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Environmental Efficiency, Productive Performance and Spillover Effects under heterogeneous Environmental Awareness Regimes

Nikos Chatzistamoulou

Phoebe Koundouri

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Dr. Nikos Chatzistamoulou

Post-doctoral researcher in Economics

Phoebe Koundouri

Professor of Economics & Econometrics

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Abstract

In this paper we explore whether environmental efficiency at a global scale is affected by the existence of heterogeneous environmental awareness and implementation regimes. By adopting a first stage non parametric metafrontier framework to handle technological heterogeneity the bias corrected productive performance of each country economy as well as the environmental efficiency via the Directional Distance Functions approach are calculated for each of the 104 country economies considered from 2006 through 2014, on an annual basis. In the second stage, we employ a fractional probit model to investigate the variability of environmental efficiency. Findings indicate that productive performance appears to be a driver of environmental efficiency only for the environmentally aware country economies. Absorptive capacity seems to play a crucial role too. A rebound effect is also observed for the universal technology as well as for the environmentally aware country economies. The less environmentally aware country economies do not seem to respond the same way to the same set of factors, indicating that there exist mechanisms that cannot be captured by observed characteristics.

Keywords: Environmental Efficiency, Sustainable Development Goals, Metafrontier & Heterogeneity, Productive Performance, Spillover Effects

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1. Introduction & motivation

Productivity has always been in the centre of attention and one of the main pillars of the prosperity of the economy at a universal level. Technological heterogeneity, technical change and innovation, competitiveness level, climate change, environmental regulation and policy directives all have their own merit on the intertemporal productivity change. It is an undeniable truth that economies at a universal level evolve following different trajectories as a result of a different development plan. At the same time, welfare improvement comes with draining scarce resources or even wasting resource endowment. Therefore, action should be taken to prevent such behaviour and ensure the prosperity of future generations.

To this end, the Sustainable Development Goals which are a United Nations Initiative are expressed as targets to achieve organized in 17 global goals related to economic development issues including poverty, hunger, health, education, global warming, gender equality, water, sanitation, energy, urbanization, environment and social justice. From a more tangible perspective, the World Bank through the World Development Indicators database, provides data on a variety of indicators related to those Global Goals.

However, although agreed among the member states, the goals do not constitute an obligation. Therefore, heterogeneous sustainable development levels exist across the globe as countries face uneven technological opportunities and access to resources affecting productivity. Put it another way, heterogeneous patterns regarding the levels of sustainable development goals implementation exist. In this vein, it is natural to ask whether the variability in those indicators could be used to explore performance patterns of heterogeneous co-existing groups. In other words, whether performance improvement is related to sustainable development levels.

In this paper, we consider a mix of Sustainable Development Goals (SDG) in order to study *whether the existence of heterogeneous environmental awareness and development groups mirrors differences in environmental efficiency change patterns.* Previous studies have employed different factors such as income level, geographical location (Oh & Lee, 2010) to study productivity change, however to the best of our knowledge no systematic attempt has been surfaced yet to group countries based on indicators related to the SDG.

The contribution of this work is twofold. First, from a conceptual standpoint, we combine a set of SDG indicators mirrored by the environment indicators from the World Bank database to construct the partitioning factor of the universal technology which incorporates information on each country taking into consideration the uneven levels of development and access to technology. Such being the case, we use all observed as well as other aspects of technological heterogeneity impossible to capture adopting the metafrontier framework. Second, we bring to the forefront the link between the SDG and productivity which for the time being it is an unexplored area.

All in all, this paper is the first attempt to study the relationship a resource efficiency measure such as environmental efficiency with other performance measures such as productive performance and spillover effects considering the existence of heterogeneous environmental awareness and implementation regimes through a heterogeneity framework To the best of our knowledge, no other studies have surfaced yet to explore such a question, and therefore it remains a void to be filled.

This paper unfolds as follows. The next section offers a brief review of the relevant literature, Section 3 presents the methods adopted and research hypotheses, Section 4 presents the data, Section 5 is dedicated to the results and discussion while Section 6 concludes the paper.

2. Related literature

There is ample literature regarding environmental performance. The topic has been explored across the globe through various empirical applications. There are country specific studies such as studies in China, Netherlands, Germany, Finland, continent specific such as U.S and Europe, as well as more general ones considering the case of OECD countries. The topics vary from assessing environmental performance starting from the lowest level of aggregation that is firm level to considering competitiveness, economic growth, innovation in explaining the variation in environmental performance patterns. Although this section does not mean to be exhaustive by listing all research efforts on the topic in a purely systematic way, it provides the reader with a roadmap on the topic.

For a long time, the famous porter hypothesis has been a beacon for research proliferation even though the literature is quite dissected validation-wise. A recent study by Rubashkina et al. (2015) tests for weak and strong versions of the Porter Hypothesis and thus relates environmental regulation and competitiveness using a panel of manufacturing industries in 17 EU countries over the period 1997-2009 to find evidence in favour of the weak version while productivity appeared to be unaffected by the stringency of environmental regulation. An earlier study by Costantini and Crespi (2008) focusing on the export flows of environmental technologies across the globe, provide support for the Porter and Van den Linde hypothesis stating that it has brought to the forefront the role of energy policy design as a mechanism towards sustainability. The Kyoto Protocol directives are also in this line boosting innovation in the energy sector. In the same line, Hart (2004) presents theoretical models falling in the context of the endogenous growth theory to model technical change and the environment, concluding that penalizing dirty ways of production is beneficial not only for social utility but also improve the growth rate of production and thus it falls in the group of studies supporting the Hypothesis.

When proceeding with cross-nation comparisons, researchers should be very cautious as there are heterogenous patterns in technology that affect performance. Therefore, the need for a methodological framework embracing all possible aspects of heterogeneity is imperative. The concept of the meta-production function of Hayami (1969) and Hayami and Ruttan (1970) materialized through the metafrontier framework of O'Donnell et al. (2006) which set a new perspective in efficiency analysis. Ever since, many empirical studies have adopted the framework to account for technology heterogeneity using various methodologies for performance assessment.

For instance, Wei et al. (2019) handle heterogeneity by applying the modified method of Metafrontier Malmquist Luenberger Index (MML). They partition the overall technology of the 97 Paris Agreement contracting countries by income level for the period 1990-2014 to find that heterogeneity affects the MML patterns across the groups. Moreover, in order to enhance the total-factor carbon dioxide emission efficiency, they emphasise that advancement and innovation energy technology are the main channels towards this direction. Wang et al., (2019) use a variant of the MML on the G20 countries from 2000 to 2014 to make environmental efficiency comparisons as well. Feng and Wang (2019) find positive evidence related to pollution migration in China for the period 2001-2016 as the emissions efficiency improved.

The cross-country examination of environmental performance patterns has been facilitated by the metafrontier framework as well. In this line, Kounetas and Zervopoulos (2019) examining convergence and divergence patterns of environmental performance in developing and developed countries find significance differences across the groups considered while Sun et al. (2019) by adopting the metafrontier framework calculate the technology gap of heterogeneous circular systems in China for the period 2007 through 2016 and reveal that geography affects performance. Li and Lin (2019) extent previous research on the influence of environment on economic growth by examining sustainable total factor productivity growth patterns in emerging economies, raising concerns about its continuation as the latter lack in innovation even though benefit by the existing technological achievements via catch-up effects.

Heterogeneity analysis shows that sustainable growth in emerging technologies could be boosted by technological spillovers from the developed ones. Chatzistamoulou et al. (2019) acknowledge the endogeneity stemming from the use of the metafrontier in investigating the relationships between performance measures and more precisely that of energy efficiency and productive performance under heterogeneous competitiveness regimes, find a weak endogenous relationship between performance measures and that the countries in the less competitive group benefit more by spillover effects compared to the competitive cluster.

The literature has been expanded to include climate and environmental footprint assessment studies focused on industry applications to explore the effect of sustainable construction on resource efficiency (Tan et al., 2011) while others focus on the environmental tax reform in the EU-27 under the Kyoto protocol, to find that technological spillover effects mitigate the negative effects of carbon leakages (Barker et al., 2007). The impact of spillover effects on resource efficiency measures such as energy efficiency, environmental efficiency and productive performance, under a technology heterogeneity framework has been acknowledged in a series of recent contributions as well (Tsekouras et al., 2016; Chatzistamoulou et al., 2019).

A significant amount of studies regarding environmental and energy efficiency i.e. resource efficiency measures have surfaced aiming to explore the economy of China. Chang et al., (2013), analyse the environmental efficiency of Chinas' transportation industry by proposing a non-radial DEA model with slack-based-measures to find that the latter lacks in efficiency as most of the provinces are far the eco-efficient version of the industry. Other sectoral studies include the work of Zofio and Prieto (2001) who calculate the environmental efficiency of the OECD's manufacturing industries under many CO2 regulatory scenarios highlighting the use of the non-parametric techniques in assessing environmental performance. Other applications of environmental efficiency estimation include the construction industry in China (Xian et al., 2019) and the international trade and telecommunications industry (Perkins & Neumayer, 2009), just to mention a few. It should be noted that the relationship among environmental policy, environmental performance and competitiveness depends on the application considered e.g. sector selected (Iraldo et al., 2011).

To sum up, it is therefore evident that despite the quite broad frame of applications scattered in the literature, there is a void to be filled regarding the impact of sustainability and especially how heterogeneous sustainability and awareness regimes affect the environmental performance of each economy. This is particularly relevant nowadays under the urgency to set economies into a smooth transition trajectory leading to a sustainable future as it is promoted by global initiatives such as the Sustainable Development Goals as well as the European Green Deal.

3. Methodological and theoretical considerations

3.1 Environmental awareness level as partitioning factor

In order to restrict the distorting role of technological heterogeneity on the benchmarking process (Dosi et al., 2010), we use statistical techniques to create relatively homogeneous groups in line with the literature (Chui et al., 2012; Lin et al., 2013; Zhang et al., 2014; Wang et al., 2016).
We combine principal components analysis (PCA) with varimax rotation as a dimension reduction tool (Genious et al., 2014), annually considering fifty-six Environment indicators mirroring aspects of several Sustainable Development Goals to construct the partitioning factor of the universal technology. Then we apply the *k-means* clustering to give rise to heterogeneous environmental awareness and implementation regimes reflecting differences about the extent of environmental awareness and SDGs' implementation across the globe (Chatzistamoulou et al., 2019).

Thus, we give rise to two regimes based on the (low) environmental awareness and implementation extent of SDGs, (onwards, LEAIR and EAIR). This paves the way to investigate the effect of many aspects associated with the SDGs on the environmental efficiency patterns across the globe. Although possible to create more than two groups, the number of entities under each production frontier would be reduced and more entities would have been falsely identified as fully efficient (Dyson et. al., 2001).

3.2 Performance evaluation under heterogeneous environmental awareness regimes

3.2.1 Productive performance; the Data Envelopment Analysis technique

A country economy $i = 1,2, \dots, n$ may be considered as a Decision Making Unit (DMU) transforming inputs $x = (x_{1i}, x_{2i}, , \dots, x_{Ni},) \in \Re_+^N$ into outputs $y = (y_{1i}, y_{2i}, , \dots, y_{Mi},) \in \Re_+^M$ under a technology set S defined as $S \equiv \{(x, y): x\ can\ produce\ y\}$. For the input-oriented productive performance scores, the technology is represented by the production possibility set $L(y) = \{x \in \Re_+^N: (x, y) \in S\}$, while for its measurement the input distance function defined as $D_I(x, y) = sup\{\theta > 0: x/\theta \in L(y)\}$ is used. In the case where two environmental awareness and implementation regimes (technologies) T^{LEAIR}, T^{EAIR} exist, the metatechnology set, denoted as T^M, can be defined as the convex hull of the jointure of the two technology sets represented as $T^M = \{(x, y: x \geq 0, y \geq 0)\ x\ can\ produce\ at\ least\ one\ of\ T^{LEAIR}, T^{EAIR}\ \}$ (Battesse et al., 2004). The technology set can be defined in the same way for the single technology.

We follow a two-stage analysis. In the first stage, by adopting the metafrontier framework (onwards universal technology) as introduced by Hayami (1969) and Hayami and Ruttan (1970) and further developed by O'Donnell et al., (2008), and employing the bootstrap version of the input-oriented Data Envelopment Analysis (DEA) technique under variable returns to scale to account for size effects (Halkos & Tzeremes, 2009), we calculate the bias corrected productive performance (*MTEff*) of each country economy with respect to the universal technology using the following formula:

$$MTEff_i \equiv \hat{\theta}(x,y) = \min\{\theta | \theta > 0, y \leq \textstyle\sum_{i=1}^{n} \gamma_i y_i; \theta x \geq \sum_{i=1}^{n} \gamma_i x_i \text{ for } \gamma_i \qquad (1)$$

such that

$$\left.\sum_{i=1}^{n} \gamma_i = 1;\ \gamma_i \geq 0\,, i = 1,2,..,K\right\}$$

Productive performance (*ProdPerf*) of each country economy is calculated within each regime by employing Eq. (1). The meta-technology ratio (*MTR*) and the corresponding technology gap (*Tg*) are calculated for each country economy on an annual basis, using the formulas below:

$$MTR_i(x,y) = \frac{MTEff_i(x,y)}{ProdPerf_i(x,y)} \qquad (2)$$

$$Tg_i(x,y) = 1 - MTEff_i(x,y) \qquad (3)$$

The technology gap is defined as the distance of the individual frontier to the universal technology, weighted with the minimum inputs which are attainable employing the group-specific technology. It may be thought of as the opportunity cost of not adopting the best available level of technology whereas it captures catching up and falling behind phenomena in the form of incoming spillovers (Chatzistamoulou et. al., 2019).

3.2.2 Environmental efficiency; the Directional Distance Functions approach

Departing from the work of Chambers et al., (1996), Chung et al., (1997) and Fare and Grosskopf (2000) we assume that the production technology T models the transformation of a vector of inputs $x \in \Re_+^N$ that each country economy employs to produce a vector of outputs $y^* \in \Re_+^M$. We can discern two kinds of outputs, the desirable output $y = (y_1, y_2 \dots, y_k) \in \Re_+^K$ and the undesirable output $b = (b_1, b_2 \dots, b_l) \in \Re_+^L$ respectively[1] (Kumar & Khanna, 2009). The underlying production process is constrained by the technology set[2] T defined as $T(x) = \{(y,b): x\ can\ produce\ (y,b)\}$ (Dervaux et al., 2009).

The directional distance function (DDF) is a representation of a multi-input, multi-output distance function. Following Chambers et al., (1998) and Picazo-Tadeo et al., (2005) the DDF on technology T is defined as:

$$\overrightarrow{D_T}\left(x, y, b; g_y, g_b\right) = max\{\beta^*: \left(x, y + \beta^* g_y, b - \beta^* g_b\right) \in T(x, y, b)\} \tag{4}$$

Indeed, the DDF projects the input-output vector (x, y) onto the technology frontier in the $\left(g_y, -g_b\right)$ direction allowing desirable outputs to be proportionally increased, whereas bad output(s) to be proportionally decreased. More precisely, it seeks the maximum attainable expansion of desirable outputs in direction $\left(g_y\right)$ and the largest feasible contraction of the undesirable outputs in direction$(-g_b)$. Considering that the technology set has been restricted only to the production of good output[3], the environmental efficiency at the European technology level i.e. metafrontier, $EnvEff^{MF}$, may be defined as follows:

$$EnvEff^{MF} = \frac{\left(1+\overrightarrow{D_T^{MF}}(x,y,b;g_y,g_b)\right)}{\left(1+\overrightarrow{D_T^{MF}}(x,y,b;g_y)\right)}, \tag{5}$$

with the environmental efficiency for the individual production frontiers to be defined in an analogous manner.

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[1] Note that the two different output sets are actually sub-vectors of the $y^* \in \Re_+^M$output set.

[2] The technology set corresponds to all technologically feasible relationships between inputs and outputs while at the same time it satisfies a set of axioms discussed in Shepard (1953; 1970) and Luenberger (1992; 1995) that is (i) inactivity is allowed, (ii)"free lunch" is not allowed (Kumar, 2006), (iii) technology is convex, bounded and closed (Chambers et al., 1996), (iv) good outputs are "null-joint" with the bad outputs and (v) free availability of inputs and outputs (see Zhou et al., 2012 for a further discussion).

[3] $\overrightarrow{D_T}\left(x, y, b; g_y\right)$ is defined as $\overrightarrow{D_T}\left(x, y, b; g_y\right) = \max\left\{\beta^*: \left(x, y + \beta^* g_y\right) \in T\left(x, y\right)\right\}$.

The environmental efficiency index ($EnvEff^{MF}$) aims to capture the contraction in increasing outputs by each industry under the potential ability of the production process convention from free disposability to costly disposal of CO_2 taking values between zero and one. Conceptually, for an industry with environmental efficiency score equal to one, the cost of transforming their production from strong disposability to weak for CO_2 should be zero while values lower than one denote a significant opportunity cost for this transformation (Kumar & Khanna, 2009).

Furthermore, environmental efficiency has been defined as the ratio of two distance functions assuming strong and weak disposability of CO_2 emissions. Since the frontier, which was constructed assuming weak disposability of pollutants, envelops the data more closely than the frontier constructed assuming strong disposability, the ratio of those two distances leads to values very close or equal to one (Zaim & Taskin 2000).

3.3 Econometric Strategy

3.3.1 Estimation using Fractional Regression Models

Much of the research on DEA based efficiency analysis during the past decades, have relied to the binary response dependent variable models to explain the variability in the performance scores attained by the first stage analysis (Gillen & Lall, 1997; Merkert & Hensher, 2011). A systematic review of modelling second stage DEA scores is provided by (Hoff, 2007).

However, Papke and Wooldridge in a series of papers (1996; 2008) have introduced a more appropriate methodology, like the generalized least squares, to handle variables that come in proportions, shares and in general variables that vary between zero and one. Put it another way, variables considered as fractions such as in the case of environmental efficiency. In the case of efficiency scores, despite the popular use of Tobit models, the censoring those apply does not appear to be applicable to variables that do not exceed those boundaries.

Despite the strong distribution assumptions attached, the flaw of those econometric approaches is that extreme values require transformations (Maddala, 1986) to be usable in the estimation process (Maddala, 1986). From the one hand, in many cases, it quite safe to proceed with conventional Tobit, Probit and Logit models, under the presence of technological heterogeneity, those models are not quite adequate to capture the nature of the variables of interest. On the other, linear models may also not be appropriate in handling incremental changes of the explanatory variables on the dependent since those estimate constant partial effects (Noreen, 1988; Maddala, 1991), especially as the latter reaches its boundaries because there might be ceiling and floor effects i.e. pilling up towards boundaries (Papke & Wooldridge, 1996; Gallani et al., 2015).

Papke and Wooldridge (1996; 2008) propose and develop the idea of fractional regression models (FRM) overcome the obstacles posed by the boundedness of some variables with observations pilling up at the corners making the functional form behind binary choice models inappropriate to predict the expected values at the corners. The FRM exploit data non-linearities to calculate the average partial effects at different percentiles of the predictor(s) distribution (Greene, 2003) whereas its usefulness has been criticised as it is not applicable to data with repeated measurements i.e. panel data, for the time being. Additionally, as FRM is actually an extension of the generalised linear models (GLM) do not require data transformations for values at the tails, account for non-linearities in the data, and achieve a better fit for the model, compared to linear estimation models. Structural parameters are estimated via quasi-maximum likelihood which produces robust and relatively efficient estimates, under the GLM assumptions (Gallani et al., 2015).

Considering the above, we combine the benefits of the metafrontier framework with the analytical power of the FRM to explore the patterns of environmental efficiency under heterogeneous environmental awareness and implementation of sustainable development goals regimes.

3.3.2 Modelling environmental efficiency

In the second stage, we turn the spotlight on modelling the environmental efficiency considering three empirical models. Such being the case, we specify and estimate the following models for the metafrontier i.e. universal technology level as well as for the two heterogeneous environmental awareness and implementation level regimes by employing three pooled fractional probit models:

$$EnvEff_{it}^{MF} = \beta_0 + \beta_1 ProdPerf_{it} + \beta_2 TechnologyGap_{it-1} + \beta_3 GCI_{it-1} + \beta_4 FraserIndex_{it} + \beta_6 EconStruIndex_{it} + \beta_7 Renewables_{it} + \beta_8 Switch_{it} + \boldsymbol{\gamma YearEffects} + u_{it} \quad (6)$$

$$EnvEff_{it}^{EAIR} = \delta_0 + \delta_1 ProdPerf_{it} + \delta_2 TechnologyGap_{it-1} + \delta_3 GCI_{it-1} + \delta_4 FraserIndex_{it} + \delta_6 EconStruIndex_{it} + \delta_7 Renewables_{it} + \delta_8 Switch_{it} + \boldsymbol{\rho YearEffects} + v_{it} \quad (7)$$

$$EnvEff_{it}^{LEAIR} = \lambda_0 + \lambda_1 ProdPerf_{it} + \lambda_2 TechnologyGap_{it-1} + \lambda_3 GCI_{it-1} + \lambda_4 FraserIndex_{it} + \lambda_6 EconStruIndex_{it} + \lambda_7 Renewables_{it} + \lambda_8 Switch_{it} + \boldsymbol{\varrho YearEffects} + v_{it} \quad (8)$$

where $EnvEff_{it}^{MF}$, $EnvEff_{it}^{EAIR}$ and $EnvEff_{it}^{LEAIR}$ correspond to the environmental efficiency of the *i-country* in year *t* with respect to the universal technology as well as of the one of each distinct regime considered.

In this paper, the main interest is placed on exploring the influence of productive performance ($ProdPerf_{it}$), absorptive capacity captured by the lagged value of competitiveness level (GCI_{it-1}) and spillover effects captured by the lagged value of technology gap ($TechnologyGap_{it-1}$) as drivers of the environmental efficiency. We use one lag to allow for the effects to diffuse into the system. We formulate the following research questions to be tested:

> H_1: *Productive performance exerts a positive and significance influence on environmental efficiency, at all levels of aggregation i.e. universal technology as well as heterogeneity regimes.*

By rejecting the null, we are inclined to think that there is a sort of inefficiency in the allocation of resources when the strategic orientation of the country is to improve productive performance within a limited time window.

The role of competitiveness has been acknowledged by the literature (Eichammer, & Walz, 2011; Tsekouras et al., 2016; 2017; Chatzistamoulou et al., 2019; Gkypali et al., 2019) and in this context it is captured by the GCI which is country-specific and time-varying. Lagged values of competitiveness capture a country's absorptive capacity indicating the ability to transform technological achievements into improved performance (Cohen & Levinthal, 1989; 1990) while it reinforces the ability and potentiality to absorb accumulated knowledge generated across aspects of the economy. This can be formally stated in the form of a testable hypothesis as:

> H_2: *The level of absorptive capacity enhances environmental efficiency at the universal level as well as that of the heterogeneous environmental awareness regime each country economy belongs to.*

By rejecting the null would imply that low technological opportunities and assimilation ability negatively affect the environmental efficiency.

The influence of incoming spillover effects in explaining performance patterns has been acknowledged before by the literature (Tsekouras et al., 2016; Chatzistamoulou et al., 2019), thus it is reasonable to include it in explaining environmental efficiency patterns. This can be formally stated in the form of a testable hypothesis as:

> H_3: *Incoming spillover effects generated at the universal technology level affect the environmental efficiency of each regime exerting a positive and significant influence.*

Thus, by rejecting the null is an indication that action is required to enhance technology sharing as well as promoting the environment indicators incorporated in each regime

Additional variables such as the Frazer index ($FraserIndex_{it}$,) and the Economy Structure index $EconStrIndex_{it}$ have been included to capture the overall performance to the Fraser Index while the economy structure index which has been created by combining[4] the share of industry, manufacturing and services on the national product capturing the production environment of each country, respectively. Rec_{it} is the share of renewable energy consumption, at the country level, capturing the use of resource-saving and environmentally aware technologies paving the way for environmental efficiency improvement. The variable $Switch_{it}$ captures switches between the two regimes at the universal technology level and has been included in the model to give a dynamic flavour into the analysis. Year dummies are used to capture year heterogeneity while u_{it}, υ_{it} and v_{it} are the disturbance terms. The parameters to be estimated are $\boldsymbol{\beta}, \boldsymbol{\delta}, \boldsymbol{\lambda}, \boldsymbol{\gamma}, \boldsymbol{\rho}$ *and* $\boldsymbol{\varrho}$.

4. Data & variables

We devise a unique panel by coordinating, matching and harmonizing several distinct yet complementary publicly available databases covering 104 country economies on a global scale over nine years, from 2006 through 2014. Therefore, the panel includes 936 observations. The novelty of this dataset is found on the use of indicators of the World Bank Environment category, associated with the Sustainable Development Goals (SDGs) initiative, to create the partitioning factor to give rise to alternative environmental awareness and implementation regimes (EAIR).

As far as the estimation of the first stage is concerned, we collect data on two outputs and three inputs. Outputs include the Gross Domestic Product (GDP) capturing the desired output of each country economy (measured in mil. US$) and the anthropogenic carbon dioxide emissions (CO_2) capturing the undesired output of the production processes in each of the economies (measures in kt). Inputs include the capital captured by the capital stock of each country economy (measured in mil. US$), labour proxied by the number of persons engaged in each country economy (measured in mil.) and the energy captured by the energy use (measured in kt of oil equivalent). Monetary values are in constant 2011 prices.

To create the partitioning factor, we collect data on around 140 indicators related to the use of natural resources and changes in the natural and built environment. They encompass the availability and use of environmental resources (forest, water, cultivable land, and energy) and cover environmental

[4] This has been done by employing the Principal Components Analysis (varimax rotation).

degradation (pollution, deforestation, and loss of habitat and biodiversity). They also include aspects of the built environment such as agricultural infrastructure and urbanization (World Bank, 2018). More precisely, the indicators collected mirror aspects of a wide variety of the Sustainable Development Goals initiative launched in 2015-16 by the United Nations and correspond to Goal 2 (promoting sustainable agriculture), Goal 6 (considering availability of and access to water), Goal 7 (covering reliable energy), Goal 11 (tackling urbanization challenges), Goal 12 (consumption & sustainable management of earth's resources), Goal 13 (action on climate change), Goal 14 (conservation of oceans & marine life), and Goal 15 (protection of natural habitats, biodiversity and land restoration efforts). The environment indicators illuminate many of these issues (World Bank, 2018).

Regarding the second stage analysis, additional variables have been collected. to account for as many as possible aspects of the production environment. Particularly, we include detailed data on the Global Competitiveness Index (GCI), its sub-indices (Basic requirements, Efficiency enhancers, Innovation & Sophistication) as well as on the twelve pillars it encompasses. Although GCI has been used and proved a quite useful tool in the empirical analysis (Tsekouras et al., 2016; 2017, Chatzistamoulou et. al., 2019, Gkypali et al., 2019), such detailed data on its components are employed for the first time. Moreover, the structure economy is proxied by the contribution of the industry, manufacturing, services and renewable energy use to the GDP.

Data on the Gross Domestic Product, Labour and Capital have been collected through the Groningen Growth and Development Centre (GGDC), World Penn Tables 9.0. Data on the Environment indicators have been collected through the World Sustainable Indicators (WSI) database of the World Bank. Carbon dioxide emissions, Energy use, Renewable energy use, Industry, Manufacturing & Services contribution have been collected through the World Bank. Data on GCI, components and pillars have been hand-collected through various releases of the Global Competitiveness Report published by the World Economic Forum on an annual basis, while data on the Economic Freedom index was collected through the Fraser Institute official site. Tables 1 and 2 below provide basic descriptives of the main variables and brief description of the dataset respectively.

Table 1 Basic Descriptive statistics (Means & St. Dev.) for the main variables, 2006-2014

	Universal	EAIR	LEAIR
GDP	825,045 (2,129,040)	903,698 (2,254,718)	736,381 (1,976,624)
CO_2	287,336 (1,026,434)	324,622 (1,122,714)	245,304 (905,157)
K	2,855,233 (7,207,575)	3,131,751 (7,705,912)	2,543,522 (6,595,734)
L	26.894 (90.768)	28.890 (99.073)	24.644 (80.437)
E	2,363 (2,302)	2,592 (2,384)	2,105 (2,180)
GCI score	4.29 (.63)	4.39 (.61)	4.19 (.63)
Basic requirements score	4.62 (.74)	4.74 (.70)	4.49 (.77)
Efficiency enhancers score	4.18 (.66)	4.27 (.64)	4.08 (.66)
Innovation & sophistication score	3.85 (.78)	3.93 (.79)	3.76 (.76)
REC	27.88 (25.30)	23.29 (20.87)	33.06 (28.65)
Industry	28.04 (10.12)	28.87 (10.49)	27.11 (9.60)
Manufacturing	14.50 (6.57)	14.87 (6.79)	14.09 (6.30)
Services	55.24 (9.79)	55.69 (9.81)	54.72 (9.75)

Table 2 Variables and Sources

Variable	Brief description	Units of measurement	Source
GDP	Real Gross Domestic Product, national prices	million US $	GGDC
K	Capital stock, national prices	million US $	
L	Number of persons engaged	millions	
CO_2	Anthropogenic carbon dioxide emissions	kiloton (kt)	World Bank
E	Energy use	kg of oil equivalent per capita	
Environment indicators	Indicators mirroring aspects of the Sustainable Development Goals	Mostly percentages	World Bank/ World Development Indicators Database
GCI	Overall Global Competitiveness Index score	Pure number	World Economic Forum
Basic requirements	Score in component 1, 4 pillars		
Efficiency enhancers	Score in component 2, 6 pillars		
Innovation & sophistication	Score in component 3, 2 pillars		
REC	Renewable energy consumption, % of total final energy consumption	Percentage	World Bank, Sustainable Energy for All database
Industry	Industry including construction, value added % of GDP	Percentage	World Bank
Manufacturing	Manufacturing value added (% of GDP		
Services	Value added (% of GDP)		

5. Results, discussion & policy suggestions

5.1 Exploring sustainability, competitiveness and environmental performance indices

In this section we explore three indices attached to each country economy that are used to facilitate comparisons on a global scale. First, we focus on the Sustainable Development Goals index (hereafter SDGs index), then the attention is placed on the Global Competitiveness index, its components along with its pillars and then we present evidence on the environmental performance index for the one hundred and four country economies participating in our sample. Data for these indices cover a three-year period i.e. from 2016 through 2018 but each of them needs tailored attention as each of them refers to different years.

The idea of the SDGs index surfaced in 2015 when members of the United Nations agreed on the Agenda 2030 and the Sustainable Development Goals to improve the wellbeing of nations using a commonly accepted set of targets. The SDGs is an evolution of the Millennium Development Goals that includes not only emerging and developing countries but also covers industrialized nations. Specifically, the SDG Index and Dashboards Report providing insights on the performance of country economies on the seventeen SDGs[5], is co-produced by the Bertelsmann Stiftung and the Sustainable Development Solutions Network (SDSN) every year since 2016 using publicly available data from official sources such as the World Bank, World Health Organization and other institutions and governmental sources as well. Therefore, SDGs act as the roadmap to bridge gaps among country economies to lead societies from an unsustainable to a sustainable point by 2030.

Based on the SDGs index overall score, ranging from 0 to 100, for the period 2016-2018, we categorize the country economies in champions and followers using the *k-means* clustering procedure. Table 3 below presents the groups. Six out of ten country economies fall into the champions group indicating that perform quite in promoting and implementing the target of the goals overall. Table 4 is a transition probability matrix referring to whether countries shift between the SDGs performance groups over time. More precisely, we quantify mobility, of the same units, between different states from one year to the other. In cross-sectional time series data, we can estimate the probability that a unit will change its status. Rows refer to initial values and columns reflect the final values. Each period, 85.26% of the champions in the dataset retained their status in the next one while the remaining 14.74% lowered their performance and fell into the followers' group. Although country economies in the champions group had a chance of 14.74% to become followers in the next year the followers had a 4.42% chance

[5] SDG 1: No poverty, 2: Zero Hunger, 3: Good Health and Well-being, 4: Quality Education, 5: Gender Equality, 6: Clean Water and Sanitation, 7: Affordable and Clean Energy, 8: Decent Work and Economic Growth, 9: Industry, Innovation and Infrastructure, 10: Reduced Inequalities, 11: Sustainable Cities and Communities, 12: Responsible Consumption and Production, 13: Climate Action, 14: Life Below Water, 15: Life on Land, 16: Peace, Justice and Strong Institutions and 17: Partnerships for the Goals.

to change status and become champions. Based on a rule of thumb, when elements in the main diagonal are above 33.33%, the matrix is significant. Therefore, the probabilities reported below pinpoint towards the direction of time persistence regarding switches between groups.

Table 3 Group performance based on SDGs index

	Year			
	2016	**2017**	**2018**	**Period**
Champions	72.27	74.71	74.22	73.81
	(5.82)	(4.89)	(4.59)	(5.16)
	50%	58.65%	58.65%	
Followers	54.16	60.80	61.56	58.53
	(7.37)	(5.45)	(5.07)	(6.99)
	50%	41.35%	41.35%	

Table 4 Transitions between SDGs groups

	SDGs index group	
SDGs index group	**Champions**	**Followers**
Champions	**85.26%**	14.74%
Followers	4.42%	**95.48%**
Total	41.35%	58.65%

Shifting the attention to another aspect of each country economy's profile, that of competitiveness, we use the GCI for all the countries in the sample, however in this case we need to exclude the last year available i.e. 2018 due to compatibility issues with the previous years. In 2018 the World Economic Forum introduced the New GCI 4.0 which still encapsulates twelve pillars which are now allocated to four new components such as the Enabling Environment, Human Capital, Markets and Innovation Ecosystem). Thus, we use only 2016 and 2017 here. The GCI has been proved to be a useful index in empirical analysis (Chatzistamoulou et al., 2019, Tsekouras et al., 2016; 2017). Although many proxies of competitiveness are potentially available (Balkyte & Tvaronavičiene, 2010), those come in the expense of subjectivity, as only one aspect is being considered in contrast to the multi-faceted GCI. Another attractive feature is that it accommodates for the same aspect of the production environment across country economies facilitating cross country comparisons.

As shown in Figure 1 below, the distribution of the GCI appears to be bimodal indicating that two competitiveness groups co-exist in the sample. Using the *k-means* clustering procedure again, we construct the competitive cluster (CC) and the less competitive cluster (LCC) as in Chatzistamoulou et al. (2019). Table 5 below shows time persistence of competitiveness indicating that time is needed to improve competitiveness, especially for the LCC. As GCI is multi-faceted, it could be argued that improving any of the pillars would have a positive effect on the overall competitiveness. Table 6 below decomposes GCI in its components and pillars for the first time in empirical analysis, to the best of our knowledge. It is evident that the CC outperform LCC in every facet of GCI.

Figure 1 Distribution of the GCI overall score, 2016-2017

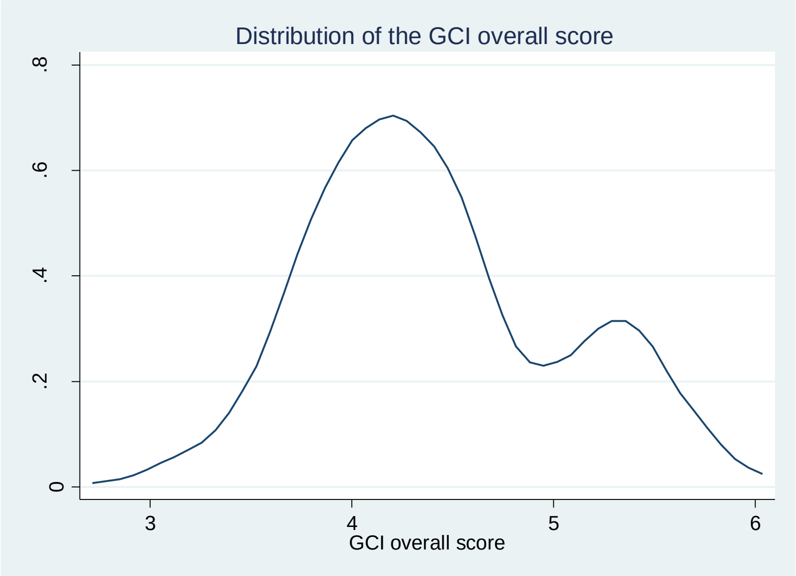

Table 5 Transitions between GCI groups

	GCI cluster	
GCI cluster	**CC**	**LCC**
CC	**94.44%**	5.56%
LCC	0.00%	**100.00%**

Table 6 Focusing on the facets of Global Competitiveness Index, 2016-2017

Global Competitiveness Index	CC	LCC
GCI overall score	5.19	4.07
	(.34)	(.35)
Basic Requirements	5.63	4.36
	(.36)	(.50)
Efficiency Enhancers	5.12	3.98
	(.33)	(.38)
Innovation & Sophistication	4.90	3.53
	(.60)	(.36)

5.2 Universal environmental efficiency

Table 7 below presents the estimation results of the models represented by the Eqs. (6)-(8) presented in earlier section. The estimation results of the fractional probit regression (marginal effects) for the three models employed to explain the variability in the environmental efficiency patterns across the alternative technological structures considered. At this point, we should not neglect to mention that although there is amply literature regarding the assessment of the environmental efficiency in various applications as it has been highlighted in the literature, the existing body of research does not provide with unambiguous guidelines regarding its drivers. Such being the case, the models presented below aim at shedding light towards the direction of gaining some insight on how this resource efficiency measure responds to external stimulus.

The first column corresponds to the estimation results for the case of the metafrontier, that is the universal technology. Productive performance at the global level does not seem to be a driver of the average country in general (H_1 is not accepted). This is in line with the study of Chatzistamoulou et al., (2019), who consider another resource efficiency measure that of the energy efficiency, to find that productive performance at the universal level does not appear to be one of its drivers. Chatzistamoulou and Kounetas (2020) by studying the environmental performance of the thirteen industries of the manufacturing and transportation sectors in seventeen European countries for the period 1999-2006 that is the first implementation period of the Kyoto protocol directives, find that productive performance at the European level exerts a negative and significance influence on environmental efficiency while when they examine the same relationship across the competitiveness distribution results appear to be change with the relationship ranging from none to inconclusive. Thus, it becomes apparent that explaining the effect of productive performance on environmental efficiency is not straightforward.

Additional evidence from Chatzistamoulou and Koundouri (2020) who study the relationship between resource efficiency measures such as environmental and energy efficiency under the Flagship initiative of the Europe 2020 Strategy for Green Growth and Circularity, are in line with the results of Chatzistamoulou and Kounetas (2020) where a negative and significant relationship is found. However, Chatzistamoulou and Koundouri (2020) introduce a feedback loop between the resource efficiency measures to find that energy efficiency is a main driver of environmental efficiency in a dataset of the EU-28 for 2010 to 2014, exerting a positive and significant influence. Moving on, absorptive capacity seems to exert a positive and significant influence on environmental efficiency in line with other studies e.g. Chatzistamoulou and Koundouri (2020).

Absorptive capacity is the ability to internalize and exploit any technological and institutional opportunity to enhance performance (Cohen & Levinthal, 1989;1990). Taking the latter into consideration, under the borderless, in technological terms environment, every country economy has the potential to be benefited by the existence of technological achievements. Even though the assimilation ability and internalization mechanisms are not common across the globe, it seems that on average, there is a positive effect (H_2 is not rejected). The conditions of the production environment appear to be a significant in explaining the variability of environmental efficiency. More precisely, the economy structure index encapsulating the variance of the individual variables, shows that if the conditions of the economy are not appropriate so as to ensure reliable production, this negatively affects environmental performance as this measure is derived by the overall production technology set. Thus, it makes sense that adverse shocks in the economy mix are translated in reduced performance. However, there is a negative influence triggered by increased use of renewables which implies a rebound effect. The latter stems from the switch in alternative energy sources which are overused and lead to the effect that aspire to diverge from, that is inefficient use of scarce resources.

5.3 Heterogeneous environmental awareness and implementation regimes

Shifting the attention to the technological regime i.e. group, that is environmentally aware and implements to a certain extent the sustainable development goals (EAIR) as mirrored by the environmental indicators, we find that productive performance appears to be a significant driver of environmental efficiency (H_1 is partially accepted). However, the effect is a negative one indicating that the two performance measures are not heading towards the same direction. This is not a peculiar finding as a similar relationship between productive performance and energy efficiency, another resource efficiency measure of the same family of performance measures, for the group of competitive countries has been documented before (Chatzistamoulou et al., 2019). This might be attributed to the fact that more advanced economies even under the adoption of cutting-edge cleaner technologies have the margin to consider greener production scenarios. This could be facilitated by the introduction of a more concrete legal framework that provides the incentive to replace existing technologies with one that are more environmentally attuned.

It seems that incoming spillover effects emanating from the universal technology (Teskouras et al., 2016) are not strong enough the penetrate this regime (H_3 is not accepted). The latter highlights the need for further promotion and implementation of any of the sustainable development goals to benefit the country economies. In the current level, production as well as institutional conditions do not allow for full spillover effects exploitation. This is in line with the fact that absorptive capacity does not exert an influence at all on environmental efficiency (H_2 is not accepted), indicating that all the pillars and indicators embracing market conditions, economy dynamism and technological readiness (Sala-i-Martin et al., 2008) should be improved. Additionally, the production environment indicators and particularly the renewables, pinpoint towards the same direction as a rebound effect is documented as well.

Finally, focusing on the technological regime that is less environmentally aware and implements to a lesser extent the sustainable development goals (LEAIR), as mirrored by the environment indicators category, it is evident that there a great deal of complexity. The drivers that seems to exert an influence on the environmental efficiency of the other two cases, do not appear to be present here (H_1-H_3 are not accepted). The fact that the same set of drivers does not have an impact in this case highlights the importance of heterogeneity and underlines the necessity to take it under consideration. Therefore, a one size-fits-all policy regarding enhancing the environmental performance does not appear to be an appropriate strategy, a tailored set of measures for sophisticated intervention instead. We should not neglect to mention that those results are only part of the broader research agenda that aspires to shed light on the explanation of performance patterns under technological heterogeneity and thus should be taken into consideration with caution. Nevertheless, this is the first attempt the study the impact of sustainable development goals, as mirrored by the environment indicators provided by the World Bank, on a not so straightforward resource efficiency measure such as the environmental efficiency and the results, despite preliminary, set a frame to be filled by the evidence provided by future studies.

Table 7 Estimation results – marginal effects

	Universal Technology	**EAIR**	**LEAIR**
Performance measures			
Productive performance	.010 (.008)	-.053* (.029)	.041 (.036)
Spillover effects	-	-.037 (.024)	.087 (.056)
Absorptive capacity	.002** (.001)	.006 (.004)	.002 .003
Institutions Quality			
Frazer index	.000 (.001)	.001 (.001)	.003 (.003)
Production environment			
Economy structure index	-.002* (.001)	-.002 (.001)	-.001 (.002)
Renewables	-.000+** (.000)	-.000+* (.000)	-.000+ (.000)
Other sources of heterogeneity			
Regime switch	.001 (.002)	-	-
Year effects	Yes	Yes	Yes
Model information			
Log-likelihood	-15.826	-6.939	-11.382
Obs	760	375	370
Model p-value	.000	.026	.004

Notes: (i) all models include constants, (ii) robust standard errors in parentheses, (iii) stars indicate statistical significance at 1%***, 5% ***, 10% *, (iv) "+" indicates a very small number.

6. Conclusions

Resource efficiency has been put in the centre of the public agenda to a smoother transition to sustainability. This has attracted the attention across the globe, however to a different extent due to the technological, institutional and other idiosyncratic characteristics of each country economy. To measure the effect of production on environmental quality several measures have been introduces. The efficiency analysis toolbox has been extended to incorporate the Directional Distance Function technique to provide calculations on the environmental efficiency of the decision-making units. Moreover, it is known that the extent of environmental awareness and environmental protection directives and guidelines follows a heterogeneous pattern across the globe which need to be considered when attempting to evaluate performance fluctuations.

To study the effect of heterogeneous patterns of environmental efficiency under alternative environmental awareness structures, we devise a balanced panel including 104 country economies on a global scale for nine years from 2006 to 2014. Then we employ a non-parametric metafrontier framework and a bootstrap Data Envelopment Analysis under variables returns to scale to calculate the bias corrected productive performance and technology gap values on an annual basis. The environmental efficiency is calculated through the Directional Distance Functions approach. To investigate the variability of environmental efficiency, we employ a set of additional exogenous in the framework of a fractional probit model.

Findings show a quite differentiated mosaic of the same set of factors on each of the technological regimes considered. For the universal technology, productive performance does not seem to be a main driver, but this is not the case for absorptive capacity. Productive performance appears to have a significant effect only on the environmentally aware country economies. However, the less environmentally aware group of country economies seems to respond. All in all, partitioning the universal technology brings to the forefront that policy making should take into consideration technological heterogeneity in order to design a sustainable policy transition.

This is the first study to put under the microscope the World Bank Environment Indicators mirroring aspects of the Sustainable Development Goals initiative of the United Nations introduced in 2015, to study the patterns of environmental efficiency at a global scale under a heterogeneity framework. We should also acknowledge that the availability of variables is quite limited for the time being, thus conclusions should be drawn with caution.

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