Sustainability Transition Through Awareness to Promote Environmental Efficiency

Nikos Chatzistamoulou and Phoebe Koundouri

Abstract The 17 Sustainable Development Goals, United Nations' Agenda 2030, the Paris Agreement, the European Green Deal, and the current global policy momentum towards green efficiency, motivate the need for a better understanding of the determinants of environmental efficiency to tackle climate change. By adopting a non-parametric metafrontier framework, the productive performance and environmental efficiency through the Data Envelopment Analysis and Directional Distance Function for each of the 104 countries from 2006 through 2014 are calculated. We contribute to the understanding of environmental efficiency patterns through partitioning the metafrontier via a factor encapsulating 56 environmental indicators to give rise to heterogeneous environmental awareness regimes. By adopting fractional probit models, we show econometrically that productive performance appears to be a major driver of environmental efficiency *only* for the environmentally aware country economies whereas a direct rebound effect is also documented. This is a result with major "policy sequencing" implications. Absorptive capacity reflecting the ability and potentiality of the country to benefit from technological developments seems to play a crucial role as well. The less environmentally aware cluster does not seem to respond the same way to the set of factors considered, indicating that complexity and latent mechanisms affect green efficiency.

Keywords Environmental efficiency · Productive performance · Spillover effects · Directional distance function · Sustainability · Green efficiency

N. Chatzistamoulou (✉) · P. Koundouri
School of Economics and Research Laboratory On Socio-Economic and Environmental Sustainability–ReSEES, Athens University of Economics and Business, Athens, Greece
e-mail: chatzist@aueb.gr

P. Koundouri
e-mail: pkoundouri@aueb.gr

N. Chatzistamoulou
Department of Economics, University of Ioannina, Ioannina, Greece

P. Koundouri
Director, Sustainable Development Unit, ATHENA Research Center, Co-Chair, UN SDSN Europe Fellow, Academy of Art and Science, Marousi, Greece

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1 Introduction

Environmental performance enhancement has always been in the center of attention and one of the main pillars of the prosperity at a universal level. Technological heterogeneity, the ability of each country to adopt and internalize technical progress, i.e., absorptive capacity (Cohen and Levinthal, 1990; Zhang et al., 2010), knowledge spillover effects as the carriers of new but potential complex technological achievements and developments that affect performance (Girma, 2005; Casu et al., 2016; Tsekouras et al., 2016) along with the policy directives, all have their own merit on boosting environmental performance. Augmenting the latter argument, under the Sustainable Development Goals Initiative (United Nations, 2015) and the new growth strategy of Europe, that is the European Green Deal[1] (EGD) (European Commission COM (2019) 640), there is a systematic mobilization towards sustainability transition and green growth.

In particular, the Sustainable Development Goals (SDGs) Initiative expressed as targets to be achieved allocated in 17 goals, recently have been restructured in six transformations (Sachs et al., 2019). Those transformations aim at promoting environmental quality through eco-friendly technologies and sustainable ways of production and consumption, among others. Although agreed by the member states, the goals do not constitute an obligation. In this line, the European Green Deal among its main policy areas,[2] includes a climate package for stakeholder engagement referring to every aggregation level (e.g., policy makers, financial institutions, businesses, civil Non-Governmental Organizations, countries) in order to promote commitment and implementation of the directives. The common objectives of the SDGs and the EGD are highlighted via a thorough mapping of the recent report of Koundouri and Sachs (2021) for the Sustainable Development Solutions Network (SDSN, 2021).

It therefore becomes apparent that heterogeneous environmental awareness levels exist across the globe as countries face uneven technological opportunities and access to resources affecting environmental performance. Even though previous studies have employed different factors such as income level and geographical location (e.g., Oh and Lee, 2010) to study performance change, no systematic attempt has been surfaced yet, neither to group countries based on indicators related to the SDGs nor to study environmental awareness through a metaproduction-metafrontier framework. Therefore, it remains a void to be filled.

The contribution of this study is multi-fold. *We adopt the metafrontier-metaproduction framework to account for technological heterogeneity, (ii) we give rise to heterogeneous environmental awareness regimes* via *partitioning the overall technology by a factor encapsulating aspects of several sustainable development*

[1] For a detailed presentation, https://eur-lex.europa.eu/resource.html?uri=cellar:b828d165-1c22-11ea-8c1f-01aa75ed71a1.0002.02/DOC_1&format=PDF and https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en.

[2] The policy areas included by the EGD are clean energy, climate action, sustainable industry, eliminating pollution, biodiversity, from farm to fork, sustainable agriculture, sustainable mobility, building and renovating.

goals proxied by environmental indicators, (iii) we study whether the heterogeneous environmental awareness regimes exert differential effect on environmental efficiency of the country economies by employing fractional probit models, and (iv) the technical analysis provided herein contributes to one of the most important sides of environmental transition, that is the stakeholders.

Findings indicate that awareness matters towards the transition to sustainability. In particular, productive performance appears to be a driver of environmental efficiency *only* for the environmentally aware country economies. Those countries need to further promote and develop the partnerships among the SDGs as well as endorse the directives described in the action plans of EGD. Absorptive capacity seems to play a crucial role as well. A rebound effect is also observed for the global technology as well as for the environmentally aware country economies. However, the less environmentally aware country economies do not seem to respond the same way to the set of factors considered, indicating that complexity and latent mechanisms affect green efficiency. In those countries, the directives regarding stakeholder engagement become predominant, as that would set the latter in a resilient and sustainable trajectory.

This chapter unfolds as follows. The next section offers a brief overview of the related literature, Sect. 3 presents the methodology and research hypotheses, Sect. 4 presents the data, Sect. 5 is dedicated to the results and discussion while Sect. 6 concludes the chapter.

2 Related Literature

There is ample literature regarding environmental performance and every attempt to be exhaustive would be unintentionally incomplete. The Porter Hypothesis has been a beacon for research proliferation even though the literature is quite mixed. Indicatively, Rubashkina et al. (2015) test for weak and strong versions of the Porter Hypothesis and relate it to environmental regulation and competitiveness using a panel of manufacturing industries in 17 European Union (EU) countries over the period 1997–2009 to find evidence in favor of the weak version, while productivity appears to be unaffected by the stringency of environmental regulation. Costantini and Crespi (2008) focus on the export flows of environmental technologies across the globe, providing 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 for the improvement of the growth rate of production. Thus, it falls in the group of studies supporting the Hypothesis.

A significant number 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) analyze the environmental efficiency of China transportation industry by proposing a non-radial Data Envelopment Analysis (DEA) model with slack-based-measures to find that the latter lacks in efficiency. Other sectoral studies, such as the work of Zofio and Prieto (2001) who calculate the environmental efficiency of the Organization for Economic Cooperation and Development (OECD) manufacturing industries under many carbon dioxide emission regulatory scenarios, highlight 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 and 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 or sector selected (Iraldo et al., 2011).

Cross-nation performance comparisons raise the issue of technological heterogeneity as country economies do not share identical technology and resource endowments affecting performance. Therefore, the need for a methodological framework embracing all possible aspects of heterogeneity is imperative. The concept of the metaproduction function of Hayami (1969) and Hayami and Ruttan (1970) materialized through the metafrontier framework of O'Donnell et al. (2008) set a new perspective in efficiency analysis.

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). 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).

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. 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.

It is therefore evident that despite the empirical studies scattered in the literature, there is a void to be filled regarding the impact of environmental awareness on the environmental efficiency. This is particularly relevant nowadays under the urgency to set economies into a smooth transition trajectory leading to a sustainable future as promoted by the SDGs as well as the EGD.

3 Methodological and Theoretical Considerations

3.1 Constructing Environmental Awareness Clusters

To handle technological heterogeneity on the benchmarking process (Dosi et al., 2010), statistical techniques often used 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 employ the principal component analysis with varimax rotation (Genious et al., 2014), to construct a partitioning factor for the global technology by considering 56 environment indicators mirroring aspects of several sustainable development goals from World Bank Environment Indicators database. Then, we apply the *k-means* clustering procedure to construct two clusters reflecting differences in environmental awareness.

That being said, we construct the environmentally aware (EA) and the less environmentally aware (LEA) cluster, respectively. In this context, *an environmental awareness regime is considered as a production frontier to benchmark the country economies. It encompasses the technological complexity, differences in resource endowments, country objectives to preserve environmental quality, and efforts to mitigate negative effects of climate change through implementing an active strategy of protecting scarce resources.* This paves the way to investigate the effect of a plethora of technological and environmental aspects on environmental efficiency on a global scale to promote sustainability.

Environmental awareness as means to proxy the mindset towards sustainability of production gains ground gradually. That being said, Giudici et al. (2019) investigate the effect of sensitivity to environmental issues by local governments, firms, and residents, framing the former as local environmental awareness on green start-ups creation. Although it is feasible to create more than two groups, the number of entities under each environmental awareness 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 Heterogeneity

3.2.1 Productive Performance; The Data Envelopment Analysis Technique

A country economy $i = 1, 2, \ldots, n$ may be considered as a production entity transforming inputs $x = (x_{1i}, x_{2i}, , \ldots, x_{Ni},) \in \Re_+^N$ into outputs $y = (y_{1i}, y_{2i}, , \ldots, y_{Mi},) \in \Re_+^M$ under a technology set S defined as $S \equiv \{(x, y) : xcanproducey\}$. For the input-oriented productive performance, the technology is represented by the production possibility set $L(y) = \left\{x \in \Re_+^N : (x, y) \in S\right\}$, 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 production frontiers (technologies) T^{EA}, T^{LEA} 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 $T^{M} = \left\{(x, y : x \geq 0, y \geq 0) x can produce at least one of T^{EA}, T^{LEA}\right\}$ (Battesse et al., 2004). The technology set can be defined in the same way for the single technology.

By adopting the metafrontier framework (global technology-MF) 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 DEA under variable returns to scale to account for size effects (Halkos and Tzeremes, 2009), the bias corrected productive performance of each country economy with respect to the global technology is calculated using the following formula:

$$\widehat{ProdPerf}_{i,t}^{MF} \equiv \widehat{\theta}(x, y) = \min\left\{\theta \middle| \theta > 0, y \leq \sum_{i=1}^{n} \gamma_i y_i; \theta x \geq \sum_{i=1}^{n} \gamma_i x_i \text{for } \gamma_i \right. \quad (1)$$

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 cluster by employing Eq. 1. The metatechnology ratio (*MTR*) and the corresponding technology gap (*Tg*) are calculated for each country economy on an annual basis, using the formulas below:

$$MTR_{i,t}(x, y) = \frac{\widehat{ProdPerf}_{i,t}^{MF}(x, y)}{\widehat{ProdPerf}_{i,t}(x, y)} \quad (2)$$

$$Tg_{i,t}(x, y) = 1 - MTR_{i,t}(x, y) \quad (3)$$

The technology gap measures the distance between the individual frontier and the metafrontier capturing spillover effects (Chatzistamoulou et al., 2019).

3.2.2 Environmental Efficiency; The Directional Distance Functions Approach

Assuming 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 $y^{*} \in \Re_{+}^{M}$ as presented in the work of Chambers et al. (1996), Chung et al. (1997), and Fare and Grosskopf (2000), we discern the desirable $y = (y_1, y_2 \ldots, y_k) \in \Re_{+}^{K}$ and the undesirable output $b = (b_1, b_2 \ldots, b_l) \in \Re^L_+$, respectively[3] (Kumar and Khanna, 2009). The underlying production process is constrained by the technology set (Chambers et al., 1996; Kumar, 2006; Luenberger, 1992; 1995; Shepard, 1953; 1970; Zhou et al., 2012) T defined as $T(x) = \{(y, b) : x can produce (y, b)\}$ (Dervaux et al., 2009). The directional distance function (DDF) may be represented by a multi-input and multi-output distance function on technology T (e.g., Chambers et al., 1998; Picazo-Tadeo et al., 2011) and can be defined as:

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

The input–output vector (x, y) is projected onto the technology frontier in the $\left(g_y, -g_b\right)$ direction which allows desirable outputs to be proportionally increased, whereas undesired output(s) to be proportionally decreased. The maximum attainable expansion of desirable outputs in direction $\left(g_y\right)$ and the largest feasible contraction of the undesirable outputs in direction $(-g_b)$ is of major interest. Since the technology set is restricted only to the production of desired output, the environmental efficiency at the metafrontier, $EnvEff^{MF}$, is:

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

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

The environmental efficiency index $\left(EnvEff^{MF}\right)$ captures the contraction in increasing outputs by each country economy under the potential ability of the production process convention from free disposability to costly disposal of carbon dioxide emissions taking values between zero and one. For a DMU with environmental efficiency score of one, the cost of transforming their production from strong disposability to weak for emissions should be zero while moving to the opposite direction is considerably costly (Kounetas and Zervopoulos, 2019; Kumar and Khanna, 2009). Environmental efficiency has been defined as the ratio of two distance functions assuming strong and weak disposability of the undesired output, however, the ratio of those two distances leads to values very close or equal to one due to the weak disposability assumption (Zaim and Taskin, 2000).

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

3.3 Econometric Strategy and Research Questions

3.3.1 Fractional Regression Models

The second stage analysis following the DEA during the past decades, employs mostly binary response dependent variable models to explain the variability in the performance scores attained by the first stage (Gillen and Lall, 1997; Merkert and Hensher, 2011). A systematic review of modelling second stage DEA scores is provided by Hoff (2007).

Papke and Wooldridge (1996; 2008) introduce a more appropriate methodology to handle variables that come in proportions, shares, and in general variables that vary between zero and one. Particularly, in the case of efficiency scores, despite the popular use of limited dependent and censored variable models those (i) cannot adequately capture the nature of the variable, (ii) the censoring does not appear to be applicable if the variable of interest does not exceed those boundaries, (iii) the mechanics of linear models are not capable in handling incremental changes of the explanatory variables on the dependent especially as the latter crowd closely at the boundaries making inappropriate to predict the expected values at the corners (Noreen, 1988; Maddala, 1991; Papke and Wooldridge, 1996; Gallani et al., 2015).

To cope with the limitations of the abovementioned models, Papke and Wooldridge (1996; 2008) propose and develop the idea of fractional regression models (FRM) without the requirement of data transformation at the tails whereas Greene (2003) mentions that FRM exploit data non-linearities to calculate the average partial effects at different percentiles of the predictor(s) distribution. Criticism on the FRM is found on the grounds that the latter do not apply to repeated measurements but since we consider each year as a separate production function, it is consistent with our approach. Structural parameters are estimated via quasi-maximum likelihood which produces robust and relatively efficient estimates, under the GLM assumptions (Gallani et al., 2015). All in all, since environmental efficiency range between zero and one should be considered as fraction and that is the reason why we exploit its potential herein.

3.3.2 Modelling Environmental Efficiency

We specify and estimate the following models for the global technology level as well as for the two environmental awareness clusters, by employing three pooled fractional probit models:

$$\begin{aligned} EnvEff_{it}^{Global\ technology} &= \beta_0 + \beta_1 ProdPerf_{it} + \beta_2 Spillovers_{it-1} \\ &+ \beta_3 AC_{it-1} + \beta_4 FraserIndex_{it} \\ &+ \beta_6 EconStruIndex_{it} + \beta_7 Renewables_{it} \\ &+ \beta_8 Switch_{it} + \boldsymbol{\gamma YearEffects} + u_{it} \end{aligned} \tag{6}$$

$$\begin{aligned} EnvEff_{it}^{EA} &= \delta_0 + \delta_1 ProdPerf_{it} \\ &+ \delta_2 Spillovers_{it-1} + \delta_3 AC_{it-1} \\ &+ \delta_4 FraserIndex_{it} + \delta_6 EconStruIndex_{it} \\ &+ \delta_7 Renewables_{it} + \delta_8 Switch_{it} \\ &+ \boldsymbol{\rho YearEffects} + \upsilon_{it} \end{aligned} \tag{7}$$

$$\begin{aligned} EnvEff_{it}^{LEA} &= \lambda_0 + \lambda_1 ProdPerf_{it} \\ &+ \lambda_2 Spillovers_{it-1} + \lambda_3 AC_{it-1} \\ &+ \lambda_4 FraserIndex_{it} + \lambda_6 EconStruIndex_{it} \\ &+ \lambda_7 Renewables_{it} + \lambda_8 Switch_{it} \\ &+ \boldsymbol{\rho YearEffects} + \nu_{it} \end{aligned} \tag{8}$$

where $EnvEff_{it}^{Globaltechnology}$, $EnvEff_{it}^{EA}$, and $EnvEff_{it}^{LEA}$ correspond to the environmental efficiency of the *i-country economy* in year *t* with respect to the global technology as well as of each cluster considered.

We formulate and test three research hypotheses corresponding to each variable of interest, the productive performance ($ProdPerf_{it}$), absorptive capacity (AC_{it-1}) captured by the lagged value of competitiveness level, and spillovers ($Spillovers_{it-1}$) captured by the lagged value of technology gap as drivers of the environmental efficiency. Particularly:

H_1: Productive performance exerts a positive and significant influence on environmental efficiency.

The role of absorptive capacity has been acknowledged by the literature indicating the ability to transform technological achievements into improved performance (Cohen and Levinthal, 1989; 1990; Eichammer and Walz, 2011). The lagged global competitiveness index (GCI) which is country-specific and time-varying has been used to capture a country's absorptive capacity (Gkypali et al., 2019) while it reinforces the ability and potentiality to absorb accumulated knowledge generated universally. In the form of a testable hypothesis, it can be stated as:

H_2: Absorptive capacity enhances environmental efficiency.

By rejecting the null would imply that low technological opportunities and assimilation ability negatively affect the environmental efficiency. The influence of spillovers in explaining performance patterns has been acknowledged before (Tsekouras et al. 2016; Chatzistamoulou et al. 2019), thus it is reasonable to include it in explaining performance patterns. This can be stated as:

H_3: Spillover effects exert a positive and significant influence on the environmental efficiency of each cluster.

Additional variables such as the Frazer index ($FraserIndex_{it}$,) and the Economy Structure index $EconStrIndex_{it}$[4]have been included to capture characteristics of the overall production environment of each country economy. Rec_{it} is the share of renewable energy consumption capturing the use of resource-saving paving the way for environmental efficiency improvement. The variable $Switch_{it}$ captures switches between the two clusters at the global technology level. Year effects have been included while u_{it}, υ_{it}, andv_{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

We devise a unique panel by coordinating, matching, and harmonizing several distinct yet complementary publicly available databases covering 104 country economies over a nine-year period, from 2006 through 2014. Therefore, the panel includes 936 observations.

The novelty of this dataset is found on the use of 56 indicators referring to the use of natural resources, changes in the natural and built environment encompassing the availability and use of environmental resources related to environmental degradation, in creating the partitioning factor to give rise to alternative environmental awareness clusters. The indicators mirror and illuminate many aspects of a wide variety of the SDGs such as 2, 6, 7, 11, 12, 14, and 15 (World Bank, 2018). It is not worthless to mention that this is the first time such data are employed to explore environmental awareness.

We collect data on two outputs and three inputs. Outputs include the Gross Domestic Product (GDP) capturing the desired output (measured in mil. US$) and the carbon dioxide emissions (CO_2) capturing the undesired output (measured in kt). Inputs include the capital captured by the capital stock (measured in mil. US$), labor proxied by the number of persons engaged (measured in mil.), and the energy captured by the energy use (measured in kt of oil equivalent) of each country economy, respectively. Monetary values are in constant 2011 prices.

Additional variables have been collected to account for as many as possible aspects of the production environment. Particularly, absorptive capacity (Cohen and Levinthal, 1990) of each country economy captured by the lagged GCI encapsulating 12 pillars representing each country's potential and market conditions among others (Sala-i-Martin and Artadi, 2004; Sala-i-Martin et al., 2008) produced annually by the World Economic Forum, has proved a quite useful tool in the empirical analysis (Tsekouras et al., 2016; 2017; Chatzistamoulou et. al., 2019, Gkypali et al., 2019). The structure of the economy, proxied by the contribution of the secondary, manufacturing, services sectors, the share of renewable energy use to the total energy use,

[4] The economy structure index which has been created by combining the share of secondary, manufacturing and services sector on the national product.

and data on the economic freedom captured by the multi-faceted Fraser index have been included.

Data on the Gross Domestic Product, Labor, 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, secondary, manufacturing and services sector contribution to the gross domestic product have been collected through the World Bank. Data on the GCI has been hand-collected through various releases of the Global Competitiveness Report published by the World Economic Forum annually, while data on the Economic Freedom index was collected through the Fraser Institute official site. Table 1 below provides the basic descriptive statistics and source of the main variables.

5 Results and Discussion

Table 2 below presents the estimation results (marginal effects) of the fractional probit models in Eqs. 6–8. The first column corresponds to the estimation results for the case of the global technology. Productive performance at the global level does not seem to be a driver of environmental efficiency (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 global level does not appear to be one of its drivers.

Absorptive capacity seems to exert a positive and significant influence on environmental efficiency as it captures the ability to internalize and exploit any technological and institutional opportunity to enhance performance (Cohen and Levinthal, 1989; 1990). Taking the latter into consideration, under the borderless technology, every country economy has the potential to be benefited by the existence of technological achievements. Even though the assimilation ability and internalization mechanisms may not be similar, it seems that a positive effect arises (H_2 is not rejected). Although many proxies of competitiveness are potentially available (Balkyte and Tvaronavičiene, 2010), those are characterized by subjectivity, as only one aspect is being considered. The multi-faceted GCI accommodates for several pillars[5] common across country economies facilitating comparisons.

The conditions of the production environment appear to be a significant driver in explaining environmental efficiency. Specifically the economy structure index indicates that if the composition of the production environment at the country level has not incorpotated clean technologies, negatively affects resource efficiency (York

[5] Pillars include Institutions, Infrastructure, Macroeconomic Environment, Health and Primary Education, Higher Education and Training, Goods market efficiency, Financial market development, technological readiness, market size, business sophistication and innovation.

Table 1 Basic descriptive statistics (Means and St. Dev.) for the main variables, 2006–2014

	Brief description	Units of measurement	Source	All countries - Global Technology	Environmentally Aware	Less Environmentally Aware
GDP	Real Gross Domestic Product	million US $	GGDC	825,045 (2,129,040)	903,698 (2,254,718)	736,381 (1,976,624)
CO_2	Carbon dioxide emissions	kiloton (kt)	World Bank	287,336 (1,026,434)	324,622 (1,122,714)	245,304 (905,157)
K	Capital stock	million US $	GGDC	2,855,233 (7,207,575)	3,131,751 (7,705,912)	2,543,522 (6,595,734)
L	Persons engaged	millions	GGDC	26.894 (90.768)	28.890 (99.073)	24.644 (80.437)
E	Energy use	kg of oil equivalent per capita	World Bank	2,363 (2,302)	2,592 (2,384)	2,105 (2,180)

Table 2 Estimation results–marginal effects

	Global technology	Environmentally Aware cluster	Less Environmentally Aware cluster
Performance measures			
Productive performance	0.010 (0.008)	− 0.053* (0.029)	0.041 (0.036)
Spillovers	–	− 0.037 (0.024)	0.087 (0.056)
Absorptive capacity	0.002** (0.001)	0.006 (0.004)	0.002 0.003
Aspects of production environment			
Economy structure index	− 0.002* (0.001)	− 0.002 (0.001)	− 0.001 (0.002)
Frazer index	0.000 (0.001)	0.001 (0.001)	0.003 (0.003)
Renewables	− 0.000 + ** (0.000)	− 0.000 + * (0.000)	− 0.000 + (0.000)
Regime switches	0.001 (0.002)	–	–
Year effects	Yes	Yes	Yes
Model information			
Log-likelihood	−15.826	−6.939	−11.382
Obs	760	375	370
Model p-value	0.000	0.026	0.004

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

et al., 2003; Carattini et al., 2015). This is not the case for the Fraser index which seems to have influence on environmental efficiency.

However, there is a negative influence triggered by increased use of renewables which pinpoints towards a direct rebound effect (Binswanger, 2001; Hertwich, 2005; Deng and Newton, 2017). Last but not least, given that cluster switching does not systematically affect environmental efficiency, indicates that production paradigms take time to change, and country economies need time to adjust, internalize, and reform.

Shifting the attention to the environmentally aware cluster, we find that productive performance exerts a negative but significant influence on environmental efficiency (H_1 is partially accepted). This finding indicates that the two performance measures are not heading towards the same direction. This finding comes with policy sequencing implications when designing environmental policies to promote performance. 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 so as to develop greener production scenarios. This is not a peculiar finding as a similar relationship between productive performance and energy efficiency has been documented before (Chatzistamoulou et al., 2019). Absorptive capacity does not exert a systematic effect on environmental efficiency (H_2 is not accepted), indicating that in order to promote assimilation of technological achievements, pillars should be improved (Sala-i-Martin et al., 2008). Country economies of this cluster appear to have limited potential to accommodate technological achievements or opportunities for catch-up with the current developments (H_3 is not accepted). The latter could be attributed to the localized nature of spillovers, as economy sectors are not equally developed across countries. In this line, Braun et al. (2010) highlight the distinct nature of spillovers, to those from the same and other related technologies. Furthermore, the systematic effect of the use of renewables on environmental efficiency, pinpoints towards a rebound effect.

Finally, focusing on the less environmentally aware cluster, it is evident that there is a great deal of complexity. The factors affecting environmental efficiency of the environmental aware cluster have a differential effect in this case (H_1–H_3 are not accepted). Such finding underlines the necessity to take technological heterogeneity into account. However, the fact that spillovers appear to exert a rather weak effect on environmental efficiency of this cluster, could indicate that those country economies do not manage to exploit knowledge and technological achievements due to the intrinsic complexity. It is not uncommon for technological knowledge to be tangled and its diffusion proves to be problematic and hard to be assimilated due to the complexity embodied (Kogut and Zander, 1992), especially with environmental practices developed in countries with more advanced technological domains (Rivkin, 2000).

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 could have an impact instead. Nevertheless, results should be considered with caution as this is the first attempt to study the impact of sustainability, as mirrored by the environment indicators. Results leave the discussion on the drivers of environmental efficiency open for fruitful discussion.

6 Conclusions and Remarks

Resource efficiency has been put in the center of the public agenda to lead a smoother transition to sustainability. This has attracted the attention globally, however to a different extent due to the technological, institutional, and other idiosyncratic characteristics of each country economy. It thus becomes apparent that the extent of environmental awareness, protection directives, and guidelines follow heterogeneous patterns universally. This needs to be accommodated in the analysis when attempting to evaluate performance patterns. The efficiency analysis toolbox has been extended to incorporate the Directional Distance Function technique to provide calculations on the environmental efficiency of the production entities to monitor their performance.

To study environmental efficiency under alternative environmental awareness production frontiers, we devise a balanced panel including 104 country economies over a nine-year period, from 2006 to 2014. Then, we employ the non-parametric metafrontier framework and the bootstrap Data Envelopment Analysis under variable returns to scale, to calculate the bias corrected productive performance and technology gap values annually. The environmental efficiency is calculated through the Directional Distance Functions approach. We investigate the drivers of environmental efficiency, through a fractional probit model.

Findings show a quite differentiated mosaic of effects depending on the cluster considered. For the global technology, productive performance does not seem to be the 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 cluster does not seem to respond the same way on the drivers explored. The latter might be an indication of technological complexity meaning that knowledge is localized, rigid, and hardly transferable. This highlights the need for restructuring the production paradigm and build on the aspects of the economy that could be used to adopt externally generated knowledge such as a coherent institutional framework, human capital, and technology stock to recombine available resource endowments.

It goes without saying that this study is not free of limitations. First and foremost, more indicators could be considered in order to get a better representation on environmental awareness across countries for a longer period of time to let the effects diffuse to the system, should more data become readily available. Also, policy-related variables could be incorporated in the analysis to explain environmental performance. However, those are latent since there is not an official registry for each country with implementation details, for the time being.

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