Environmental Productivity and Convergence of European Manufacturing Industries. Are they Under Pressure?

Stergiou, Eirini and Rigas, Nikos and Kounetas, Konstantinos

Department of Economics, University of Patras, Rio 26504, Patras, Greece., Department of Economics, University of Patras, Rio 26504, Patras, Greece., Department of Economics, University of Patras, Rio 26504, Patras, Greece.

20 November 2021

Environmental Productivity and Convergence of European manufacturing industries. Are they under pressure?

Stergiou Eirini

Department of Economics, University of Patras, Rio 26504, Patras, Greece.

e.stergiou@upnet.gr

Rigas Nikos

Department of Economics, University of Patras, Rio 26504, Patras, Greece.

nrigas@upnet.gr

Kounetas Konstantinos

Department of Economics, University of Patras, Rio 26504, Patras, Greece.

kounetas@upatras.gr

Abstract

European industries are under pressure regarding their environmental performance and productivity growth. The current energy crisis offsets governments efforts to achieve carbon neutrality while removing significant degrees of freedom in terms of firm's competitiveness. This paper studies environmental productivity and its components at a European industrial level using a dataset of 13 industries of the manufacturing sector from 27 European countries over the 1995-2014 period. Our results point out that industrial environmental productivity has deteriorated across Europe with best practice change being the main contributor. In addition, referring to the technological leaders in Europe, the findings point out that low tend to follow the middle-high technology industries. Finally, the non-convergence hypothesis and the creation of discrete clubs for the productivity index case and its components are supported.

keywords: European Industries; Metafrontier Malmquist–Luenberger index; Convergence; Technological heterogeneity

JEL Classifications: C61; D24; L60; Q43; Q56

1 Introduction & Motivation

Productivity amelioration is considered as the main driver of economic growth. Nonetheless, the extensive industrial rapid growth has caused unequivocal environmental problems because of the pollutant emissions augmentation (IPCC, 2021). European Commission (EUCOM) has repeatedly stated its aim to be in the frontline of tackling climate change and become a greenhouse neutral continent by 2050. To meet the commitments made by the Paris Accord, EU members have implemented an exemplary shift from an adaptive abatement to a proactive promotion of a climate neutral economy (EUCOM, 2018, 2019, among others). The European Green Deal (EUCOM, 2019) sets unique standards for climate protection, ensuring both energy security and dependence and strengthening European economy (Skjærseth, 2021). Consequently, climate protection with a sustainable energy transition not only reduces geopolitical fragmentation, but also creates economic opportunities especially in the manufacturing sector exploiting environmental friendly and innovative technologies and improving its productivity.

The manufacturing sector is considered as an essential factor of employment and prosperity, and thus, it constitutes a cornerstone towards a strong European economy (EUCOM, 2020). In the last decades, the necessity of green transition, the impending structural changes of the sector, moving to a wider development of a sustainable or green economy, and the bet of achieving the goal of green growth creates a new mix that affects manufacturing sector's productivity. In this sense, European Union (EU) puts a great emphasis on the twin, namely the ecological and digital, transition and the creation of environmentally innovative non-polluting technologies (EUCOM, 2020). However, many European firms are rather skeptical to participate in this paradigm shift due to the cost increases in international trade and energy transition, the price system that does not reflect the true cost of using environmental resources, the requirement of large, uncertain private investments and the lack of efficacious public funding on new technologies. Furthermore, a possible crowd out effect is in presence where emissions-intensive companies might leave the EU because of its high emission prices and relocate to places with significantly lower or no emission prices (carbon leakage) (Aichele and Felbermayr, 2015). Finally, the current energy crisis seems to further impede the efforts on investing in innovative technologies in order to meet the target of a carbon neutral economy.

National and international authorities have recognized the potential positive impact of the development of alternative clean energy resources, energy conservation (Stergiou and Kounetas, 2021a) and the implementation of green technologies (Maskus, 2010). Thus, technological improvement and structural change have encouraged economies and especially industries of the manufacturing sector in boosting their economic growth by simultaneously decreasing carbon emissions (Haščič et al., 2010; Nikzad and Sedigh, 2017). Nevertheless, the economic growth-environmental degradation nexus is considered as a continuous long-lasting challenge. Due to different systemic, social, institutional, technological and cultural characteristics, the productivity levels vary between industries and countries. For the successful formation and implementation of energy and environmental policies, it is of great importance to investigate the convergence conditions of environmental productivity across the manufacturing industries of European countries. The existence of convergence, or otherwise, would help to determine in which direction actions are necessary and whether current implemented policies have been effective.

In literature, there have been a lot of studies that examine productivity growth of economies. In most cases, the Malmquist productivity index is employed to evaluate the productivity change over time (Malmquist, 1953).The non-parametric Data Envelopment Analysis (DEA) Malmquist index measures Total Factor Productivity (TFP) growth by estimating the distance functions and reflects both the efficiency change and frontier technology shift (Färe et al., 2008). Nevertheless, traditional Malmquist indices can't assess the impact of bad outputs of the production process on productivity and, hence, may lead to biased productivity estimations. To fill this gap, the Malmquist-Luenberger (ML) index was introduced by Chung et al. (1997). The Directional Distance Function (DDF) is utilized in the computation of the ML index which considers the harmful by-products as outputs.[1] Thus, it seeks for the largest feasible increase in desirable outputs and reduction in undesirable outputs. A great number of studies have employed the ML index to examine productivity growth by incorporating environmental aspects (Färe et al., 2001; Weber and Domazlicky, 2001; Kumar, 2006; Pasurka, 2006; Mahlberg and Sahoo, 2011, among others).

Although the ML index has been extensively used in environmental studies, it does not take into account the heterogeneity that may exist among groups. To overcome the different production environments, Oh (2010) suggested the Metafrontier ML (MML) index, a combination of the conventional ML index and the concept of metafrontier (Battese and Rao, 2002), as a more accurate method to estimate productivity growth by considering the group heterogeneity. Compared to the ML

[1]Before the introduction of the ML index, undesirable outputs were often used as inputs. However, the treatment of bad outputs as inputs is not consistent with the materials balance approach.

index, the studies utilizing the MML index are evident to a lesser extent (i.e. Chen et al., 2011; Chiu et al., 2012; Lin et al, 2013). Nonetheless, the integration of the metafrontier framework, albeit it constitutes a stepping stone to heterogeneity's presence, it does not actually give any information on whether these differences are eliminated and the various industries converge in the long-term. The convergence analysis is a new approach that is mostly used in energy and emission studies (Camarero et al., 2014; Brännlund et al., 2015; Haider and Akram, 2019; Stergiou and Kounetas, 2021b, among others). In this regard, it may provide evidence concerning the convergence at the European level and point out possible groups of economies in which specific policies should be implemented diversely.

This study contributes to the field by evaluating the environmental productivity growth of 13 industries of the manufacturing sector with different levels of technologies, technical skills, energy and CO_2 intensities from 27 European countries from 1995 to 2014. To our knowledge, no previous empirical study has been carried out for the entire set of manufacturing industries in a European level, since most of them focus on the estimation of scores for every industry individually. Firstly, we employ a non-radial directional distance function (DDF) approach to measure productivity growth and its components under a metatechnology framework. The incorporation of the metatechnology concept allows us to reveal at hand possible differences at national and European technologies and investigate technological heterogeneity. Thus, we are able to compute the industrial productivity scores both within each European country and Europe in general. At the same time, we make use of the industry classification provided by Eurostat in order to examine if different technology groups affect productivity growth disproportionately. Secondly, through the convergence analysis, our purpose is to provide an insight into the convergence of environmental productivity and its components across the European manufacturing industries for the first time.

The findings of the study indicate that, overall, environmental productivity has declined from 1995 to 2014 for the European industries. Decomposing the productivity into technical change, best practice change and technical gap change, it becomes clear that industrial productivity is affected mostly by the innovation of industries within their national frontiers. Moreover, after 2010 the majority of industries undergoes a drastic deterioration of their productivity levels, implying a notable consequence of the financial crisis occurred in 2008 while the middle-low technology industries lag behind in terms of innovation leadership. In addition, the convergence analysis presents a rather complex classification of industries across European countries for the productivity index and its decomposition factors as distinct numbers of clubs are being formed. Therefore, the existence of various growth patterns suggests that universal common environmental policies in Europe would not present the expected positive outcomes for the entire set of industries and countries in the long run.

The rest of the paper is organized as follows. Section 2 describes the methodology employed in the analysis and Section 3 presents the data and the variables. Empirical results are discussed in Section 4 while Section 5 concludes the study.

2 Methodological Framework

2.1 Metafrontier Malmquist Luenberger index

European industries are called upon to meet the simultaneous goal of sustainable development and growth. Let us assume a set of industries i=1,2,...,I existing in t=1,...,T time periods. Further we assume that all industries use a set of inputs N, such that x $\in R_+^N$ in order to produce M desirable outputs, $y \in R_+^M$ and J undesirable outputs, $b \in R_+^J$. The aforementioned analogy can be represented by the production techonology set (P) which can be expressed as follows:

$$P = \{(x,\ y,\ b):\ x\ can\ produce\ (y,\ b)\} \tag{1}$$

which is a multi-output production technology with desirable (final product) and undesirable outputs (emissions). Production technology T requires the standard axioms of Oh (2010) in order to be valid. More specifically, the first axiom explains that reducing undesirable outputs can not be achieved without a cost. The reduction of undesirable outputs presupposes the simultaneous reduction of desirable outputs. As a result, potential resources are employed on the abatement of undesirable output rather than the expansion of desirable output. The second axiom depicts the strong disposability. In other words, the reduction of desirable outputs does not necessarily drive to a depletion in undesirable output. In order to achieve a reduction in undesirable outputs, technological innovation is needed. The adoption of new innovative technologies will manage to limit the quantity of undesirable outputs. The third axiom of null-jointness certifies that even a minimum quantity of undesirable output will produced in order to produce some desirable. The last axiom originates from the law of physics that dictate that perfect combustion is almost impossible to be achieved, thus toxic emissions are produced (Wielgosiński, 2012).

The existence of different European industrial sectors provides the presence of heterogeneity in energy consumption and CO_2 emissions releases. Hence, we adopt the metafrontier framework (Stergiou and Kounetas, 2021a) which is based on the concept of metafrontier introduced by Battese and Rao (2002) and was first used and introduced by Oh (2010) and since then has significant recognition (Beltrán-Esteve et al., 2019; Lee, 2021; Chung et al., 2015). The concept of MML requires its' decomposition in three definitions of benchmark technology sets: a contemporaneous benchmark technology, an intertemporal benchmark technology and a global benchmark technology. In order to further explain the MML index we need to define the following concepts:

Contemporaneous (C) benchmark technology is defined as a reference production set made from observations (industries in our case) at one time only for a specific group (Tulkens and Eeckaut, 1995). The contemporaneous benchmark technology is given by $P^t_{R_h} = (x^t, y^t, b^t) : x^t canproduce(y^t, b^t)$, where R_h depicts a group, h=1,....,H and $t = 1, ..., T$. In our research, each of the 27 countries is considered as the contemporaneous group of reference for the examined set of industries.

Intertemporal (I) benchmark technology takes into consideration the observations of the whole time period concerning a specific group (Tulkens and Eeckaut, 1995). The number of intertemporal benchmark technology sets is equal to the number of groups and is given by $P^I_{R_h} = P^1_{R_h} \cup P^2_{R_h} \cup ... \cup P^T_{R_h}$. Research at hand covers a 20 years period of time (1995-2014). The intertemporal benchmark group includes the industries of each country for a 20 year span.

Finally, the Global (G) benchmark technology is a single reference production set which is constructed from observations throughout the entire time period and for all groups (Tulkens and Eeckaut, 1995). It can be more easily understood as the benchmark technology that envelops all intertemporal benchmarks. It is defined as follows: $P^G = P^I_{R_1} \cup P^I_{R_2} \cup ... \cup P^I_{R_H}$. The global benchmark technology group customized to our data is a single group with observations from all countries and all years.

We further continue with the decomposition of the MML index into productivity growth components. Namely these components are efficiency change (EC), best practice gap change (BPC) and technical gap change (TGC). Using the distances of the benchmark technologies the

MML index is created as follows:

$$
\begin{aligned}
&MML(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1 + \overrightarrow{D}^G(x^t, y^t, b^t)}{1 + \overrightarrow{D}^G(x^{t+1}, y^{t+1}, b^{t+1})} = \\
&\frac{1 + \overrightarrow{D}^t(x^t, y^t, b^t)}{1 + \overrightarrow{D}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \\
&\times \frac{(1 + \overrightarrow{D}^I(x^t, y^t, b^t))/(1 + \overrightarrow{D}^t(x^t, y^t, b^t)}{(1 + \overrightarrow{D}^I(x^{t+1}, y^{t+1}, b^{t+1}))/(1 + \overrightarrow{D}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}))} \\
&\times \frac{(1 + \overrightarrow{D}^G(x^t, y^t, b^t))/(1 + \overrightarrow{D}^I(x^t, y^t, b^t)}{(1 + \overrightarrow{D}^G(x^{t+1}, y^{t+1}, b^{t+1}))/(1 + \overrightarrow{D}^I(x^{t+1}, y^{t+1}, b^{t+1}))} \\
&= \frac{TE^{t+1}}{TE^t} \times \frac{BPR^{t+1}}{BPR^t} \times \frac{TGR^{t+1}}{TGR^t} = EC \times BPC \times TGC
\end{aligned}
\tag{2}
$$

In the equation above we note that EC describes how close (or farther away) a DMU moves towards the contemporaneous benchmark technology when comparing period *t+1* to period *t*. Hence, EC $>$ 1 is interpreted as an efficiency improvement relative to the contemporaneous benchmark technology frontier. On the contrary, when facing EC $<$ 1, the DMU is lagged behind. The BPC measures the alteration of the contemporaneous benchmark technology frontier compared to the intertemporal benchmark technology frontier during two periods. Hence, BPC $>$ 1 suggests that the contemporaneous benchmark technology frontier moves closer to the intertemporal benchmark technology frontier, while BPC $<$ 1 suggests that the first moves farther away from the latter. Having in mind that we deal with desirable and undesirable outputs, BPC can be explained as the innovation effect deriving from the reduction of undesirable and the increase of desirable output. TGC gauges the alteration between the intertemporal benchmark technology frontier and the global benchmark technology frontier during two periods. TGC $>$ 1 suggests that the gap between the intertemporal benchmark technology frontier and the the global benchmark technology frontier is decreased between two periods for a DMU and captures the technical leadership effect. Finally, MML $>$ 1 corresponds to productivity gains, while MML$<$ 1 corresponds to productivity losses.

2.2 Non-radial Directional Distance Function

The traditional DDF method aims on the decrease of inputs and bad outputs and the simultaneous increase of good outputs at the same rate, overestimating the efficiency when slack are present. To overcome this limitation, (Zhou et al., 2012) proposed the non-radial approach which can be expressed as follows:

$$\overrightarrow{D_P}(\mathbf{x},\mathbf{y},\mathbf{b};\mathbf{g}) = sup\big\{\mathbf{w}^P\beta : ((\mathbf{x},\mathbf{y},\mathbf{b}) + diag(\beta) * \mathbf{g})\epsilon \text{ P}\big\} \tag{3}$$

where *diag* represents the matrices, $\text{w}^P = (\text{w}^x,\ \text{w}^y,\ \text{w}^b)^P$ describes a normalised weight vector relevant to the number of inputs and outputs, $g = (-x, y, -b)$ is the directional vector and $\beta = (\beta_x, \beta_y, \beta_b)^P \geq 0$ represents the scaling vector denoting the individual inefficiency measures for the employed variables.[2]

The non-radial DDF measure of the inefficiency can be estimated by solving the following linear programming problem:

$$\overrightarrow{D}_{cond}(x^q, y^q, b^q; g) = \max\ \text{w}_n^x\beta_n^x + \text{w}_m^y\beta_m^y + \text{w}_j^b\beta_j^b \tag{4}$$

s.t

$$\sum_{cond}\sum_{i=1}^{I}\lambda_i^q x_{in}^q \leq x_n' - \beta_n^x g_{xn}, \quad n = 1, ..., N$$

$$\sum_{cond}\sum_{i=1}^{I}\lambda_i^q y_{im}^q \geq y_m' + \beta_m^y g_{ym}, \quad m = 1, ..., M$$

$$\sum_{cond}\sum_{i=1}^{I}\lambda_i^q b_{ij}^q = b_j' - \beta_j^b g_{bj}, \quad j = 1, ..., J$$

$$\lambda_i^q \geq 0 \quad i = 1, 2, ..., I, \qquad \beta_n^x, \beta_m^y, \beta_j^b \geq 0$$

where the *cond* represents the condition for constructing the three environmental production technologies, namely contemporaneous, intertemporal and global technologies. To estimate and decompose the MML, we solve six different linear problems: $\overrightarrow{D}_C(\mathbf{x},\mathbf{y},\mathbf{b})$, $\overrightarrow{D}_I(\mathbf{x},\mathbf{y},\mathbf{b})$ and $\overrightarrow{D}_G(\mathbf{x},\mathbf{y},\mathbf{b})$ for $q = t, t+1$.

2.3 Convergence Analysis in terms of MML and its components

The hypothesis of convergence among manufacturing industries across Europe is tested under the technique proposed by Phillips and Sul (2007). The specific approach identifies groups of individuals in a panel that share similar patterns of convergence even if there is no full convergence for the entire panel. In this sense, the major advantage of this method

[2] If $\overrightarrow{D}$ is equal to zero, the evaluated industry will be efficient and will be located along the best-practice frontier in the g direction.

is that it discloses the existence of multiple convergence clubs and individuals that diverge. The regression-based test is combined with a clustering procedure in order to provide manifold equilibrium points of convergence accounting for the heterogeneity of individuals. Let Y_{it} be the industrial productivity and its three decomposed factors. Y_{it} can be decomposed as:

$$Y_{it} = \delta_i \mu_t + \epsilon_{it} \tag{5}$$

where δ_i measures the idiosyncratic distance between the common factor μ_t and the systematic part of Y_{it}, μ_t represents the aggregated common behavior of the dependent variable Y_{it}, a common variable variable of influence on the individual (industry) behavior and ϵ_{it} the error term.

PS extended Eq.(5) allowing δ_i to have a random component that absorbs the error term u_{it} and permitting possible convergence behavior in δ_{it} over time to the common factor μ_t, both of which are time-varying. Therefore, the new model is written as follows:

$$Y_{it} = \delta_{it} \mu_t \tag{6}$$

In order to eliminate the common component and test whether δ_{it} converges to a constant δ, they defined the relative transition parameter h_{it} as:

$$h_{it} = \frac{Y_{it}}{\frac{1}{N}\sum\limits_{i=1}^{N} Y_{it}} = \frac{\delta_{it}}{\frac{1}{N}\sum\limits_{i=1}^{N} \delta_{it}} \tag{7}$$

which measures how the variable of interest for individual i evolves in relation to the panel average. Thus, if the factor loading coefficients converge to δ, the relative transition parameters h_{it} converge to unity and the cross-sectional variance (H_t) converges to zero as t $\rightarrow \infty$.

$$H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{it} - 1)^2 \rightarrow 0, \text{as t} \rightarrow \infty \tag{8}$$

The null hypothesis of the test can be formulated through a semiparametric model for δ_{it}:

$$\delta_{it} = \delta_i + \frac{\sigma_i \xi_{it}}{L(t)t^a} \tag{9}$$

where $\xi_{it} \sim$ iid(0,1) across i, α 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. The null hypothesis is tested by utilizing the following log t regression:

$$log(H_1/H_t) - 2logL(t) = \hat{c} + \hat{b}logt + u_t, \text{t} = \text{[rT],...,T} \tag{10}$$

where L(t)= log(t+1) and $\hat{b} = 2\hat{a}$, where α is the estimate of speed convergence in H_0. Full panel convergence exists when $\hat{b} \geqslant 0$ while higher values of $\hat{b}$ will indicate faster rate of convergence. The null hypothesis is rejected when t-statistic $t_b <$ -1.65. PS suggested starting the regression at point t = [rT], where [rT] is the integer part of rt and r = 0.3. At this point it is worth mentioning that the rejection of the null hypothesis only indicates that there is not full convergence in the panel; there might be a variety of subgroups that display distinct convergence patterns. To do so, the utilization of the clustering algorithm provides the identification of the number of convergence clubs within the panel dataset and the members/individuals that form each club.[3]

3 Data and Variables

In order to examine the issues surrounding our main research question, we devised a unique balanced dataset that integrates information on both input and output variables. As shown in Table A1, the dataset includes thirteen industries of the manufacturing sector from twenty-seven European countries over the 1995-2014 period.[4] The sample period and industries of the study have been selected with reference to the availability of complete and comparable data at the industry level. Hence, the employed dataset consists of 7020 observations on a panel dimension.

For the computation of productivity growth, capital stock (K), Labor (L), Intermediate Inputs (II) and Energy use (E) are employed as inputs whilst Gross Value Added (GVA) and carbon dioxide emissions (CO_2) as the desirable and undesirable outputs respectively. More specifically, capital is measured in million Euros, labor is captured by the total hours worked by employees, expenditure on intermediate inputs (II) in million Euros and the total energy use (E) in Terajoules. For the output set, GVA is expressed in million Euros and CO_2 emissions in kilotons. All

[3]See Appendix C for more details regarding the clustering algorithm.

[4]Data on 2-digit manufacturing industries have been employed according to the International Standard Industrial Classification (ISIC) (Kounetas et al., 2012).

monetary variables have been deflated and are expressed in Euros in constant 1995 prices. Data for the entire set of variables were collected through the World Input Output Database (WIOD), with the only exception of carbon dioxide emissions that were drawn from European Commission-EU Science Hub. Tables 1 and 2 present the descriptive statistics and the mean values for the variables of each industry. Overall, 5 out of 13 industries (38%) exceed the total average of capital, labor and emissions, 6 out of 13 (46%) of intermediate inputs, 2 out of 13 (15%) of energy use and 7 out of 13 (54%) of value added. More specifically, the industry of Food, Beverages and Tobacco (FBT) displays the highest values of capital, labor and intermediate inputs while in terms of energy consumption the industry of Coke, Refined Petroleum Products (CRP). Turning our attention on the outcomes of the industrial production activities, the Electrical and Optical Equipment (ELO) and the Basic Metals and Fabricated Metal Products (BMF) industries demonstrate the largest values regarding the desirable and the undesirable output respectively.

Table 1: Descriptive statistics of input and output variables

Variables	Mean	Std. Dev.	Min	Max
Inputs				
K	1783.481	6172.057	0.002	122809.200
L	573.674	2840.068	0.385	85547.430
II	10251.070	21807.550	0.033	255747.400
E	18951.480	190024.700	0.001	5387029
Outputs				
Desirable output				
GVA	4353.254	9626.136	0.066	125754.300
Undesirable output				
CO_2	2913.568	6861.270	0.011	67864.280

Table 2: Mean values of input and output variables by industry

Industry	K	L	II	E	GVA	CO_2
BMF	2111.305	601.928	14741.080	18360.020	6663.865	9049.716
	(5090.849)	(1643.624)	(24519.970)	(81486.430)	(12099.310)	(12898.770)
CHM	3037.470	577.089	13709.840	32638.310	6296.234	5730.989
	(10117.560)	(2625.875)	(23202.790)	(147909.200)	(10732.650)	(7634.023)
CRP	1075.987	94.186	8320.517	162634.800	805.176	5753.308
	(3781.465)	(388.756)	(16011.870)	(643909.600)	(1234.323)	(7844.577)
ELO	1779.629	633.701	14708.750	764.191	8163.453	440.615
	(4472.635)	(2841.244)	(25775.090)	(3560.666)	(16693.020)	(655.544)
FBT	3969.416	1338.833	22137.810	7317.737	7013.298	2947.465
	(11259.580)	(4908.860)	(33540.420)	(29841.060)	(10698.520)	(4029.772)
MAC	2475.289	1221.127	12446.560	1754.294	6526.545	591.347
	(10227.900)	(6629.304)	(26239.910)	(9249.056)	(14281.120)	(946.249)
MAN	981.904	551.277	4312.299	809.051	2266.534	480.700
	(3184.590)	(2121.045)	(6967.805)	(3330.029)	(3749.846)	(1051.468)
ONM	1365.899	414.298	4285.881	8120.561	2577.305	8874.495
	(3705.203)	(1475.408)	(6786.938)	(33049.950)	(4105.624)	(12933.650)
PPP	1511.334	339.444	8134.268	8142.662	4390.967	1706.116
	(2853.502)	(894.618)	(12056.470)	(36955.310)	(6913.431)	(2217.376)
RUP	1439.307	502.245	5617.671	1868.550	2912.871	517.754
	(4583.417)	(2166.929)	(10059.830)	(9344.177)	(5489.390)	(917.277)
TXT	847.326	504.616	4903.745	1274.174	2333.874	751.358
	(3034.681)	(1745.060)	(9964.843)	(5865.505)	(4320.070)	(1795.850)
TRE	1950.683	421.297	17080.100	440.566	5344.759	687.972
	(5165.857)	(1400.904)	(37872.970)	(2270.042)	(11979.870)	(1198.941)
WCP	639.706	257.730	2865.447	2244.340	1297.418	344.550
	(1582.777)	(733.227)	(3888.937)	(8794.995)	(1827.396)	(450.852)

Note: Standard deviation in parenthesis

4 Results & Discussion

4.1 European industrial environmental productivity growth

To calculate the MML index[5], we proceed with the selection of the group frontiers, namely the contemporaneous, intetemporal and global benchmark technology. Figure 1 displays the average trend of environmental productivity growth, efficiency change, technical change and technology gap ratio throughout the sample period. On the whole, productivity growth and best practice change present, on average, a variety of fluctuations having a different behavior compared with the other two components. For the case of productivity growth, the largest decrease occurs

[5] Codes in R are available upon request.

from 2011 to 2012 during the global financial crisis, whilst the largest increase, in absolute terms, from 2012 to 2013 denoting a short recovery period. Technical change, namely the BPC, follows a similar path with productivity growth, albeit with a smoother decline from 2011 to 2012. In other words, productivity is positively affected by innovative activities concentrated on emissions mitigation and environmental security. Conversely, the efficiency change and technology gap change reach an average score around unity from 1996 to 2014.

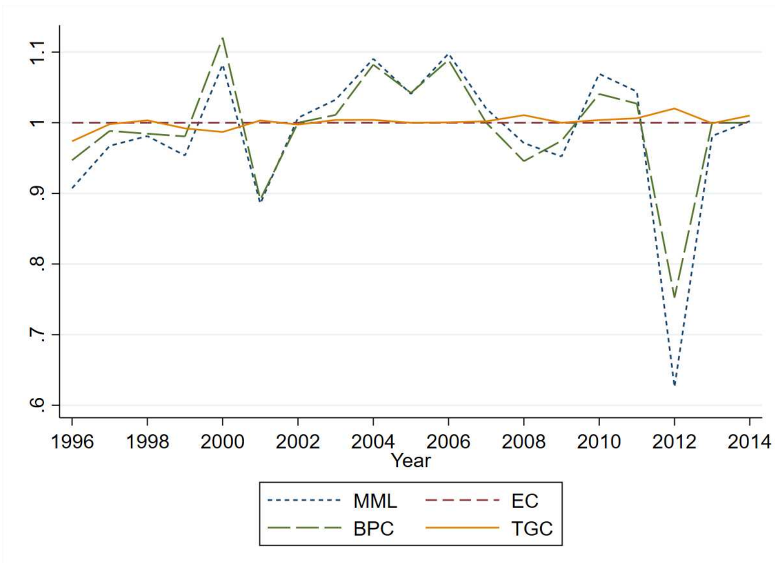

Figure 1: Average industrial productivity growth and its decomposition factors for the 2000-2014 period

Apart from the findings regarding MML index at an aggregate level, it is interesting to examine individual industrial performance. Table 3 and Figure 2 report the empirical results of productivity growth accounting for undesirable outputs and its decomposition factors for each industry over the examined period. The average value of productivity is 0.978 indicating a decrease by 2.2% with none of the participating industries presenting an increase. More specifically, the entire set of industries has been through productivity deterioration on average, albeit some of them present more severe loses (BMF, CRP, ONM, FBT and CHM) while others move closer to unity (MAC, MAN and WCP). Industries with low productivity are considered to have the biggest changes in environmental protection policies over the last five years.[6] Prior to

[6]Our dataset covers the period 1995-2014, thus policy implementation is not activated.

that, little progress has been made while it is imperative to mention that productivity in almost all industries has suffered big drops after the financial crisis in 2008. Refering to the China case, the majority of studies examining green productivity growth in specific industries of the manufacturing sector, have highlighted the importance of strict environmental regulations in the improvement of environmental productivity (i.e. Chen, 2010; Zhang et al., 2011; He et al., 2013). Thus, policymakers and national/local governments should focus on the efficacious implementation of environmental policies in firms, industries, regions and countries in Europe.

Table 3: Average industrial productivity change, efficiency change, best practice gap change, and technical gap ratio change

IND	MML	TGC	BPC	EC	IND	MML	TGC	BPC	EC
BMF	0.959	0.996	0.994	1.005	PPP	0.979	1.006	0.998	1.002
	(0.198)	(0.139)	(0.244)	(0.159)		(0.153)	(0.114)	(0.208)	(0.129)
CHM	0.976	0.996	1.003	0.999	RUP	0.984	0.998	0.998	1.006
	(0.174)	(0.118)	(0.213)	(0.106)		(0.146)	(0.115)	(0.183)	(0.090)
CRP	0.958	0.981	0.998	0.996	TXT	0.987	1.003	1.002	1.000
	(0.343)	(0.262)	(0.258)	(0.104)		(0.182)	(0.150)	(0.193)	(0.088)
ELO	0.988	1.004	0.995	0.997	TRE	0.976	1.001	0.990	0.996
	(0.180)	(0.111)	(0.180)	(0.077)		(0.222)	(0.141)	(0.203)	(0.109)
FBT	0.972	0.999	1.002	0.999	WCP	0.992	1.004	0.993	1.009
	(0.180)	(0.120)	(0.217)	(0.138)		(0.176)	(0.136)	(0.171)	(0.089)
MAC	0.991	1.005	1.001	0.999	Aver.	0.978	0.999	0.998	1.000
	(0.165)	(0.114)	(0.181)	(0.092)		(0.196)	(0.142)	(0.208)	(0.112)
MAN	0.992	1.001	1.003	1.001					
	(0.175)	(0.132)	(0.188)	(0.094)					
ONM	0.957	1.001	0.999	0.994					
	(0.176)	(0.132)	(0.242)	(0.146)					

Note: Standard deviation in parentheses

by industry.png by industry.png

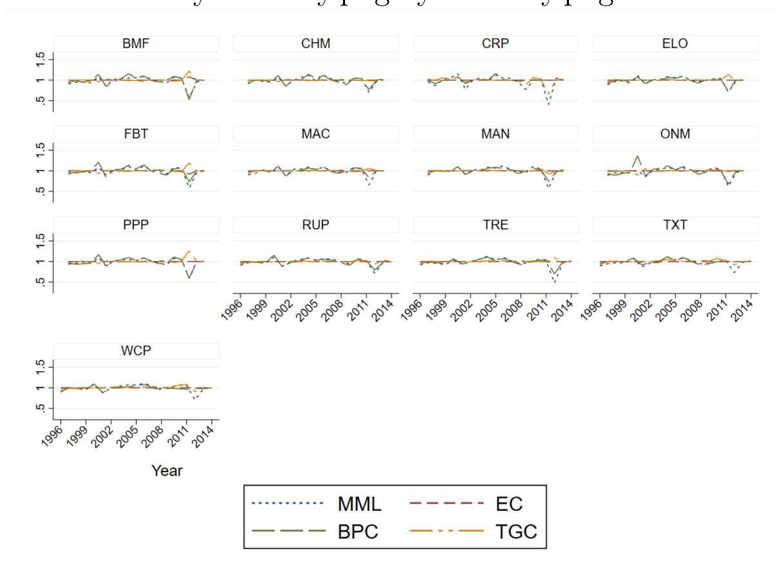

Figure 2: Productivity growth, efficiency change, technical change and technical gap ratio for European industries from 1996 to 2014

As explained in the methodology section, MML is a productivity index composed by three other indices, namely, EC, BPC and TGC. EC captures the move towards or away from a contemporaneous benchmark technology. The average value of EC for all industries is almost equal to unity, revealing neither a catching up nor a lagging behind effect has occurred throughout the examined period. Finally, looking closer to the EC results of each industry we detect that five of them present slightly larger (namely, BMF, MAN, PPP, RUP and TXT) than unity values and the rest of them less than or equal to one.

Turning our attention to the best practice gap index (BPC) the manufacturing sector is 0.998, indicating that the level of technical innovation diminishes from 1995 to 2014. Thus, a shift of the contemporaneous frontier further away from the intertemporal frontier occurs. Compared with EC and TGC, BPC constitutes the most significant cause of environmental productivity's increase in the European manufacturing sector. The industries of CHM, FBT, MAC, TXT and MAN present the highest values consisting the champions group, whilst the industries of TRE and WCP the lowest, suggesting technical progress and deterioration respectively. Increasing concerns and policies about energy and environment have fostered advancement in technology. However, the implementation of new (green) technology systems, improvements in energy efficiency and reduction of bad outputs are much harder for the heavy industries (EEA, 2018). Similar to our results, Chen and Golley (2014) and Li and

Lin (2016) revealed that the main contributor of environmental productivity is technical change. Moreover, the latter indicated that energy and emissions-intensive sectors such as chemicals, plastics, iron and steel present lower levels of environmental productivity and technical innovation in general. Regarding the time evolution of the technical change, a similar pattern is observed for the majority of industries. More specifically, industries display a technical decrease from 2001 to 2002 and 2011 to 2012, with the exception of CRP, TXT and WCP. Conversely, from 2013 and onward there is a sharp technical increase for the former industries. Overall, the largest technical progress occurs in the ONM industry during the 1999-2000 period.

Finally, technical gap change (TGC) average value for the 20-year period is 0.999 indicating a very small deterioration in the technical leadership. For example, technical leadership entails industries' efforts to adopt best available environmental technologies and practices (BAT) at European level. More specifically, the gap between global and intertemporal frontiers was expanded. Examining the TGC values of each industry we detect some heterogeneity. The industries of PPP, MAC and ELO present the highest values implying that the technology gap between the intertemporal frontiers of those three industries and the global frontier has diminished, on average, for all years. The industries with the lowest average technical gap change are these of CRP, BMF and CHM. In these cases the index is below unity, with the industry of Coke having a 1.9% shortfall on average. In terms of time evolution, a similar pattern can be detected for the majority of industries with the most common characteristic being a big drop of the index in the 2010-2012 period.

4.1.1 Environmental productivity growth and technology groups performance

Our methodological framework allow us to incorporate in our estimations technological and environmental spillover effects associated with intersectoral linkages that can be generated both at national level and across different countries and industries (Saliola and Zanfei, 2009). Thus, the promotion of knowledge generation techniques and the transfer of scientific and technological achievements could improve the technological level of an industry. Although transmission channels of knowledge spillover are present (Los and Verspagen, 2002) and vertical associations between firms are in operation (Isaksson et al., 2016), phenomena of technological isolation (Tsekouras et al., 2017), co-evolving and different environmental constraints exists (Manning et al., 2012), preventing industries of fully exploiting the environmental available information (Constantini et al., 2017). Thus, since the BPC and TGC indices pinpoint the industries that exhibit technological innovation and leadership respectively, they are utilized to identify the "innovative industries". In this sense, if the values of BPC and TGC are higher than unity, it means that the specific industry would be characterized as a group and metafrontier innovator respectively.[7] The former are characterized as champions industries into their country group and the latter are the leaders among all industries in Europe.

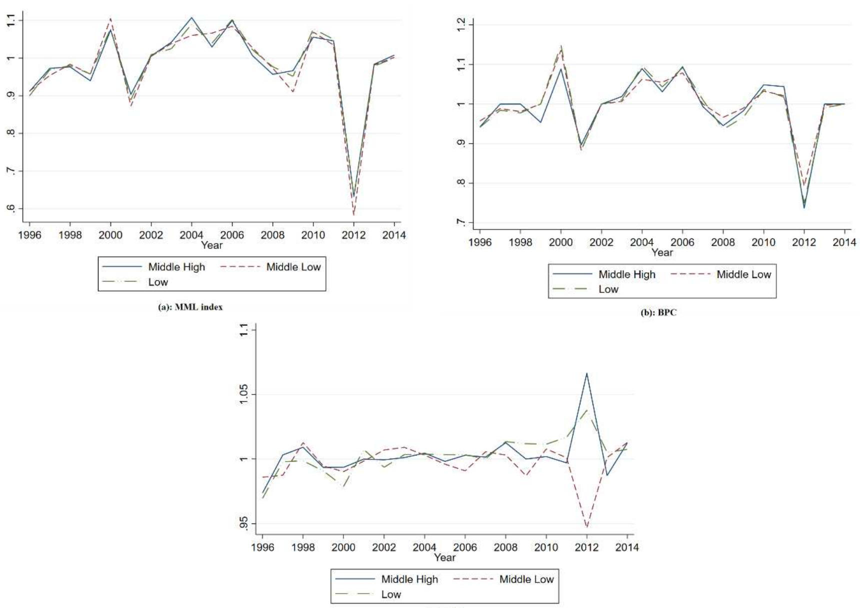

Figure 3: MML, BPC and TGC rends from 1996 to 2014 for the technology groups

An *ex-post* classification of the manufacturing industries into technology groups has been conducted in accordance with Eurostat to examine whether there are any similar pattern in terms of technology progress.[8] For the case of BPC, as shown in Fig. 3, it is observed that there are no significant differences between the technology groups. The middle-low and low group display higher values from 1999 to 2000 than the middle-high group while the latter presents lower average values than the two other groups from 2011 to 2012. Our results point out that industries belonging to the low and middle-low group come closer to each other by diminishing the distance of their frontiers. Therefore, industries of the

[7]See Oh (2010) for further details on innovation classification.

[8]See Table A1 for the technology classification of industries. In our case, there was no industry classified in the High technology group.

middle-high group confront great challenges in terms of mitigating their emissions through the implementation of innovation techniques (Lee, 2021). Even though they invest huge amount of capital in knowledge generation/innovation technologies, up to a certain point their green innovation technologies would not be so efficacious and the additional costs would exceed their benefits. Conversely, the low technology industries seem to improve their innovative activities and reach out the middle-low ones demonstrating a positive behavior in their innovation activities due to the knowledge and technology spillovers existing in the European level. Indicatively, three out of six industries belonging to the former group present a BPC value larger than unity (FBT, MAN, TXT), narrowing the gap and enhancing innovation to mitigate the emissions and support the sustainability goals.

In the case of TGC the results differ. The classification to middle-high, middle-low and low technology industries when controlling for technical leadership discloses dissimilarity for the three groups. A great discrepancy occurs during 2011-2013. At that time, middle-high and low group have an increase in their TGC values about 6% and 4% respectively whilst the middle-low group demonstrates a drop of 5%. It is worth mentioning that the low technology group has a beneficial technical leadership (value above 1) since 2002. By taking a closer look at Table 3, it is evident that all three technology groups in the last year present a TGC value greater than unity. Even the middle-low technology group faces a 1% increase, implying that the gap between the global and the inertemporal frontier was reduced. A possible explanation for the initial drop and the subsequent increase is that the European legislation for CO_2 emissions mitigation that was first implemented at 2011 (EU-COM, 2013) built a wall of difficulties for technological leadership. Once industries with middle-low technology managed to overtake this obstacle they exhibited better technological leadership. Middle-high and low technology industries did not face such difficulties but rather experienced an enhancement in their technological leadership.

The MML classification follows a strict pattern for all groups. In every peak or drop the three groups follow the same pattern. We observe a 40% drop at 2012 for all groups. Middle-high and low technology groups had a positive but small TGC index while their BPC index faced a drop which constitutes the main driver for the drop in MML. The diffusion of green technologies and the development of fundamentally new technologies are required to transform nations into sustainable environment. In this sense, new technologies, such as carbon capture and storage technologies in the industrial sector, are not the only measure towards the reduction of bad outputs, but also technologies that are already available in markets and would actually provoke changes in the institutional management and concepts (UNIDO, 2014). As already mentioned, our results point out that low technology industries follow a similar path with middle high ones. Thus, it is more likely for the former to potentially focus on a high level of synergies with the latter in particular parts or the entire production process rather than investing on new technologies as their capital is insufficient for the incorporation of entirely new systems.

4.2 Convergence analysis of environmental productivity growth

Having estimated the environmental productivity growth, we focus our attention in the examination of convergence employing the Phillips and Sul (2007) methodology. Table 4 presents the results for the club-clustering of the MML productivity index. The algorithm initially classifies the European industries dataset into 9 subgroups. The point estimates of γ are all significantly positive and less than 2.0. Thus, there is strong evidence of conditional convergence but little evidence of convergence level within each of these clubs. The middle panel of Table 4 reports the tests conducted to determine whether any of the original subgroups can be merged to form larger convergence clubs. Except for clubs 1, 2, 3, 7, 8 and 9, there is evidence to support merges of the original groupings. The right panel of Table 4 displays the final empirical classification from the clustering analysis into seven growth convergence clubs of industries.

The first club includes 16 European industries from Basic Metals and Fabricated Metal Products, Chemicals, Coke and Refined Petroleum Products, Electrical and Optical Equipment, Wood and Cork Products and Food and Beverages. Industries of the first club belong to countries like Germany, Finland, France and Belgium. We are able to identify heterogeneous clubs 3, 4 and 5 that include the majority of European industries composed of all countries and manufacturing sectors. Conversely, clubs 6 and 7 constitute, mostly, individual countries' coke and refined petroleum (please see Fig.A1 for an analytical presentation of clubs). The same information contained in Table 4 can be represented graphically, as depicted in Fig.4, using the relative transition paths calculated in relation to the average, that is, the series of h_it for all the European industries examined in our dataset.

Table 4: Convergence club classification: Productivity

Initial classification										**Final classification**	
$\hat{\gamma}$ (SE of $\hat{\gamma}$)		**Tests of club converging** $\hat{\gamma}$ (SE of $\hat{\gamma}$)								$\hat{\gamma}$ (SE of $\hat{\gamma}$)	
Club 1 [16]	0.664	Club1+2								Club 1 [16]	0.664
	(0.213)	-0.496*									(0.213)
Club 2 [65]	0.082	(0.245)	Club2+3							Club 2 [65]	0.082
	(0.256)		-0.485*								(0.256)
Club 3 [76]	1.000		(0.222)	Club3+4						Club 3 [175]	0.323
	(0.226)			0.323							(0.207)
Club 4 [99]	0.878			(0.207)	Club4+5					Club 4 [77]	0.005
	(0.317)				-0.017						(0.121)
Club 5 [51]	0.993				(0.188)	Club5+6				Club 5 [11]	0.658
	(0.284)					0.005					(0.605)
Club 6 [26]	1.289					(0.131)	Club6+7			Club 6 [5]	1.141
	(0.301)						-0.117				(0.82)
Club 7 [11]	0.658						(0.2)	Club7+8		Club 7 [2]	0.354
	(0.605)							-0.537*			(0.134)
Club 8 [5]	1.141							(0.248)	Club8+9		
	(0.82)								-1.071*		
Club 9 [2]	0.354								(0.235)		
	(0.134)										

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.
Note[3]: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.

A simple glance over the MML productivity relative transition path unveils the following findings. Overall, all clubs start from the same initial point but some diversion in the dynamics of convergence process is present. Clubs 3, 4 and 5 behave in an identical way during the examined period. Moreover, concerning the first cluster of European industries, even though their relative transition starts at similar levels with the above-mentioned clubs, it shows a completely inverse picture after the global financial crisis. Although the majority of clubs seems to accelerate the downward trajectory, club 1 displays an upward trend and a significant amelioration. Last but not least, the second group (consisting of 65 observations) presents a steady and very smooth improvement after 2009.

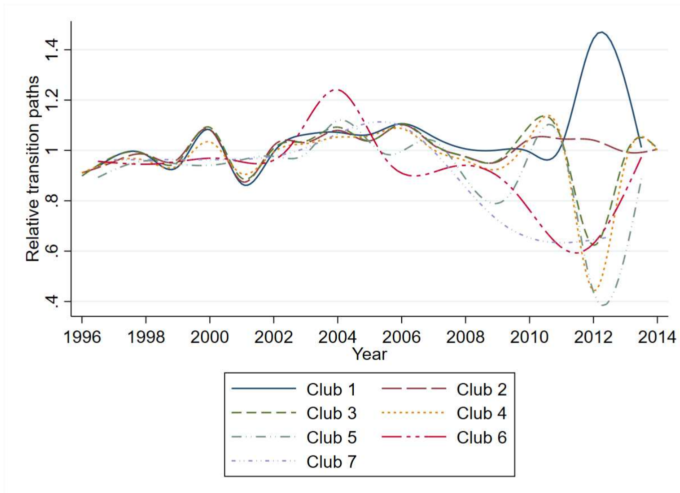

Figure 4: Relative transition paths in terms of productivity growth

Table 5: Convergence club classification: Efficiency Change

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 [3]	0.262	Club1+2								Club 1 [16]	0.241
	(0.317)	-0.069									(0.093)
Club 2 [3]	0.210	(0.17)	Club2+3							Club 2 [37]	-0.198
	(0.254)		0.467								(0.253)
Club 3 [7]	0.688		(0.117)	Club3+4						Club 3 [219]	-0.205
	(2.198)			0.785							(0.327)
Club 4 [3]	0.478			(0.086)	Club4+5					Club 4 [54]	-0.126
	(0.612)				-0.482*						(0.352)
Club 5 [37]	-0.198				(0.252)	Club5+6				Club 5 [25]	0.011
	(0.253)					-0.721*					(0.333)
Club 6 [34]	1.163					(0.247)	Club6+7				
	(0.266)						-0.205				
Club 7 [185]	0.094						(0.327)	Club7+8			
	(0.472)							-1.63*			
Club 8 [54]	-0.126							(0.354)	Club8+9		
	(0.352)								-1.294*		
Club 9 [25]	0.011								(0.33)		
	(0.333)										

Table 5 presents the results of club classification for the efficiency change. Nine clubs are identified from the PS algorithm. Seven of these subgroups form convergence clubs. Although the estimate γ is negative for clubs 5 and 8 the t-statistic is not statistically different from zero, suggesting convergence among these clubs. Thus, nine distinct groups of convergence initially exist. The club merging algorithm for the individual industries led us to some amalgamation of clubs as shown at the right part of Table 5. As shown in Fig.A2, the most multitudinous club is cluster 3, covering a 64% of the total observations. However, there are four other clubs. Club 1 consists of medium-low and low industries from small and open economies and eastern Europe countries (with the exception of UK and Denmark). On the other hand, club 2 encompasses more industries (8 to 12, including also two medium-high) from the majority of countries but in this case they are scattered in a more homogeneous set of countries. Club 4 demonstrates a more heterogeneous structure since it contains the entire set of the examined industries and presents a mixed behavior regarding the participating countries. Finally, club 5 consists of medium-high and low industries mainly from Scandinavian countries and countries form the Baltic sea.

Overall, the results for the efficiency change reveal no diversion in the dynamics of the convergence process for the 1996-2010 period, as displayed in Fig.5. However, after 2010 it becomes clear the effect of the global crisis and the diverse behavior of Clubs 1 & 2 compared with clubs 4 & 5. Concerning the latter, although their relative transition starts at similar levels with the other groups, they are placed near to 1.2 and display an upward trend and a significant improvement. Specific industries, such as BMF, ONM, WCP, CHM, CRP, TXT, PUP and ELO of some countries behave indifferently comparing with the other clusters. In addition, the most numerous club (club 3), starts from an initial value of one and presents a steady behavior for the entire period.

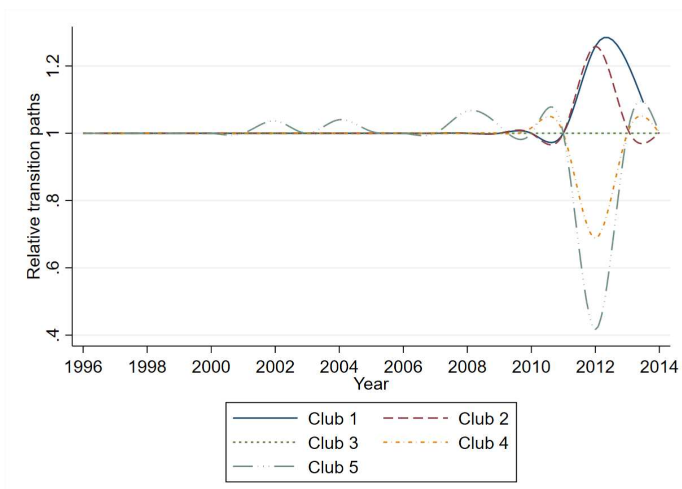

Figure 5: Relative transition paths in terms of efficiency change

Table 6: Convergence club classification: Best practice Change

Initial classification		**Tests of club converging**		
$\hat{\gamma}$ (SE of $\hat{\gamma}$)		$\hat{\gamma}$ (SE of $\hat{\gamma}$)		
Club 1 [150]	-0.496	Club1+2		
	(0.301)	-1.087*		
Club 2 [97]	1.258	(0.311)	Club2+3	
	(0.335)		-0.435*	
Club 3 [95]	0.263		(0.238)	Club3+4
	(0.215)			-0.484*
Club 4 [9]	0.207			(0.146)
	(0.266)			

Turning our attention to the best practice change, we can notice a stable behavior regarding the established clubs between the initial and final classification, as displayed in Table 6. As shown in Fig. A3, the first club includes the 42% of the total observations and consists of industries mostly from Austria, Germany, Finland, Sweden and UK. Its relative transition path, depicted in Fig.6, reveals no diversion in the dynamics of the convergence process. Clubs 2 and 3 consist of significant high number of industries from all countries. The second group includes several countries, with the majority belonging to countries such as Greece, Latvia and Bulgaria. In contrast, countries from South Europe (Spain, Portugal and Malta) and from Eastern Europe (Poland, Hungary and Slovenia) constitute the most observed countries of the club. However, club 4 differentiates in terms of industries and countries. It consists of nine observations from different industries[9] but mainly from countries like Cyprus, Czech Republic, Greece, Italy, Ireland, Malta and Spain. The relative transition paths are demonstrated in Fig.6. Even though the transition paths start at similar levels, there is a significant deterioration for all of them, with the only exception of club 1. This behavior is more intense in the case of the fourth group which shows the largest reduction in terms of BPC.

[9]It does not have any observation for the BMF, MAC, PPP and TXT industry.

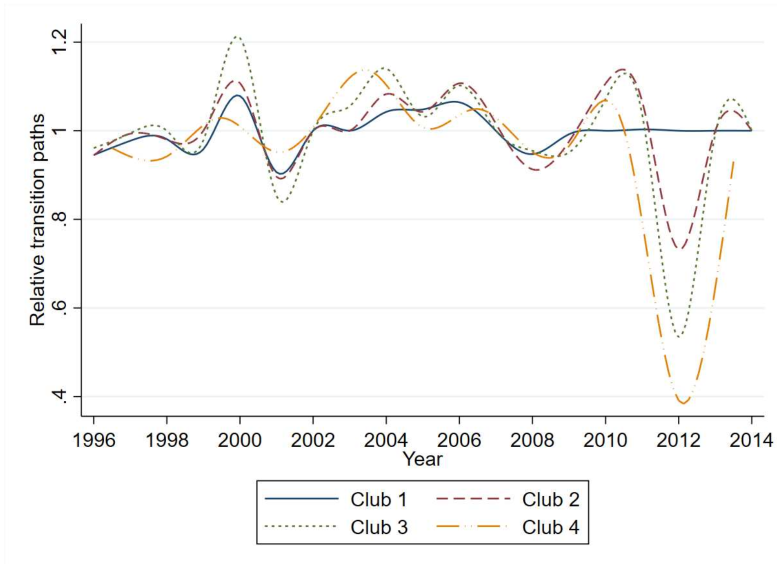

Figure 6: Relative transition paths in terms of best practice change

Table 7 shows that eight convergence subgroups are initially formed for the technology gap change case. The first group has a fitted coefficient that is significantly negative, revealing evidence of divergence. However, the t-statistic is not statistically different from zero suggesting convergence among the members of this club. The final classification supports the existence of seven clubs that converge which indicates substantial diversity in the performance among industries of EU and raises the possibility of some transitioning between the groups. Our results regarding the final classification does not support the traditional division between North and South Europe or countries that belong to the Eurozone area. However, a closer look reveals some interesting patterns, as displayed in Fig.A4. The first club with all industries includes seventeen countries with the majority of the industries belonging in countries such as France and Germany, but also in Malta and Bulgaria. The second club consists of industries belonging to countries like Austria, France, The Netherlands, UK and countries with a transition economy like Latvia. The third group presents a more compact behavior as it consists of central European countries. Conversely, Clubs 4 and 5 consist of countries mainly from Southern Europe like Cyprus and Greece. It is worth mentioning that for club 4, the industry of BMF and for club 5, MAN and RUP do not participate at all in the formation of each club respectively.

Fig.7 demonstrates the transition paths of the seventh clubs and reveals a rather complex behavior for all cases, except for club 3, one of the most multitudinous clubs, that remains close to unity with no significant fluctuations. For the rest of the clubs, different behavior and steady states are more than obvious. Moreover, a clear distinction between the rest of the groups exists after the crisis in 2010. Clubs 1 and 2 seems to reveal significant improvements regarding technology gap chance presenting a significant increase at 2012 whilst an inverse condition holds for clubs 4 to 7.

Table 7: Convergence club classification: Technology gap Change

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 [36]	0.143	Club1+2							Club 1 [36]	0.143
	(0.262)	-0.853*								(0.262)
Club 2 [99]	0.188	(0.2)	Club2+3						Club 2 [99]	0.188
	(0.261)		-0.769*							(0.261)
Club 3 [98]	0.429		(0.232)	Club3+4					Club 3 [98]	0.429
	(0.3)			-0.879*						(0.3)
Club 4 [85]	-0.418			(0.233)	Club4+5				Club 4 [85]	-0.418
	(0.264)				-1.302*					(0.264)
Club 5 [20]	0.287				(0.133)	Club5+6			Club 5 [20]	0.287
	(0.223)					-1.013*				(0.223)
Club 6 [2]	1.020					(0.161)	Club6+7		Club 6 [5]	1.02
	(0.463)						-0.172*			(0.463)
Club 7 [5]	1.509						(0.097)	Club7+8	Club 7 [8]	0.115
	(0.446)							0.115		(0.122)
Club 8 [6]	0.798							(0.121)		
	(0.212)									

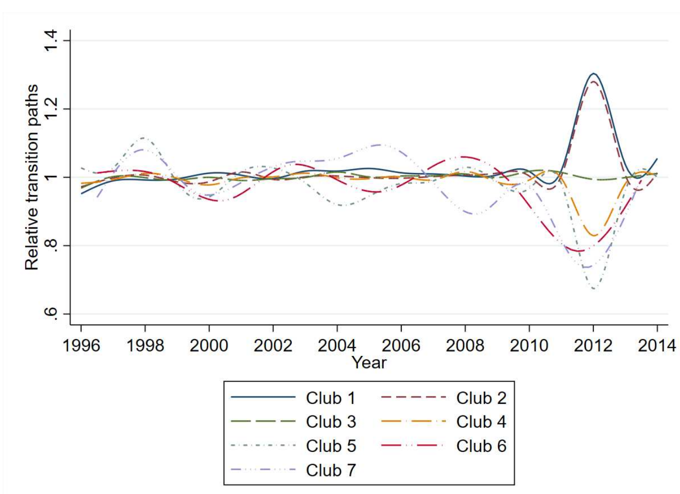

Figure 7: Relative transition paths in terms of technology gap change

5 Concluding remarks

Industrial development can have a leading role in the achievement of numerous social and economic objectives. However, it is vital for sustainability reasons to counterbalance the economic with the environmental impact of industries, regions and countries. The diffusion and the promotion of technology constitute substantial components for competitiveness and long-term economic growth, especially when referring to the manufacturing sector. Thus, the implementation of green technologies should be at the core of any industrial effort for enhancing growth and productivity levels. This study provides new evidence for the European manufacturing sector by integrating the effect of environmentally harmful byproducts in the measure of productivity. The MML index, based on the non-radial DDF, was utilized to evaluate the environmental productivity performance of 13 industries of the manufacturing sector from 27 European countries over the 1995-2014 period. Our analysis accounts for technological heterogeneity and decomposes productivity growth into technical efficiency change, best practice gap change and technical gap change. This gives us the opportunity to estimate the direct impact within its country and the indirect one calculating the effect of technological spillovers with the existence of inter-linkages between different technologies across countries.

According to our results, industrial environmental productivity has deteriorated across Europe over the study period. Best practice change was the main contributor to this decline while both measures present their lowest values during the period 2011-2012. This signifies that the financial crisis occurred in 2008 had a severe impact on the implementation of new technology systems and the investment in innovation procedures for industries afterwards. This effect is evident for the majority of industries from 2010 and onward as their productivity levels declined substantially. Technical change and technical gap change do not exhibit radical changes which indicates that industries neither catch up nor improve their technological leadership during the 1995-2014 period. Nevertheless, when referring to the technological leaders in Europe, our results point out that low technology industries tend to follow the middle-high ones. Hence, distinct European governments and authorities should support the aforementioned industries in order to influence promptly more middle-low industries through spillover effects and knowledge diffusion. Finally, policymakers should help in the removal of barriers to adopt eco-innovative and environmental friendly technologies.

These differences may be due to the occurrence of convergence since various industries from different countries are capable of developing faster and catch up with the technologically advanced industries. The results confirm the existence of convergence among industries of European countries and the formation of distinct groups of industries that converge to different points in each measure. Therefore, environmental policies should be revised regularly as a universal environmental policy might not be efficacious for the industrial environmental productivity growth due to global, regional and sectoral factors.

The findings of this study could provide policymakers credible information for the design of better specified environmental policies. More specifically, the advancement of green investment through the EU environmental strategies and mechanisms might require extreme modifications and reinforcements of the current policies across European members and their industrial structures. Notwithstanding the foregoing, policymakers should give emphasis on the integration of novel environmental technologies into industrial production process. The optimization of cleaner production technologies, the allocation of incentives for the use of particulate abatement equipment at industrial combustion facilities, the knowledge-sharing and access to information channels are only some of the possible means to support catch-up and achieve environmental productivity growth. Lastly, the design of a stable regulatory framework ensuring its stability and the generation of positive externalities through environmental spillovers between industries in different sectors and countries should be at the top of policy priorities.

Finally, despite the numerous issues addressed in this study, we would like to highlight some interesting topics for further examination in this burgeoning field of research. First of all, the examination of additional sectors of the economy and the incorporation of a wider time period and harmful by-products, when available, would be beneficial for a further analysis. Secondly, a more in-depth exploration and the disentanglement of the determinants of environmental productivity or the introduction of further assumptions on the scale properties could become a reliable tool for policymakers and national governments.

6 Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A1: List of European Countries and Manufacturing Industries

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

Figure A1: Final convergence clubs in terms of productivity growth

Club 1: (16)

BMF (LUX, SVK), **ONM** (IRL, LTU, SVK, EST), **WCP** (IRL, ROU, DNK), **CHM** (MLT), **CRP** (MLT, ROU,GBR), **TXT** (MLT), **RUP** (DNK)

Club 2: (37)

BMF (FRA, BEL, ITA, POL, ESP, DNK), **TXT** (AUT, HUN, LUX, SVN, ESP, CYP), **CHM** (GRC, AUT, ROU, BGR, GBR), **WCP** (HUN, BEL, PRT, BGR, CZE), **ONM** (ITA, NLD, PRT, GBR, DNK, AUT), **ELO** (LTU, LUX), **RUP** (BEL, NLD, ROU, EST), **PPP** (NLD, CYP, DNK)

Club 4: (54)

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

Club 5: (25)

PPP (FIN, GRC), **CHM** (HUN, SWE, EST, FIN), **CRP** (IRL, PRT), **ELO** (IRL), **FBT** (IRL, LUX, PRT, BGR, SWE, GBR, AUT), **BMF** (LVA, SWE, CYP), **TRE** (ROU, SWE), **ONM** (SVN, BGR), **MAC** (SWE), **MAN** (SWE)

Club 3: (219)

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

Figure A2: Final convergence clubs in terms of efficiency change

Club 1: (150)

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

Club 2: (97)

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

Club 3: (95)

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

Club 4: (9)

CRP (CYP), **ELO** (CYP), **CHM** (CZE), **WCP** (GRC), **MAN** (IRL), **TRE** (IRL), **ONM** (ITA), **FBT** (MLT), **RUP** (ESP)

Figure A3: Final convergence clubs in terms of best practice change

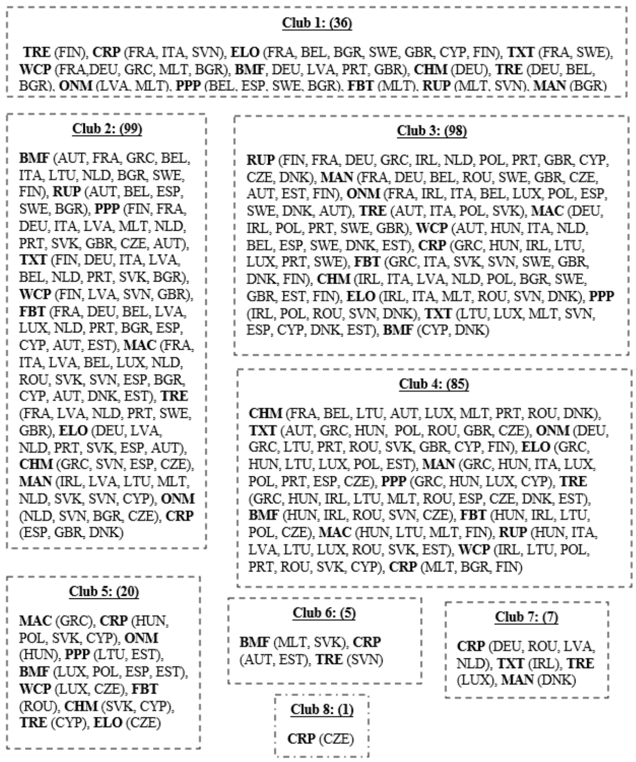

Figure A4: Final convergence clubs in terms of technology gap change

The clustering algorithm of Phillips and Sul convergence is presented as follows:

- Step 1 (Ordering): Order the individuals of the panel according to the last observation.

- Step 2 (Core Group Formation): Identification of 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.

- Step 3 (Club membership): Selection of the members of the core group (Step 2) by adding one at a time. Adding one member at a time and calculating t-statistic from the beginning. If t-statistic is greater than a chosen critical value c*,[10] then the new member 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.

[10]PS set c = 0 which ensures a high confidence of accuracy.

- Step 4 (Recursion and Stopping): The non-selected members of Step 3, will form a complementary group. We run another log(t) regression 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 uncover subgroups of convergence. If no core group is found in Step 2 then these members will diverge.

References

Aichele, R., & Felbermayr, G. (2015). Kyoto and carbon leakage: An empirical analysis of the carbon content of bilateral trade. *Review of Economics and Statistics*, 97(1), 104-115.

Battese, G. E., & Rao, D. P. (2002). Technology gap, efficiency, and a stochastic metafrontier function. *International Journal of Business and Economics*, 1(2), 87.

Beltrán-Esteve, M., Giménez, V., & Picazo-Tadeo, A. J. (2019). Environmental productivity in the European Union: A global Luenberger-metafrontier approach. *Science of The Total Environment*, 692, 136-146.

Brännlund, R., Lundgren, T., & Söderholm, P. (2015). Convergence of carbon dioxide performance across Swedish industrial sectors: an environmental index approach. *Energy Economics*, 51, 227-235.

Camarero, M., Castillo-Giménez, J., Picazo-Tadeo, A. J., & Tamarit, C. (2014). Is eco-efficiency in greenhouse gas emissions converging among European Union countries?. *Empirical Economics*, 47(1), 143-168.

Chatzistamoulou, N., Kounetas, K., & Tsekouras, K. (2019). Energy efficiency, productive performance and heterogeneous competitiveness regimes. Does the dichotomy matter?. *Energy Economics*, 81, 687-697.

Chen, S. Y. (2010). Green industrial revolution in China: a perspective from the change of environmental total factor productivity. *Economic Research Journal*, 45(10), 21-34.

Chen, K. H., & Yang, H. Y. (2011). A cross-country comparison of productivity growth using the generalised metafrontier Malmquist productivity index: with application to banking industries in Taiwan and China. *Journal of Productivity Analysis*, 35(3), 197-212.

Chen, S., & Golley, J. (2014). 'Green'productivity growth in China's industrial economy. *Energy Economics*, 44, 89-98.

Chiu, C.E., Liou, J.L., Wu, P.I., & Fang, C.L., (2012). Decomposition of the environmental inefficiency of the Metafrontier with undesirable output. *Energy Economics*, 34, 1391-1399.

Chung, Y. H., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: a directional distance function approach. *Journal of Environmental Management*, 51(3), 229-240.

Chung, Y., & Heshmati, A. (2015). Measurement of environmentally sensitive productivity growth in Korean industries. *Journal of Cleaner Production*, 104, 380-391.

Choi, Y., Oh, D. H., & Zhang, N. (2015). Environmentally sensitive productivity growth and its decompositions in China: a metafron-

tier Malmquist–Luenberger productivity index approach. *Empirical Economics*, 49(3), 1017-1043.
Costantini, V., Crespi, F., Marin, G., & Paglialunga, E. (2017). Eco-innovation, sustainable supply chains and environmental performance in European industries. *Journal of Cleaner Production*, 155, 141-154
European Commission, (2013). Commission of the European Union DECISION No 377/2013/EU OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 24 April 2013 derogating temporarily from Directive 2003/87/EC establishing a scheme for greenhouse gas emission allowance trading within the Community (accessed on 22 July 2021)
European Commission, (2018). A Clean Planet for all: A European strategic long-term vision for a prosperous, modern, competitive and climate neutral economy. (accessed on 22 July 2021)
European Commission, (2019). The European Green Deal. (accessed on 22 July 2021)
European Commission, (2020). A New Industrial Strategy for Europe. (accessed on 22 July 2021)
Färe, R., Grosskopf, S., & Pasurka, Jr, C. A. (2001). Accounting for air pollution emissions in measures of state manufacturing productivity growth. *Journal of Regional Science*, 41(3), 381-409.
Färe, R., Grosskopf, S., & Pasurka Jr, C. A. (2007). Environmental production functions and environmental directional distance functions. *Energy*, 32(7), 1055-1066.
Färe, R., Grosskopf, S., & Margaritis, D. (2008). Efficiency and productivity: Malmquist and more. *The measurement of productive efficiency and productivity growth*, 5, 522-622.
Haider, S., & Akram, V. (2019). Club convergence analysis of ecological and carbon footprint: evidence from a cross-country analysis. *Carbon Management*, 10(5), 451-463.
Haščič, I., Johnstone, N., Watson, F., & Kaminker, C. (2010). Climate Policy and Technological Innovation and Transfer: An Overview of Trends and Recent Empirical Results, *OECD Environment Working Papers*, No. 30, OECD Publishing, Paris.
He, F., Zhang, Q., Lei, J., Fu, W., & Xu, X. (2013). Energy efficiency and productivity change of China's iron and steel industry: Accounting for undesirable outputs. *Energy Policy*, 54, 204-213.
IPCC, (2021). Summary for Policymakers. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press. In Press.

Isaksson, O. H., Simeth, M., & Seifert, R. W. (2016). Knowledge spillovers in the supply chain: Evidence from the high tech sectors. *Research Policy*, 45(3), 699-706.

Kounetas, K., Mourtos, I., & Tsekouras, K. (2012). Is energy intensity important for the productivity growth of EET adopters?. *Energy economics*, 34(4), 930-941.

Kumar, S. (2006). Environmentally sensitive productivity growth: a global analysis using Malmquist–Luenberger index. *Ecological Economics*, 56(2), 280-293.

Lee, H. (2021). Is carbon neutrality feasible for Korean manufacturing firms?: The CO2 emissions performance of the Metafrontier Malmquist–Luenberger index. *Journal of Environmental Management*, 297, 113235.

Li, K., Impact of energy conservation policies on the green productivity in China's manufacturing sector: Evidence from a three-stage DEA model. *Applied energy*, 168, 351-363.

Lin, E. Y. Y., Chen, P. Y., & Chen, C. C. (2013). Measuring green productivity of country: A generlized metafrontier Malmquist productivity index approach. *Energy*, 55, 340-353.

Los, B., & Verspagen, B. (2002). An introduction to the analysis of systems of innovation: scientific and technological interdependencies. *Economic Systems Research*, 14(4), 315-322.

Mahlberg, B., & Sahoo, B. K. (2011). Radial and non-radial decompositions of Luenberger productivity indicator with an illustrative application. *International Journal of Production Economics*, 131(2), 721-726.

Malmquist, S. (1953). Index numbers and indifference surfaces. *Trabajos de estadística*, 4(2), 209-242.

Manning, S., Boons, F., Von Hagen, O., & Reinecke, J. (2012). National contexts matter: The co-evolution of sustainability standards in global value chains. *Ecological Economics*, 83, 197-209.

Maskus, K. (2010), Differentiated Intellectual Property Regimes for Environmental and Climate Technologies, OECD Environment Working Papers, No. 17, OECD Publishing, Paris, .

Nikzad, R., & Sedigh, G. (2017). Greenhouse gas emissions and green technologies in Canada. *Environmental Development*, 24, 99-108.

Oh, D. H. (2010). A metafrontier approach for measuring an environmentally sensitive productivity growth index. *Energy Economics*, 32(1), 146-157.

Pasurka Jr, C. A. (2006). Decomposing electric power plant emissions within a joint production framework. *Energy Economics*,

28(1), 26-43.
Phillips, P. C., & Sul, D. (2007). Transition modeling and econometric convergence tests. *Econometrica*, 75(6), 1771-1855.
Saliola, F., & Zanfei, A. (2009). Multinational firms, global value chains and the organization of knowledge transfer. *Research policy*, 38(2), 369-381.
Skjærseth, J. B. (2021). Towards a European Green Deal: The evolution of EU climate and energy policy mixes. *International Environmental Agreements: Politics, Law and Economics*, 21(1), 25-41.
Stergiou, E., & Kounetas, K. (2021a). European Industries' Energy Efficiency under Different Technological Regimes: The Role of CO2 Emissions, Climate, Path Dependence and Energy Mix. *The Energy Journal*, 42(1).
Stergiou, E., & Kounetas, K. E. (2021b). Eco-efficiency convergence and technology spillovers of European industries. *Journal of Environmental Management*, 283, 111972.
Tsekouras, K., Chatzistamoulou, N., & Kounetas, K. (2017). Productive performance, technology heterogeneity and hierarchies: Who to compare with whom. *International Journal of Production Economics*, 193, 465-478.
Tulkens, H., & Eeckaut, P. V. (1995). Non-parametric efficiency, progress and regress measures for panel data: methodological aspects. *European Journal of Operational Research*, 80(3), 474-499.
Weber, W. L., & Domazlicky, B. (2001). Productivity growth and pollution in state manufacturing. *Review of Economics and Statistics*, 83(1), 195-199.
Wielgosiński, G. (2012). *Pollutant formation in combustion processes*. Advances in chemical engineering, 295-324.
Zhang, C., Liu, H., Bressers, H. T. A., & Buchanan, K. S. (2011). Productivity growth and environmental regulations-accounting for undesirable outputs: Analysis of China's thirty provincial regions using the Malmquist–Luenberger index. *Ecological Economics*, 70(12), 2369-2379.
Zhou, P., Ang, B. W., & Wang, H. (2012).Energy and CO2 emission performance in electricity generation: a non-radial directional distance function approach. *European journal of operational research*, 221(3), 625-635.