DEU, SWE, POL, ITA, MLT and DNK are the most eco-efficient, on average, under the metafrontier framework. This strengthens the fact that technological diffusion and spillovers tend to assist them faster for their adjustment on environmental and economic norms. Conversely, CZE, LUX, GRC, LVA, EST, BGR, ROU and CYP hold the lowest values, on average in the particular indicators. Countries that are placed in the lowest average rankings of eco-efficiency, possess scores under 40% indicating a tendency for European countries that own a "smaller" de-

[22] `https://www.ipcc.ch/site/assets/uploads/2018/02/ipcc_wg3_ar5_chapter10.pdf`

[23] `https://ec.europa.eu/environment/industry/stationary/ied/legislation.htm`

[24] Directives 1994/63/EC, 2009/126/EC, 91/689/EEC, 96/61/EC, 2010/75/EU, 2015/2193/EU

gree of development and economy to fall behind the largest ones. It is obvious that economies with "smaller-scale" do not give so much attention to the climate policies or invest on reducing their emissions as they are not capable of learning from the big ones.

4.2 Does European industries catch-up in terms of eco-efficiency?

The introduction of a metafrontier and the associated incoming spillovers (Tsekouras et al., 2017) allow for the estimation of possible performance differentials. We try to assess the speed at which each industry, operating at its own technology, catch-up the European metatechnology. Many environmental studies have implemented the convergence analysis in order to examine whether there is any space for common emission policies for European industries and countries (e.g. Camarero et al., 2013; Gómez-Calvet et al., 2016; Kounetas, 2018). Even though there are several approaches in the literature for the measurement of convergence (e.g. Carree and Klomp, 1997; Quah, 1993a; Durlauf and Quah., 1999), in this study we have decided to implement a catch-up ratio of eco-efficiency in order to evaluate the speed at which industries catch-up to the European best technology. In this direction, investments in technological innovation (Sagar and van der Zwaan, 2006), absorptive capacity (Cohen and Levinthal, 1990), R&D efforts and learning by doing knowledge diffusion (Carraro et al., 2003) could potentially minimize the gap between the common technology frontier and the national one. Moreover, some industries are capable of exploiting new technologies (e.g. biomass and photovoltaics) and employing alternative raw material resources or fuels to become more efficient, in terms of the environment, and catch-up more rapidly than others (Treffers et al., 2005).

Table 10 and Figure 4 present the changes of catch-up index over different time periods. It is obvious that when we evaluate the role of environmental pressures or the economic performance separately, the majority of the countries show a decline in the catch-up index from 1995 to 2011. The only exceptions are the cases of BGR, CZE, POL and SVK. However, if we examine the change between the two separate periods, 1995-2001 and 2002-2007, it is observed that more countries increased their catch-up index[25]. The results indicate a progressive increase in the speed of convergence in terms of eco-efficiency after the introduction of stricter environmental and economic policies. On the other hand, examining the environmental pressures individually and their catch-up

[25] Time periods were selected based on the Kyoto Protocol where its ratification on behalf of the EU occurred on 31 May 2002 and the beginning of the economic crisis in Europe in 2008

evolution through the years, they display a downward trend on average with the only exception of NH_3 that demonstrates some ups and downs in particular years. The increase of the catch up index in the 1995-2001 and 2002-2007 period signifies that industries in the particular time periods were able to react successfully to the pressures from the European regulations and policies concerning both economic and environmental perspectives at a national level. However, because of the enormous wave of economic crisis that occurred in the 2008-2011 period, the speed of catch up begun to decrease. As Camarero et al. (2013) suggested, the eco-efficiency presents a strong relationship with economic development even though a generalized hypothesis that richer countries own a more eco-efficient attitude cannot be validated.

Table 11 reports the results concerning the tests for convergence. We perform three separate tests (the Levin et al. (2002) (LLC) and the Fisher-type test following Choi (2001)) to explore the presence of a unit root. These tests own the same null hypothesis of non-stationarity. However, their alternatives are contrary. The Fisher type allows for different autoregressive coefficients, while the Levin-Lin-Chu test requires the same one. Finally, the null hypothesis of Hadri (2000) (HLM) test is based on (trend) stationarity for all series against the alternative that some of the panels have a unit root.

When referring to the LLC test, our results suggest that the null hypothesis of non-stationarity is strongly rejected in every scenario indicating a process of convergence towards the metafrontier. On the contrary, the Fisher-type test implies different outcomes fo the null hypothesis. As this test has the advantage of including various p-values obtained from different unit root tests performed on each panel[26], it holds a higher level of significance than the LLC test. Overall, the null hypothesis is rejected for the cases of CU^1, CU^{CO_2}, CU^{CH_4}, CU^{NO_X}, CU^{SO_X}, CU^{CO} and CU^{NH_3}. This points out that when industries are concentrated on reducing their environmental pressures collectively or individually while maintaining the same level of the economic output, a direction of convergence could occur. Finally, with the utilization of the HLM test we strongly reject the null hypothesis and we conclude that convergence takes place but not across all countries. Hence, convergence exists but it is not allocated for all industries of the different European countries and all scenarios.

[26]The test uses four methods, two are based on an inverse x^2 where the second one is valid only if N goes to infinity (less relevant for our case), one of an inverse normal and one of an inverse logit.

4.3 Decomposition of European carbon emissions

The findings of the previous section indicate the idiosyncratic role of CO_2 emissions regarding eco-efficiency estimations. As Figure 4 displays from the above-mentioned convergence analysis, the pollutant that owns the lowest level of catching-up is that of CO_2 emissions. In this direction, the investigation of CO_2 emissions determinants using the Kaya identity should shed light to the particular query.

Table 12 and Figure 6 present the accumulated effects of CO_2 emissions by period as well as over the entire time period. At this point, we have to notice that the decomposition was conducted in rolling base years' form because we could aggregate the results in sub-periods[27] (Granel, 2003; O'Mahony, 2013) while it involves cumulative errors. The main positive impact is the change in average output per capita (PC) which is followed by the emission coefficient effect (EC) even though it has a decreasing trend. Moreover,the share of fuel consumed (FM) and the energy intensity (EI) effect have a descending path over the 1990 - 2011 period. However, the effect of each factor alters in every sub-period. For the cases of EC, FM and EI, the change presents an increasing trend as the time periods pass by whilst the change of PC owns a reducing trend.

The economic growth that exists in Europe after the economic crisis has a significant reflect on the developing trends of CO_2 emissions. However, our analysis illustrates differences across the sub-periods. The 1995 - 2001 and the 2002 - 2007 periods, which could be characterized as a pre-environmental and pre-economic crisis' periods, present similar changes on EC and EI while the total change of emissions remains more or less at the same level. On the other hand, emissions fall during the 2008-2011 period where the global financial crisis occurred. The affluence effect includes the term of decoupling and eco-efficiency which examines the relationship between undesirable effects on the environment and economic growth. Rapid economic growth acts as a scale effect in the increment of energy consumption and carbon emissions. In the future, the global aim is the stall in emissions amid an economic expansion (i.e. Deutch, 2017).

The EC and the FM effects measure the carbon content per fossil fuel and the substitution of fuels respectively because of a modification in the convenient forms of energy. It can be seen that both coefficient effect decreased from 1995 to 2011. Large - scale transformations in fossil fuels (e.g. changes on fuel quality, decrease of benzene and hydrocar-

[27]The sub-periods were selected in this way so as to reflect main economic and environmental events that occurred in Europe.

bons in fuel gazoline) along with the technological development and new ways of reducing costs of extracting oil led to a reduction on the carbon content (i.e. Bruckner et al., 2014). These results are consistent with the Kyoto policies and directives that the EU has published for countries to mitigate the emissions in conjunction with the economic growth.

Finally, the EI factor presents the most significant negative effect as in many decomposition analysis studies (Schleich et al., 2001; Ma and Stern, 2008; O'Mahony, 2013). Energy intensity is described as energy per output and comprises the technological evolution. Socio-economic development, sectoral shifts and technical effects, lifestyle habits and climate changes can affect alterations on energy intensity (ENEA, 2015).

As far as the decomposition of each industry is concerned, it is obvious that big differences across industries and time periods exist. For the case of the change of the emission coefficient for fuel (EC), the industries of CRP and CHM possess the lowest levels in all periods except for the period of 2008-2011 where CRP presents the highest value. This signifies that the particular industry, which owns one of the highest percentages in the production of undesirable outputs, altered its carbon content because of the change in the fossil fuel consumption at 2008-2011 period in order to comply with the Kyoto norms and reduce its CO_2 emissions. The effect of substitution of fossil fuel (FM) displays a similar path for all industries, remaining at the same level, apart from the case of BMF with reference to the entire period. Differences in the structure, in the efficiency of the economy and the energy system, socioeconomic lifestyle and technological choices might affect the impact of energy intensity in the aggregate change of emissions per capita. Comparing the different time periods chosen in our sample, we can notice that BMF, CRP and CHM industries have the lowest values in all cases. On the other hand, the effect of affluence is the most dominant positive driver where the industries of BMF, CRP, CHM and ONM own the higest value in the specific factor. In conclusion, the per capita emission change was positive for the majority of the industries, with the cases of BMF, CRP and CHM being the only exceptions.

5 Conclusions

Europe has experimented a huge increase of pollutants since the 90's because of the simultaneous rapid economic growth that occurred. EU environmental Directives have proposed various ways to the EU countries in order to mitigate their emissions while focusing on their economic development and sustainability. The problem of the pollutants' and energy consumption's reduction has been regarded as a fundamental objective for European policies in the last few decades. In this sense, the objective of eco-efficiency which comprises both ecological and economic issues, is receiving increasing importance as it can be employed as an instrument to promote decisions about sustainability.

This paper contributes to the previous literature in various ways. Firstly, by utilizing European industries from the manufacturing sector as our entities, we present how distinct directional distance functions lead to different aspects of eco-efficiency and the implementation of the same environmental norms and policies in each case could become catastrophic. The assumption of different scenarios provides us an extensive number of indicators that could benefit policymakers, industries and countries to set alternative goals regarding each time their economic or ecological priorities. The methodological framework that is followed allows us to evaluate industries under a national and a European frontier and identify their magnitude with respect to both situations. Secondly, since the establishment of a common "market" of guidelines in both the economy and environment, we aim to disclose the extend at which industrial eco-efficiency converges or whether new compliances are necessary for enhancing the sustainability standards. Accordingly, a catch-up index is adopted as an indicator of the differences in the speed of convergence towards the metafrontier between industrial eco-efficiency in order to evaluate whether common emission policies for European industries and countries could be a successful philosophy. Thirdly, as CO_2 emissions per capita hold the largest percentage of pollutants in the environment and the fact that they increased in European Union the last decade, the identification of the driving forces that affect their change is important in the policy formulation.

Our findings reveal that eco-efficiency levels diverge irrespectively the scenario and regime employed. High levels of eco-efficiency exist when industries compete into their national frontier whilst the opposite occurs when a common European technology set is utilized as technological spillovers and the broadness of the production environment cause differences among them. Moreover, when industries focus either on reducing their pollutants as a whole or increasing their economic performance rather than on concentrating on the reduction of a specific pollutant, they become more eco-inefficient. The fact that energy intensive European industries are characterized as eco-inefficient strengthens the necessity for adjustments between the ecological and economic prosperity as 60-80% of industrial emissions are originated from these particular industries. In this way, zero-emission solutions will result in substantially investment and operational costs without any increase of value added for the side of the consumer. On the other hand, our convergence analysis points out that a progressive increase in the speed of convergence in terms of eco-efficiency took place after the introduction of stricter environmental and economic policies as industries converge within European Union towards the best available technology. Lastly, the decomposition analysis of emissions per capita utilizing the Kaya identity indicates that changes in carbon content per unit of fossil fuel, the fuel switching in the production process and energy intensity own an increasing effect through time whilst the change in average output per capita a descending trend. Technological innovation, the introduction of cleaner fuels in the production, fuel quality and more environmental concentrated technologies along with differences on economic growth and socio-political development and sectoral shifts consist some of the reasons for the particular results. Overall, the change in emissions per capita for the 1995 to 2011 period has been decreased within the European borders.

Finally, we would like to highlight that this paper could become a reliable source of information for policymakers in order to propose more efficient policies in governments and countries focusing on the industries of the manufacturing sector of the economy. As the latter one composes a novelty in literature, industries could be the key for the future in order to mitigate global emissions and constrain climate change as much as possible. Exploring further extensions of the directional distance functions with the inclusion of slacks or other non-radial slack based models, as proposed by Färe and Grosskopf (2010) in their parer, could provide more insights on the measure of eco-efficiency. Moreover, a deeper quantitative analysis and insight on the factors that provoke the changes in pollutants or introducing more specific determinants of sustainability issues might also be beneficial elements for further research. Also, because of the limitations on environmental performance, the enlargement of the dataset by combining more years and countries could could be considered as a following study.

Acknowledgments

The authors would like to express their sincere gratitude to Professors Kostas Tsekouras and Oreste Napolitano for their insightful comments and suggestions that helped us to substantially improve this work.Finally, the authors are grateful to the participants of the 16th European Workshop on Efficiency and Productivity Analysis, held in London (Loughborough University) on 10-13 June 2019 and the 30th European Conference on Operational Research (EURO 2019) held in Dublin, Ireland on 23–26 June 2019, for their useful comments and suggestions on earlier versions of this paper.

Funding

This research was supported by Grant (56650000) from the Research Committee of the University of Patras via "C. CARATHEODORI" program.

Appendix A

Table 1: Factors of the Decomposition analysis

Factor	Description
EC	Carbon content per unit of fossil fuel
FM	Substitution of fossil fuel types
EI	Energy requirement per unit GVA
PC	Average GVA per capita
CPC	Total carbon emissions per capita aggregating the factors

Table 2: 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 3: Summary Statistics of economic and environmental variables

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 4: Mean values of growth rates of variables across industries

Industry	GVA	CO_2	CH_4	N_2O	NO_x	SO_x	CO	NMVOC	NH_3
BMF	111.511	-141.924	-165.555	-1.188	-366.034	-1188.671	-3574.178	-233.541	-2.233
CHM	163.136	-100.896	-1.152	-586.333	-260.250	-1257.940	-316.784	-1113.229	-97.102
CRP	6.502	0.353	-444.141	0.149	-194.731	-1919.514	-182.306	-362.414	0.209
ELO	429.7734	-11.385	-1.742	-0.172	-68.749	-107.955	-107.458	-64.375	-0.948
FBT	27.204	-22.958	20.808	0.450	-208.124	-645.499	-235.861	-14.781	-10.554
LEF	-12.105	-3.634	-3.148	-0.161	-15.293	-26.516	-27.565	-93.700	-0.094
MAC	118.662	-16.015	-1.475	-0.178	-65.379	-88.352	-182.676	-96.382	-1.136
MAN	1.228	-2.123	2.208	0.032	-58.506	-51.486	-398.635	-227.224	0.001
ONM	5.498	1.346	20.781	1.965	-712.075	-768.108	-88.933	-20.838	5.775
PPP	16.546	-17.177	9.158	0.397	-54.102	-495.529	-121.997	-232.734	1.429
RUP	61.345	-10.269	-0.774	-0.305	-34.476	-92.701	-90.173	-55.420	-0.590
TXT	-40.149	-36.074	-5.773	-0.412	-95.635	-282.671	-130.609	-51.886	-0.573
TRE	141.736	-13.648	2.160	-0.429	-44.336	-165.788	-81.389	-394.783	-0.877
WCP	6.724	-0.320	-6.614	-0.165	-6.604	-101.713	-288.756	-144.569	-0.330
TOTAL	74.115	-26.766	-41.090	-41.882	-156.021	-513.746	-416.237	-221.848	-7.644

Table 5: Eco-efficiency indicators

Eco-efficiency	Mean	St. Dev.	Min	Max
$ECOE^1_F$	0.711	0.345	0.003	1
$ECOE^1_{MF}$	0.229	0.300	0.001	1
$ECOE^2_{CO2\|F}$	0.504	0.491	0.001	1
$ECOE^2_{CO2\|MF}$	0.341	0.307	0.001	1
$ECOE^2_{CH4\|F}$	0.876	0.231	0.001	1
$ECOE^2_{CH4\|MF}$	0.731	0.334	0.001	1
$ECOE^2_{N2O\|F}$	0.889	0.199	0.001	1
$ECOE^2_{N2O\|MF}$	0.579	0.441	0.001	1
$ECOE^2_{NOX\|F}$	0.877	0.213	0.001	1
$ECOE^2_{NOX\|MF}$	0.633	0.445	0.001	1
$ECOE^2_{SOX\|F}$	0.854	0.276	0.001	1
$ECOE^2_{SOX\|MF}$	0.619	0.444	0.001	1
$ECOE^2_{CO\|F}$	0.849	0.246	0.001	1
$ECOE^2_{CO\|MF}$	0.533	0.448	0.001	1
$ECOE^2_{NMVOC\|F}$	0.789	0.317	0.001	1
$ECOE^2_{NMVOC\|MF}$	0.428	0.460	0.001	1
$ECOE^2_{NH3\|F}$	0.815	0.299	0.001	1
$ECOE^2_{NH3\|MF}$	0.614	0.409	0.001	1
$ECOE^3_F$	0.744	0.320	0.004	1
$ECOE^3_{MF}$	0.229	0.299	0.001	1
$ECOE^4_F$	0.648	0.328	0.001	1
$ECOE^4_{MF}$	0.188	0.245	0.001	1

Table 6: Eco-efficiency scores of $ECOE^1$, $ECOE^3$ and $ECOE^4$ under both Frontier and Metafrontier framework across industries

Industry	$ECOE^1_F$	$ECOE^1_{MF}$	$ECOE^3_F$	$ECOE^3_{MF}$	$ECOE^4_F$	$ECOE^4_{MF}$
BMF	0.555	0.115	0.717	0.184	0.456	0.103
CHM	0.567	0.154	0.743	0.195	0.536	0.089
CRP	0.565	0.199	0.526	0.170	0.433	0.059
ELO	0.873	0.445	0.892	0.439	0.875	0.423
FBT	0.783	0.150	0.853	0.206	0.640	0.131
LEF	1.000	0.471	0.997	0.371	0.739	0.238
MAC	0.747	0.267	0.760	0.268	0.734	0.263
MAN	0.707	0.182	0.682	0.165	0.677	0.186
ONM	0.505	0.090	0.556	0.093	0.500	0.070
PPP	0.639	0.164	0.752	0.200	0.657	0.158
RUP	0.714	0.256	0.686	0.245	0.695	0.260
TXT	0.873	0.258	0.851	0.237	0.798	0.253
TRE	0.784	0.287	0.775	0.278	0.773	0.265
WCP	0.647	0.172	0.629	0.151	0.562	0.134
TOT	0.711	0.229	0.744	0.229	0.648	0.188

Table 7: Eco-efficiency scores of environmental pressures under the Metafrontier framework across industries

Industry	CO_2	CH_4	N_2O	NO_x	SO_x	CO	NMVOC	NH_3
BMF	0.068	0.819	0.755	0.776	0.663	0.569	0.550	0.790
CHM	0.150	0.722	0.429	0.715	0.633	0.616	0.483	0.476
CRP	0.175	0.756	0.684	0.703	0.460	0.688	0.397	0.733
ELO	0.285	0.776	0.655	0.664	0.697	0.570	0.481	0.630
FBT	0.175	0.772	0.622	0.685	0.656	0.554	0.455	0.694
LEF	0.293	0.665	0.571	0.557	0.634	0.512	0.358	0.533
MAC	0.145	0.718	0.538	0.579	0.611	0.479	0.429	0.607
MAN	0.088	0.679	0.448	0.572	0.677	0.461	0.318	0.552
ONM	0.065	0.886	0.737	0.707	0.715	0.637	0.583	0.638
PPP	0.104	0.720	0.572	0.600	0.539	0.491	0.418	0.631
RUP	0.241	0.691	0.547	0.593	0.607	0.474	0.337	0.589
TXT	0.127	0.693	0.551	0.609	0.581	0.494	0.440	0.591
TRE	0.148	0.712	0.551	0.628	0.649	0.495	0.409	0.520
WCP	0.104	0.626	0.441	0.470	0.546	0.426	0.342	0.612
TOT	0.341	0.731	0.579	0.633	0.619	0.533	0.428	0.614

Table 8: Eco-efficiency scores of $ECOE^1$, $ECOE^3$ and $ECOE^4$ under both Frontier and Metafrontier framework across countries

Country	$ECOE_F^1$	$ECOE_{MF}^1$	$ECOE_F^3$	$ECOE_{MF}^3$	$ECOE_F^4$	$ECOE_{MF}^4$
AUT	0.714	0.237	0.793	0.251	0.624	0.259
BEL	0.791	0.262	0.833	0.289	0.588	0.292
BGR	0.661	0.104	0.689	0.024	0.306	0.006
CYP	0.628	0.195	0.675	0.106	0.464	0.075
CZE	0.737	0.017	0.731	0.038	0.521	0.023
DNK	0.590	0.144	0.660	0.145	0.796	0.119
EST	0.573	0.229	0.637	0.100	0.330	0.086
FIN	0.536	0.269	0.524	0.264	0.786	0.255
FRA	0.681	0.324	0.779	0.454	0.696	0.295
DEU	0.741	0.426	0.754	0.573	0.731	0.262
GRC	0.582	0.079	0.653	0.085	0.485	0.101
HUN	0.462	0.234	0.498	0.220	0.421	0.215
IRL	0.663	0.156	0.597	0.159	0.573	0.167
ITA	0.897	0.280	0.912	0.403	0.734	0.305
LVA	0.877	0.247	0.914	0.156	0.405	0.025
LTU	0.741	0.267	0.823	0.253	0.377	0.287
LUX	0.933	0.227	0.907	0.132	0.784	0.175
MLT	0.809	0.653	0.746	0.498	0.567	0.319
NLD	0.891	0.238	0.891	0.278	0.702	0.281
POL	0.798	0.056	0.844	0.081	0.809	0.081
PRT	0.641	0.143	0.768	0.137	0.490	0.161
ROU	0.823	0.065	0.823	0.020	0.338	0.026
SVK	0.850	0.199	0.889	0.165	0.330	0.181
SVN	0.802	0.337	0.825	0.298	0.699	0.282
ESP	0.771	0.462	0.835	0.533	0.624	0.466
SWE	0.375	0.218	0.371	0.239	0.737	0.219
GBR	0.639	0.122	0.723	0.274	0.659	0.114
TOT	0.711	0.229	0.744	0.229	0.648	0.188

Table 9: Eco-efficiency scores of environmental pressures under the Metafrontier framework across countries

Country	CO_2	CH_4	N_2O	NO_x	SO_x	CO	NMVOC	NH_3
AUT	0.055	0.717	0.575	0.770	0.851	0.501	0.387	0.758
BEL	0.081	0.872	0.671	0.849	0.667	0.626	0.415	0.518
BGR	0.023	0.458	0.363	0.478	0.440	0.401	0.122	0.382
CYP	0.095	0.810	0.508	0.369	0.797	0.370	0.277	0.705
CZE	0.005	0.854	0.505	0.480	0.564	0.534	0.328	0.688
DNK	0.062	0.808	0.447	0.506	0.767	0.491	0.440	0.801
EST	0.075	0.656	0.339	0.380	0.251	0.169	0.147	0.552
FIN	0.645	0.753	0.647	0.612	0.486	0.597	0.607	0.709
FRA	0.160	0.886	0.814	0.919	0.845	0.759	0.716	0.575
DEU	0.286	0.847	0.815	0.855	0.861	0.685	0.733	0.778
GRC	0.016	0.612	0.319	0.501	0.220	0.425	0.318	0.741
HUN	0.107	0.734	0.433	0.832	0.577	0.507	0.520	0.657
IRL	0.056	0.800	0.517	0.550	0.692	0.512	0.370	0.690
ITA	0.017	0.855	0.844	0.936	0.862	0.830	0.676	0.477
LVA	0.173	0.650	0.432	0.290	0.621	0.327	0.288	0.669
LTU	0.094	0.755	0.526	0.518	0.579	0.492	0.287	0.456
LUX	0.125	0.339	0.336	0.322	0.481	0.227	0.244	0.544
MLT	0.653	0.685	0.634	0.641	0.684	0.675	0.640	0.675
NLD	0.051	0.845	0.696	0.872	0.692	0.570	0.500	0.606
POL	0.101	0.886	0.640	0.648	0.473	0.638	0.443	0.704
PRT	0.027	0.616	0.431	0.508	0.378	0.520	0.323	0.584
ROU	0.018	0.485	0.654	0.375	0.398	0.265	0.168	0.284
SVK	0.043	0.644	0.687	0.787	0.693	0.626	0.499	0.664
SVN	0.191	0.735	0.621	0.565	0.508	0.574	0.422	0.517
ESP	0.194	0.764	0.814	0.846	0.801	0.789	0.459	0.407
SWE	0.593	0.808	0.587	0.797	0.769	0.585	0.554	0.668
GBR	0.055	0.865	0.769	0.876	0.763	0.704	0.683	0.770
TOT	0.341	0.731	0.579	0.633	0.619	0.533	0.428	0.614

Table 10: Catch-up indexes with respect to the first and third scenario

Country	1995-2001(a)	2002-2007(b)	(a) to (b)	2008-2011(c)	(a) to (c)	1995-2001(a)	2002-2007(b)	(a) to (b)	2008-2011(c)	(a) to (c)
AUT	0.577	0.162	↓	0.156	↓	0.560	0.146	↓	0.143	↓
BEL	0.352	0.342	↓	0.276	↓	0.394	0.340	↓	0.276	↓
BGR	0.013	0.365	↑	0.036	↑	0.008	0.077	↑	0.001	↓
CYP	0.383	0.304	↓	0.211	↓	0.238	0.134	↓	0.065	↓
CZE	0.029	0.017	↓	0.020	↓	0.054	0.044	↓	0.058	↑
DNK	0.321	0.165	↓	0.171	↓	0.307	0.147	↓	0.139	↓
EST	0.570	0.372	↓	0.157	↓	0.306	0.090	↓	0.015	↓
FIN	0.586	0.423	↓	0.450	↓	0.615	0.406	↓	0.422	↓
FRA	0.737	0.331	↓	0.148	↓	0.754	0.499	↓	0.370	↓
DEU	0.769	0.426	↓	0.378	↓	0.852	0.687	↓	0.662	↓
GRC	0.223	0.110	↓	0.055	↓	0.247	0.084	↓	0.047	↓
HUN	0.585	0.470	↓	0.416	↓	0.529	0.399	↓	0.326	↓
IRL	0.400	0.141	↓	0.068	↓	0.441	0.148	↓	0.098	↓
ITS	0.296	0.350	↑	0.288	↓	0.466	0.469	↑	0.358	↓
LVA	0.282	0.295	↑	0.263	↓	0.186	0.164	↓	0.156	↓
LTU	0.353	0.434	↑	0.242	↓	0.353	0.347	↓	0.169	↓
LUX	0.356	0.172	↓	0.160	↓	0.275	0.060	↓	0.053	↓
MLT	0.921	0.820	↓	0.572	↓	0.834	0.620	↓	0.435	↓
NLD	0.445	0.171	↓	0.120	↓	0.489	0.218	↓	0.143	↓
POL	0.070	0.066	↓	0.076	↑	0.110	0.082	↓	0.092	↓
PRT	0.324	0.152	↓	0.143	↓	0.301	0.107	↓	0.075	↓
ROU	0.067	0.109	↑	0.061	↓	0.032	0.028	↓	0.007	↓
SVK	0.209	0.275	↑	0.222	↑	0.188	0.216	↑	0.129	↓
SVN	0.583	0.405	↓	0.172	↓	0.535	0.295	↓	0.136	↓
ESP	0.752	0.558	↓	0.403	↓	0.798	0.593	↓	0.425	↓
SWE	0.708	0.486	↓	0.486	↓	0.671	0.623	↓	0.612	↓
GBR	0.324	0.097	↓	0.086	↓	0.487	0.323	↓	0.266	↓

Table 11: Panel unit root tests for convergence

	LLC	Fisher				HLM
Indicator	Adj t*	Inv. X^2	Inv. Norm Z	Inv. Logit L*	Mod. Inv. X^2	Z
CU^1	-9.176***	919.158***	-3.584***	-3.566***	4.196***	89.711***
CU^3	-14.387***	772.596	-1.919*	-1.591	0.426	109.025***
CU^4	-5.904***	617.812	5.369	5.368	-3.553	120.246***
CU^{CO_2}	-16.586***	1180.959***	-8.126***	-8.548***	10.928***	70.712***
CU^{CH_4}	-6.219***	1049.961***	-2.541**	-1.593	7.559***	52.037***
CU^{N_2O}	-12.648***	585.408	0.698	0.446	-4.38	75.376***
CU^{NO_X}	-8.548***	1085.972***	-5.318***	-6.801***	8.486***	90.508***
CU^{SO_X}	-7.742***	2055.266***	-20.744***	-25.851***	33.413***	18.691***
CU^{CO}	-6.892***	983.159***	-8.706***	-8.236***	5.841***	67.109***
CU^{NMVOC}	-15.456***	742.673	-3.835	-3.634	-0.342*	91.851***
CU^{NH_3}	-28.326***	2383.627***	-27.487***	-31.281***	41.858***	37.028***

Note[1]: LLC: Levin- Lin-Chu test, Fisher: Fisher-type test, HLM: Hadri LM

Note[2]: ***, ** and * denote that variables are statistically significant at the 1%, 5%, 10% levels respectively

Note[3]: In all cases, we allowed for country fixed effects and an exclusion of time trend when possible (Baltagi, 2008).

Table 12: Decomposition of European industrial CO_2 from 1990 to 2011

Period	ΔEC	ΔFM	ΔEI	ΔPC	ΔCPC
1995-2001	0.9992	0.9992	0.9984	1.0010	0.9989
2002-2007	0.9993	0.9999	0.9986	1.0000	0.9988
2008-2011	1.0005	1.0003	0.9988	0.9980	0.9850
1995-2011	0.9993	0.9991	0.9961	1.0010	0.9965

Appendix B

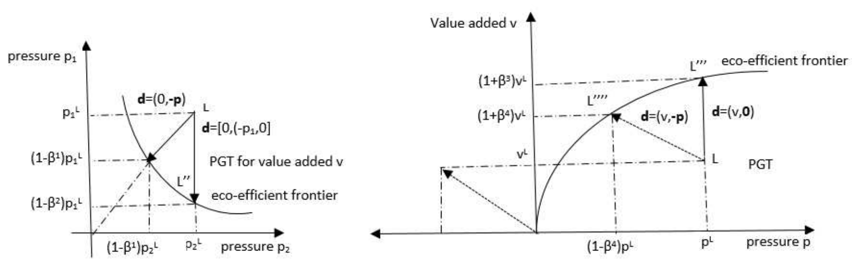

Figure 1: Eco-efficiency indicators of distinct scenarios

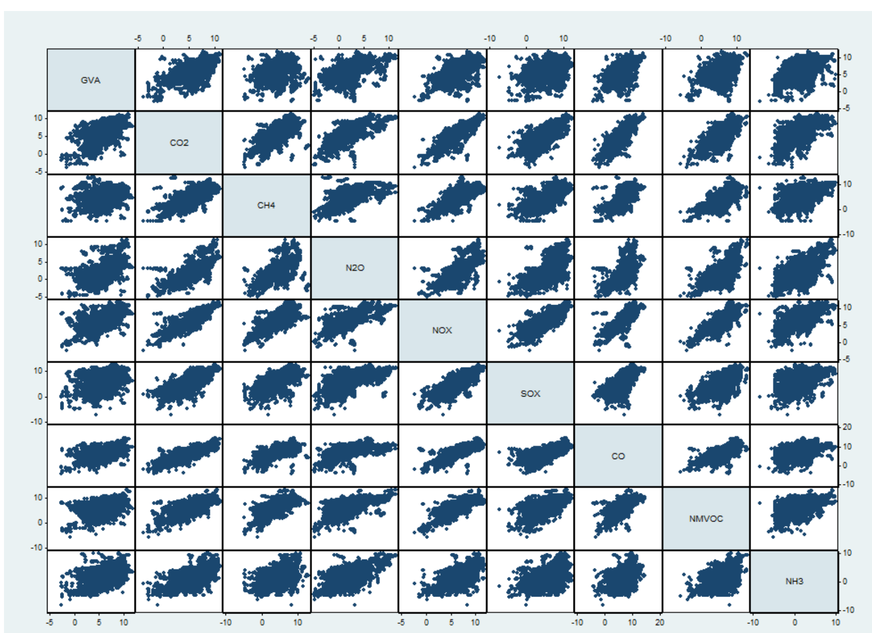

Figure 2: Scatter plots (logarithmic form) of employed variables

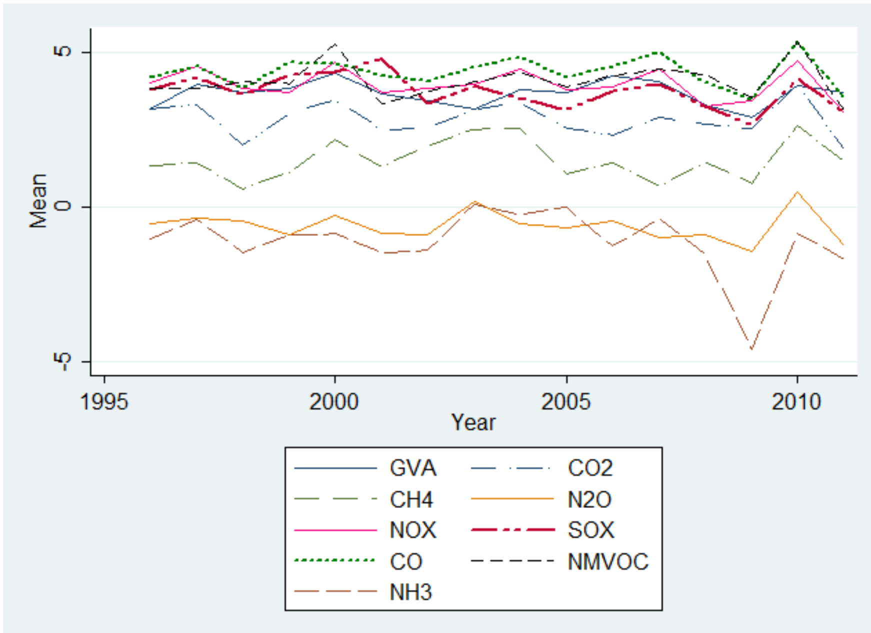

Figure 3: Mean growth rates of sample variables (logarithmic form) through time

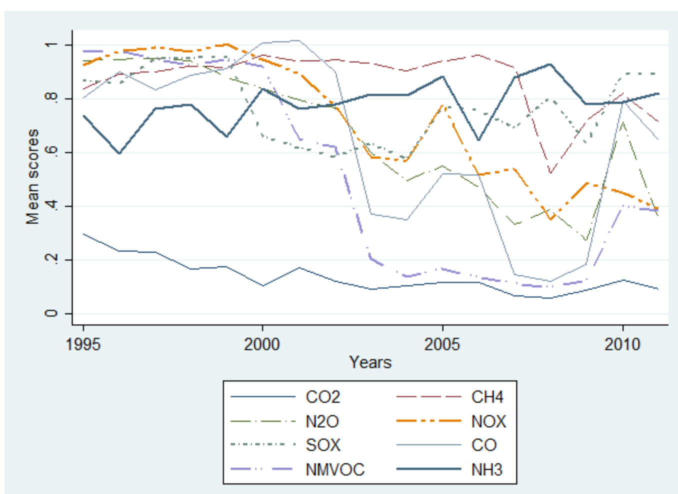

Figure 4: Catch-up indexes of pollutants

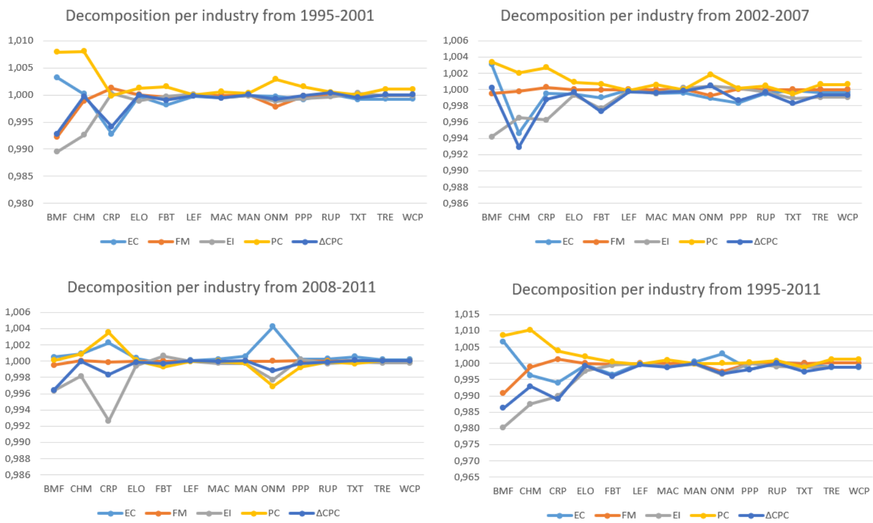

Figure 5: Decomposition of CO_2 emissions per industry for each time period

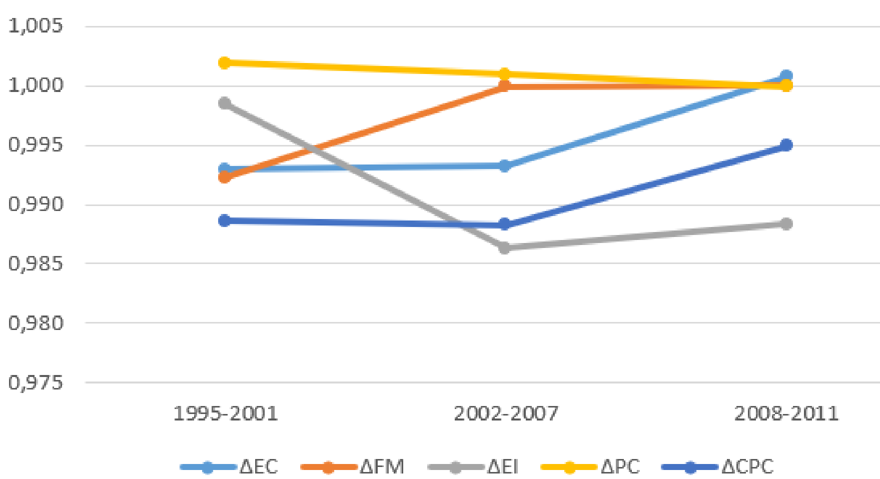

Figure 6: Accumulated decomposition of carbon emissions by time period

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