Does the Kyoto Protocol Agreement matters? An environmental efficiency analysis

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by

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Abstract

This paper uses both conditional and unconditional Data Envelopment Analysis (DEA) models in order to determine different environmental efficiency levels for a sample of 110 countries in 2007. In order to capture the effect of countries compliance with the Kyoto Protocol Agreement (KPA), we condition the years since a country has signed the agreement until 2007. Particularly, various DEA models have been applied alongside with bootstrap techniques in order to determine the effect of Kyoto protocol agreement on countries' environmental efficiencies. The study illustrates how the recent developments in efficiency analysis and statistical inference can be applied when evaluating environmental performance issues. The results indicate that the first six years after countries signed the Kyoto protocol agreement have a positive effect on their environmental efficiencies. However after that period it appears that countries avoid complying with the actions imposed by the agreement which in turn has an immediate negative effect on their environmental efficiencies.

Keywords: Environmental efficiency; Kyoto protocol agreement; Conditional full frontiers; Statistical inference; DEA.

JEL classification: C00, C6, Q5, Q58, O44,

1. Introduction

Input–Output (IO) analysis is a powerful method for analyzing environmental effects by enabling the calculation of emission multipliers (Östblom, 1998; Yamakawa and Peters 2009). Other researchers have used environmental computable general equilibrium (CGE) models in order to analyze environmental effects (Li and Rose 1995; Ferguson et al. 2005). However, the application of IO analysis to environmental issues has been applied by several authors (Gale, 1995; Forssell, 1998; Forssell and Polenske, 1998; Hoekstra and Janssen, 2006. Recently, Washizu and Nakano (2010) using the Family Income and Expenditure Survey in Japan for 2000, applied and IO analysis and constructed an eco-efficiency index of consumer behaviour. In addition Ramon and Cristóbal (2010) developed an environmental IO linear programming model in order to show how the targets of greenhouse gas (GHG) emissions set by Kyoto Protocol agreement can be reached.

A special attention has been given to environmental and ecological related applications of data envelopment analysis (DEA) models in order to find and investigate efficiency related issues (Halkos and Tzeremes, 2010a). According to Wier et al. (2005) DEA methodology can be very useful when comparing the environmental performance of units (in our case countries) by comparing their eco-efficiency levels (i.e. the lowest possible environmental effect per unit produced). Many studies have used DEA to assess the environmental performance of a set of producers by grading their ability to produce the largest equi-proportional increase in the desirable output and decrease in the undesirable output[1] (Zofio and Prieto, 2001).

Färe et al. (1986) were the first to apply classic output oriented DEA analysis to a set of USA steam electric plants defining radial efficiency measures for

[1] Undesirable or bad outputs are consider to be the environmental effects (Färe et al., 1986; 1989)

equiproportional increases of all outputs (both desirable and undesirable). In addition they allowed reference technologies to be characterized by strong and weak disposability of undesirable outputs in order to check for production congestion. Furthermore, Färe et al. (1989) treated desirable and undesirable production asymmetrically. They defined efficiency measures that allow desirable and undesirable outputs to vary by the same proportion but desirable outputs are proportionally increased while undesirable ones are simultaneously decreased.

Other studies have treated the bad outputs as inputs (Cropper and Oates 1992; Kopp 1998; Reinhard et al. 1999; Murty and Kumar 2002), while others (Scheel 2001; Seiford and Zhu 2002) have applied a linear monotone decreasing transformation of the undesirable outputs to be treated as desirable.

In addition to those studies our paper uses conditional full frontiers (Daraio and Simar, 2005) in order to measure the effect of the Kyoto Protocol Agreement (KPA)[2] for the commitment to CO_2 reductions on a sample of 110 countries' environmental efficiency levels. By applying bootstrap techniques and conditional measures this paper evaluates countries' environmental efficiency for 2007. Finally, additional conditional environmental efficiency indexes are calculated incorporating the effect of the Kyoto protocol agreement on countries environmental performance in carbon dioxide emissions.

The structure of the paper is the following. Section 2 presents the data used while section 3 discusses the proposed methodology. Section 4 comments on the empirical results derived while the last section concludes the paper.

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[2] The Protocol sets a target for the emissions of a basket of GHGs (carbon dioxide, CO2; methane, CH4; nitrogen oxide, N2O; sulphur fluoride, SF6; hydrofluorocarbons, HFCs; and perfluorcarbons PFCs). This target, which will have to be reached by the signatory countries in the period 2008–2012 (San Cristóbal 2010, p.223-224).

2. Data

Following several studies (Zofio and Prieto 2001; Taskin and Zaim 2000; Zaim and Taskin 2000; Taskin and Zaim 2001; Zaim 2004; Halkos and Tzeremes 2009; Kumar and Khanna 2009) our paper computes environmental efficiency in CO_2 emissions for 110 countries (Appendix-A1). We choose as a desirable output the real Gross Domestic Product (GDP, expressed in international prices in 2005 US dollar) and as an undesirable output the CO_2 emissions (in millions of tons). The two inputs considered are aggregate labour input measured by the total employment and total capital stock[3]. The two inputs and the desirable output have been obtained from the Development Data Group, the World Bank (World Bank 2008). The CO_2 data have been obtained from the International Energy Agency-IEA (2010). All the variables used are for the year 2007.

One of the ways that the bad output can be modelled appeared in the pioneered work by Färe et al. (1989) by assuming strong (for desirable outputs) and weak (for undesirable outputs) disposability treated environmental effects as undesirable outputs in a hyperbolic efficiency measure. Generally the property of weak disposability of detrimental variables is well known and has been used in several formulations (Färe et al. 1996, 2004; Chung et al. 1997; Tyteca, 1996, 1997; Zofio and Prieto, 2001; Zhou et al., 2006, 2007). However, although this approach is widely accepted among the environmental economists it has faced several criticisms (Hailu and Veeman 2001; Färe and Grosskopf 2003; Hailu 2003).

[3] Capital stock for the year 2007 is not available, therefore we calculated it following the perpetual inventory method (Feldstein and Foot 1971; Verstraete 1976; Epstein and Denny 1980) as $K_t = I_t + (1-\delta)K_{t-1}$, where K_t is the gross capital stock in current year; K_{t-1} is the gross capital stock in the previous year; δ represents the depreciation rate of capital stock. In our study we set δ to 6% following Wu (2004) and Zhang et al. (2011).

Another approach for modelling bad output(s) is a linear monotone decreasing transformation introduced by Seiford and Zhu (2002). Färe and Grosskopf (2004) commenting on linear monotone decreasing transformation suggested an alternative approach based on directional output distance function. However, Seiford and Zhu (2005) replied to the critic made by Färe and Grosskopf (2004) and proved that Färe and Grosskopf's proposed model based on directional output distance function is very similar to the weighted additive model (Ali et al., 1995; Thrall, 1996; Seiford and Zhu, 1998) where the bad outputs are treated as controllable inputs.

In our DEA setting we treat the bad output (CO_2 emissions) as input following the work by several authors measuring environmental efficiency (Pitman 1981; Cropper and Oates 1992; Reinhard et al. 2000; Dyckhoff and Allen 2001; Hailu and Veeman 2001; Korhonen and Luptacik 2004; Tsolas 2005; Weir et al. 2005; Mandal and Madheswaran 2010). Following those studies we apply a formulation where we treat undesirable output as input, due to the fact that both traditional inputs and undesirable output(s) incur costs for countries (Tsolas 2010). According to Mandal and Madheswaran (2010, p.1110) if the bad outputs are treated as inputs then they work as a proxy for the use of environment in the form of its assimilative capacity.

Moreover, by applying the methodology introduced by Daraio and Simar (2005) we conditioned in a second stage the effect of countries commitment to Kyoto protocol agreement on their environmental efficiencies (for the year 2007). As such an external variable has been used based on the time distance of the year in which the country has signed the agreement and the year the environmental efficiency was computed (i.e. 2007). Under the protocol agreement both developed and developing countries agreed to take measures to limit emissions and promote adaptation to future climate change impacts. All the countries that signed the Kyoto Protocol agreed to pursuing emissions cuts in a wide range of economic sectors. As such by conditioning the years from the time which the countries have agreed with the actions imposed by the KPA we will be able to capture that effect on their estimated environmental efficiencies calculated in the latter period (in our case for 2007). The information regarding the year in which each country has signed the agreement has been obtained from the United Nations Framework Convention on Climate Change (2006).

3. Methodology

3.1 Efficiency measurement

Trying to measure countries environmental efficiency in a context described by Shephard (1970) we define a set of $x \in R_{+}^{p}$ inputs which are used to produce $y \in R_{+}^{q}$ outputs. Then the feasible combinations of (x, y) can be defined as:

$$\Psi = \left\{ (x, y) \in R_{+}^{p+q} \middle| x \quad can \quad produce \quad y \right\} \tag{1}$$

In an input oriented case in Farrell's (1957) context countries' environmental efficiency operating at level (x, y) can then be defined as:

$$\theta(x, y) = \inf\{\theta | (\theta x, y) \in \Psi\} \tag{2}$$

where an inefficient country working at a level (x, y) in order to increase its efficiency needs to reduce proportionally its inputs by $\theta(x, y) \leq 1$. In addition when the countries are in the efficient frontier then $\theta(x, y) = 1$.

Following Charnes et al. (1978) we assume free disposability and convexity of the production set Ψ. Furthermore, when evaluating the performance of the countries in terms of their environmental efficiency levels, input orientation of DEA models have been applied due to the fact that input quantities appear to be the primary decision variables and therefore the decision makers have most control over the inputs compared to the outputs used (Halkos and Tzeremes 2010b, 2010c, 2010d, 2011). Following the notation by Daraio and Simar (2007) given a list of p inputs and q outputs, any productive country can be defined by means of a set of points, Ψ, which forms the production set. Therefore, efficiency measurement of a given country (x, y) relative to the boundary of the convex hull of $X = \{(X_i, Y_i), i = 1...n\}$ can be calculated as:

$$\hat{\Psi}_{DEA} = \left\{ \begin{array}{l} (x, y) \in \Re_{+}^{p+q} \left| y \leq \sum_{i=1}^{n} \gamma_i Y_i ; x \geq \sum_{i=1}^{n} \gamma_i X_i , \quad for(\gamma_1, ..., \gamma_n) \right. \\ s.t. \sum_{i=1}^{n} \gamma_i = 1; \gamma_i \geq 0, i = 1, ..., n \end{array} \right\} \tag{3}$$

The $\hat{\Psi}_{DEA}$ in (3) allows for variables returns to scale (VRS) and has been introduced by Banker et al. (1984). According to Charnes et al. (1978) constant returns to scale (CRS) is applied when the equality constrained $\sum_{i=1}^{n} \gamma_i = 1$ in (3) is omitted.

For a country operating at a level (x_0, y_0) the estimation of the input oriented DEA model is obtained by solving the linear program illustrated below as (4)-(5):

$$\hat{\theta}_{DEA}(x_0, y_0) = \inf \left\{ \theta \middle| (\theta x_0, y_0) \in \hat{\Psi}_{DEA} \right\} \tag{4}$$

$$\hat{\theta}_{DEA}(x_0, y_0) = \min \left\{ \begin{array}{l} \theta \left| y_0 \leq \sum_{i=1}^{n} \gamma_i Y_i ; \theta x_0 \geq \sum_{i=1}^{n} \gamma_i X_i ; \theta \geq 0; \right. \\ \sum_{i=1}^{n} \gamma_i = 1; \gamma_i \geq 0; i = 1, ..., n \end{array} \right\} \tag{5}$$

3.2 Efficiency bias correction and confidence intervals construction

According to Simar and Wilson (1998, 2000) DEA efficiency scores are biased by construction and therefore bootstrap techniques must be applied in order to eliminate the bias created. They introduced an approach based on bootstrap techniques (Efron, 1979) to correct and estimate the bias of the DEA efficiency indicators (Appendix-A2). The bootstrap bias estimate for the original DEA estimator $\hat{\theta}_{DEA}(x, y)$ can be calculated as:

$$\hat{BIAS}_B\left(\hat{\theta}_{DEA}(x, y)\right) = B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}(x, y) - \hat{\theta}_{DEA}(x, y) \tag{6}$$

Furthermore, $\hat{\theta}^*_{DEA,b}(x, y)$ are the bootstrap values and B is the number of bootstrap replications. Then a biased corrected estimator of $\theta(x, y)$ can be calculated as:

$$\hat{\hat{\theta}}_{DEA}(x, y) = \hat{\theta}_{DEA}(x, y) - \hat{BIAS}_B\left(\hat{\theta}_{DEA}(x, y)\right) = 2\hat{\theta}_{DEA}(x, y) - B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}(x, y) \tag{7}$$

However, according to Simar and Wilson (2008) this bias correction can create an additional noise and the sample variance of the bootstrap values $\hat{\theta}^*_{DEA,b}(x, y)$ has to be calculated. The calculation of the variance of the bootstrap values is illustrated below:

$$\hat{\sigma}^2 = B^{-1}\sum_{b=1}^{B}\left[\hat{\theta}^*_{DEA,b}(x, y) - B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}(x, y)\right]^2 \tag{8}$$

Additionally we need to avoid the bias correction illustrated in (7) unless:

$$\frac{\left|\hat{BIAS}_B(\hat{\theta}_{DEA}(x, y))\right|}{\hat{\sigma}} > \frac{1}{\sqrt{3}} \tag{9}$$

By expressing the input oriented efficiency in terms of the Shephard's (1970) input distance function as $\hat{\delta}_{DEA}(x, y) \equiv \dfrac{1}{\hat{\theta}_{DEA}(x, y)}$ we can construct 95-percent confidence intervals for $\hat{\delta}_{DEA}(x, y)$ as:

$$\left[\hat{\delta}_{DEA}(x, y) - \hat{\alpha}_{1-a/2}, \hat{\delta}_{DEA}(x, y) - \hat{\alpha}_{a/2}\right] \tag{10}$$

3.3 Testing the applicability of CCR and BCC models

In order to choose between the adoption of the results obtained by the CCR (Charnes et al. 1978) and BCC (Banker et al. 1984) models in terms of the consistency of our results obtained we adopt the method introduced by Simar and Wilson (2002). Therefore, we compute the DEA efficiency scores under the CRS and VRS assumption and by using the bootstrap algorithm described previously we test for the CRS results against the VRS results obtained such as:

$$H_o : \Psi^{\vartheta} \quad is \quad CRS \quad against \quad H_1 : \Psi^{\vartheta} \quad is \quad VRS \tag{11}$$

The test statistic is given by the following equation as:

$$T(X_n) = \frac{1}{n} \sum_{i=1}^{n} \frac{\hat{\theta} crs, n(X_i, Y_i)}{\hat{\theta} vrs, n(X_i, Y_i)} \tag{12}$$

Then the *p-value* of the null hypotheses can be approximated by the proportion of bootstrap samples as: $p - value = \sum_{b=1}^{B} \frac{I(T^{*,b} \leq T_{obs})}{B}$ (13)

where B is 2000 bootstrap replications, *I* is the indicator function and $T^{*,b}$ are the bootstrap samples and original observed values are denoted by T_{obs}.

3.4 Testing the effect of external 'environmental' variables on the efficiency scores

In order to analyse the effect the years passed since a country has signed and adopted the Kyoto protocol agreement (z) on the efficiency scores obtained we follow the probabilistic approach developed by Daraio and Simar (2005). They suggest that the joint distribution of (X, Y) conditional on the environmental factor Z=z defines the production process if Z=z. The efficiency measure can then be defined as:

$$\theta(x, y|z) = \inf\{\theta | F_X(\theta x | y, z) > 0\} \tag{14}$$

where $Fx(x|y, z) = \Pr ob(X \leq x | Y \geq y, Z = z)$. Then a kernel estimator can be defined as follows: $$\hat{F}_{X|Y,Z,n}\left(x \middle| y,z\right)=\frac{\sum_{i=1}^{n} I\left(x_i \le x, y_i \ge y\right)K\left(\left(z-z_i\right)/h\right)}{\sum_{i=1}^{n} I\left(y_i \ge y\right)K\left(\left(z-z_i\right)/h\right)} \tag{15}$$

where K(.) is the Epanechnikov kernel[4] and h is the bandwidth of appropriate size. Following, Bădin et al. (2010) we use a fully automatic data-driven approach for bandwidth selection based on the work of Hall et al. (2004) and Li and Racine (2004; 2007) least-squares cross-validation criterion (LSCV) which leads to bandwidths of optimal size for the relevant components of Z. This method is based on the principle of selecting a bandwidth that minimizes the integrated squared error of the resulting estimate[5]. Li and Racine (2007) suggest that we have also to correct the resulting h by an appropriate scaling factor, which is $n^{-\frac{q}{(4+q+r)(4+r)}}$ where q is the dimension of Y and r is the dimension of Z[6]. Therefore, we can obtain a conditional DEA efficiency measurement defined as:

$$\hat{\theta}_{DEA}\left(x,y \middle| z\right)=\inf\left\{\theta \middle| \hat{F}_{X|Y,Z,n}\left(\theta x \middle| y,z\right)>0\right\} \tag{16}$$.

Then in order to establish the influence of an environmental variable on the efficiency scores obtained a scatter of the ratios $\frac{\hat{\theta}_n\left(x,y|z\right)}{\hat{\theta}_n\left(x,y\right)}$ against Z (the years since the Kyoto agreement has been signed by a country) and its smoothed non parametric regression lines it would help us to analyse the effect of Z on the environmental efficiency scores obtained. For this purpose we use the nonparametric regression estimator introduced by Nadaraya (1965) and Watson (1964) as:

[4] Other kernels from the family of continuous kernels with compact support can also be used.

[5] See Bădin et al. (2010) for a Matlab routine that computes the bandwidth based on the LSCV criterion.

[6] For more information regarding LSCV criterion and its properties see Silverman (1986), Hall et al. (2004) and Li and Racine (2007).

$$\hat{g}(z)=\frac{\sum_{i=1}^{n}K(\frac{z-Z_i}{h})\left(\frac{\hat{\theta}_n(x,y|z)}{\hat{\theta}_n(x,y)}\right)}{\sum_{i=1}^{n}K(\frac{z-Z_i}{h})} \quad (17).$$

If this regression is increasing it indicates that Z is unfavourable to the countries' environmental efficiency whereas if it is decreasing then it is favourable. When Z is unfavourable then the environmental factor acts like an extra undesired output to be produced demanding the use of more inputs in the production activity. In the opposite case the environmental factor plays a role of a substitutive input in the production process giving the opportunity to save inputs in the activity of production.

4. Empirical Results

Following the methodology proposed by Simar and Wilson (2002) our paper tests the model for the existence of constant or variable returns to scale (analysed previously in equations 11-13). In our application we have three input factors and one outputs and we obtained for this test a p-value of $0.6 > 0.05$ (with B=2000) hence, we cannot reject the null hypothesis of CRS. Therefore, the results adopted in our study are based on the CCR model assuming constant returns to scale[7].

Table 1 provides the results of CRS analysis adopting the correction for bias using the methodology proposed by Simar and Wilson (1998, 2000). For the sample of 110 countries under the CRS assumption only four countries appear to be environmentally efficient (efficiency score = 1). These are China, Cuba, the UK and the USA. The last ten performers are reported to be Botswana, Zambia, Nigeria, Estonia, Bahrain, Senegal, Dominican Republic, Honduras, Congo and Togo. However, when looking at the bias corrected environmental efficiency results we

[7] The results under the VRS assumption are also available upon request.

realise that the environmental efficiency scores are in many cases considerably lower (looking at the descriptive statistics). For instance in the case of the USA the biased corrected (BC) environmental efficiency score is 0.728 with lower bound (LB) of 0.584 and upper bound (UB) of 0.97 in a confidence interval of 95%. Almost identical results are reported in the case of China where the biased corrected (BC) environmental efficiency score is 0.724 with a lower bound (LB) of 0.585 and an upper bound (UB) of 0.974 in a confidence interval of 95%. Daraio and Simar (2007) suggest that when the bias (BIAS) is larger than the standard deviation (STD) then the bias corrected environmental efficiencies (BC) must be preferred compared to the original estimates.

Table 1: Environmental efficiency scores, biased corrected efficiency scores and lower and upper bounds for 95% confidence intervals

Country	CRS	BC	BIAS	STD	LB	UB	Country	CRS	BC	BIAS	STD	LB	UB
Albania	0.427	0.310	-0.879	0.182	0.251	0.416	Kazakhstan	0.549	0.523	-0.090	0.002	0.497	0.543
Algeria	0.552	0.527	-0.085	0.002	0.499	0.547	Kenya	0.779	0.741	-0.066	0.001	0.701	0.771
Argentina	0.624	0.590	-0.093	0.004	0.543	0.620	Korea Republic	0.570	0.526	-0.146	0.009	0.472	0.564
Armenia	0.399	0.337	-0.461	0.056	0.288	0.391	Kuwait	0.910	0.881	-0.036	0.001	0.837	0.905
Australia	0.600	0.515	-0.277	0.023	0.446	0.591	Kyrgyzstan	0.418	0.386	-0.200	0.013	0.352	0.413
Austria	0.711	0.678	-0.069	0.002	0.631	0.705	Latvia	0.548	0.471	-0.296	0.026	0.404	0.538
Azerbaijan	0.596	0.547	-0.151	0.005	0.508	0.588	Lithuania	0.651	0.618	-0.081	0.002	0.579	0.645
Bahrain	0.322	0.281	-0.445	0.026	0.259	0.312	Luxembourg	0.680	0.650	-0.068	0.001	0.617	0.674
Bangladesh	0.565	0.528	-0.123	0.003	0.500	0.555	Malaysia	0.839	0.800	-0.058	0.002	0.743	0.833
Belarus	0.421	0.394	-0.163	0.004	0.375	0.412	Malta	0.600	0.551	-0.149	0.007	0.499	0.591
Belgium	0.717	0.678	-0.080	0.002	0.628	0.709	Mexico	0.768	0.713	-0.099	0.004	0.646	0.759
Benin	0.478	0.450	-0.131	0.007	0.413	0.474	Morocco	0.511	0.490	-0.086	0.003	0.462	0.506
Bolivia	0.561	0.518	-0.148	0.008	0.468	0.556	Mozambique	0.459	0.432	-0.135	0.008	0.394	0.456
Botswana	0.388	0.361	-0.193	0.014	0.328	0.384	Namibia	0.415	0.390	-0.152	0.010	0.356	0.411
Brazil	0.885	0.737	-0.227	0.014	0.630	0.869	Nepal	0.482	0.439	-0.206	0.009	0.406	0.475
Bulgaria	0.426	0.407	-0.113	0.003	0.390	0.421	Netherlands	0.805	0.753	-0.087	0.003	0.685	0.796
Cambodia	0.461	0.433	-0.140	0.009	0.395	0.458	New Zealand	0.702	0.681	-0.045	0.001	0.648	0.698
Cameroon	0.508	0.456	-0.225	0.015	0.409	0.502	Nigeria	0.381	0.357	-0.174	0.011	0.328	0.377
Canada	0.744	0.666	-0.157	0.009	0.583	0.736	Norway	0.794	0.754	-0.066	0.002	0.698	0.787
Chile	0.636	0.605	-0.081	0.001	0.574	0.628	Oman	0.598	0.537	-0.192	0.006	0.498	0.584
China	1.000	0.725	-0.380	0.035	0.586	0.974	Pakistan	0.753	0.709	-0.081	0.001	0.673	0.739
Colombia	0.654	0.630	-0.058	0.001	0.593	0.650	Panama	0.669	0.616	-0.129	0.006	0.555	0.662
Congo	0.277	0.242	-0.527	0.044	0.221	0.269	Paraguay	0.547	0.493	-0.202	0.010	0.447	0.536
Costa Rica	0.558	0.532	-0.088	0.002	0.506	0.552	Peru	0.636	0.605	-0.080	0.002	0.563	0.630
Croatia	0.604	0.545	-0.180	0.009	0.487	0.594	Philippines	0.970	0.911	-0.066	0.001	0.864	0.954
Cuba	1.000	0.794	-0.259	0.008	0.738	0.973	Poland	0.757	0.711	-0.086	0.003	0.647	0.752
Cyprus	0.420	0.368	-0.341	0.019	0.334	0.411	Portugal	0.711	0.676	-0.074	0.001	0.639	0.701

Czech Republic	0.646	0.615	-0.077	0.001	0.581	0.638	Qatar	0.524	0.419	-0.479	0.050	0.356	0.510
Denmark	0.755	0.723	-0.058	0.001	0.677	0.749	Romania	0.464	0.442	-0.107	0.004	0.415	0.459
Dominican Republic	0.313	0.250	-0.797	0.268	0.203	0.308	Russian Federation	0.763	0.689	-0.141	0.008	0.608	0.754
Ecuador	0.529	0.493	-0.139	0.004	0.464	0.520	Saudi Arabia	0.906	0.854	-0.067	0.001	0.794	0.893
Egypt	0.840	0.808	-0.048	0.001	0.767	0.833	Senegal	0.315	0.285	-0.332	0.029	0.257	0.310
El Salvador	0.673	0.600	-0.180	0.007	0.544	0.662	Singapore	0.559	0.539	-0.066	0.002	0.510	0.555
Eritrea	0.892	0.791	-0.143	0.006	0.697	0.878	Slovak Republic	0.596	0.577	-0.055	0.001	0.551	0.592
Estonia	0.353	0.308	-0.408	0.024	0.282	0.341	Slovenia	0.464	0.432	-0.158	0.005	0.406	0.456
Ethiopia	0.481	0.429	-0.248	0.013	0.391	0.475	South Africa	0.708	0.676	-0.067	0.002	0.630	0.704
Finland	0.785	0.757	-0.048	0.001	0.711	0.781	Spain	0.571	0.509	-0.213	0.016	0.448	0.565
France	0.770	0.660	-0.216	0.015	0.564	0.758	Sri Lanka	0.464	0.422	-0.212	0.007	0.392	0.451
Georgia	0.618	0.564	-0.156	0.004	0.523	0.605	Sudan	0.888	0.860	-0.037	0.000	0.822	0.882
Germany	0.877	0.742	-0.207	0.015	0.620	0.863	Sweden	0.827	0.782	-0.069	0.002	0.727	0.818
Ghana	0.414	0.382	-0.203	0.009	0.352	0.408	Switzerland	0.748	0.710	-0.072	0.002	0.658	0.741
Greece	0.823	0.780	-0.067	0.001	0.731	0.812	Syrian Arab Republic	0.551	0.503	-0.175	0.004	0.471	0.537
Guatemala	0.613	0.548	-0.193	0.007	0.504	0.603	Thailand	0.593	0.567	-0.078	0.002	0.532	0.589
Haiti	0.752	0.711	-0.076	0.003	0.651	0.747	Togo	0.081	0.059	-4.595	5.118	0.048	0.079
Honduras	0.305	0.271	-0.411	0.030	0.248	0.297	Trinidad and Tobago	0.742	0.668	-0.149	0.007	0.596	0.734
Hungary	0.756	0.723	-0.060	0.001	0.688	0.747	Tunisia	0.522	0.490	-0.128	0.004	0.458	0.517
Iceland	0.493	0.457	-0.162	0.006	0.425	0.486	Ukraine	0.587	0.566	-0.062	0.002	0.535	0.583
India	0.487	0.433	-0.258	0.022	0.381	0.480	United Arab Emirates	0.889	0.851	-0.050	0.001	0.802	0.881
Indonesia	0.605	0.560	-0.134	0.008	0.504	0.599	United Kingdom	1.000	0.877	-0.140	0.007	0.751	0.983
Ireland	0.772	0.743	-0.051	0.001	0.697	0.768	USA	1.000	0.728	-0.373	0.035	0.585	0.970
Israel	0.859	0.825	-0.048	0.001	0.782	0.851	Uruguay	0.838	0.797	-0.061	0.001	0.753	0.830
Italy	0.797	0.705	-0.165	0.010	0.611	0.787	Uzbekistan	0.657	0.626	-0.076	0.001	0.594	0.650
Jamaica	0.588	0.514	-0.245	0.020	0.444	0.580	Venezuela	0.840	0.799	-0.061	0.002	0.740	0.835
Japan	0.737	0.597	-0.317	0.031	0.493	0.723	Yemen	0.541	0.466	-0.296	0.015	0.424	0.528
Jordan	0.518	0.482	-0.144	0.006	0.445	0.512	Zambia	0.385	0.354	-0.232	0.017	0.320	0.381

Descriptive Statistics

	CRS	BC	BIAS	STD	LB	UB
Mean	0.628	0.575	-0.209	0.059	0.527	0.620
Std	0.184	0.169	0.445	0.488	0.159	0.181
Min	0.081	0.059	-4.595	0.000	0.048	0.079
Max	1.000	0.911	-0.036	5.118	0.864	0.983

In addition to table 1, table 2 provides the analytical results of countries' environmental efficiency taking into consideration the number of years since a country has signed the KPA. Again we test our model for the existence of constant or variable returns to scale (equations 11-13). The p-value of the test is 0.77 > 0.05 (with B=2000); hence again we cannot reject the null hypothesis of CRS and the results obtained from the CCR model have been adopted. The conditional environmental efficiency levels reveal countries' environmental policy is influenced by the adoption (or not) of the necessary reductions of CO_2 emissions.

Following the methodology presented previously the results indicate that the environmental efficient countries under the effect of the KPA (CRS|z) are Albania, China, El Salvador, Panama and the USA. The last ten performers are reported to be Morocco, Poland, Norway, Romania, Slovak Republic, Austria, Korea Republic, India, Dominican Republic and Togo.

However as previously stated the biased corrected results need to be adopted since the bias is larger than the standard deviation (Daraio and Simar 2007). Again great differences are been reported on the conditional environmental efficiencies of the countries under evaluation (looking at the standard deviations of the conditional environmental efficiency scores). For instance in the case of the USA the biased corrected conditional environmental efficiency score (BC|z) is 0.60 with lower bound of 0.52 and upper bound of 0.91 in a confidence interval of 95%. Therefore, taking into consideration the biased corrected conditional environmental efficiency scores the highest ten performers are reported to be Albania, Panama, El Salvador, Uzbekistan, Pakistan, the USA, China, Egypt, Trinidad and Tobago and Jamaica. Whereas the ten countries with the lowest biased corrected conditional environmental efficiency scores are reported to be Romania, Canada, Morocco, Austria, Japan, Slovak Republic, Korea Republic, India, Dominican Republic and Togo.

Figure 1 presents the density estimates using the "normal reference rule-of-thumb" approach for bandwidth selection (Silverman, 1986) and a second order Gaussian kernel. Subfigure 1a, indicates the differences between the environmental efficiency scores and the conditional environmental efficiency scores. It appears that the original estimates under the CRS assumption (solid line) are platykurtic compared to the original CRS conditional estimates (dotted line) which appear to be leptokurtic. The leptokurtic distributions indicate that there is a rapid fall-off in the density as we move away from the mean. Furthermore, the pickedness of the distribution suggests a clustering around the mean with rapid fall around it. In addition subfigure 1b indicates high differences between the densities of the biased corrected environmental efficiency scores (solid line) and the biased corrected conditional efficiency scores (dotted line). As can be realised the conditional estimates (original and biased corrected) are reported to be lower compared to the unconditioned environmental efficiency estimates (original and biased corrected). This in turn indicates that when we account for the effect of the KPA countries' environmental efficiency scores tend to decrease rather than to increase.

Table 2: Conditional environmental efficiency scores biased corrected efficiency scores and lower and upper bounds for 95% confidence intervals.

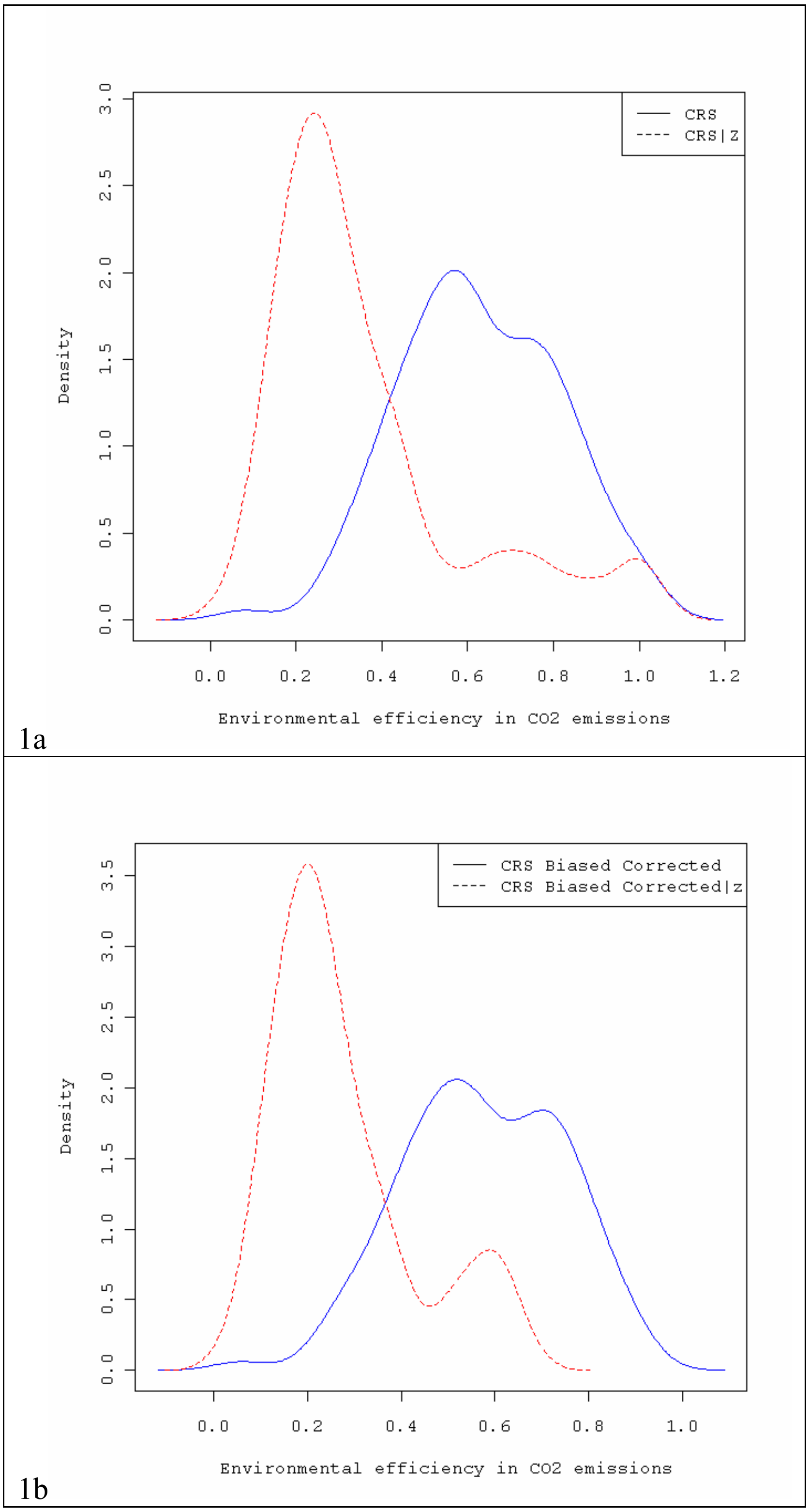
Country	CRS|z	BC|z	BIAS	STD	LB	UB	Country	CRS|z	BC|z	BIAS	STD	LB	UB
Albania	1.000	0.673	-0.485	0.025	0.580	0.897	Kazakhstan	0.277	0.247	-0.430	0.045	0.221	0.270
Algeria	0.647	0.524	-0.365	0.031	0.438	0.618	Kenya	0.382	0.290	-0.833	0.080	0.253	0.349
Argentina	0.209	0.172	-1.026	0.227	0.146	0.199	Korea Republic	0.116	0.087	-2.854	1.329	0.075	0.110
Armenia	0.301	0.200	-1.677	0.213	0.177	0.270	Kuwait	0.528	0.432	-0.420	0.023	0.381	0.491
Australia	0.573	0.391	-0.812	0.099	0.328	0.537	Kyrgyzstan	0.223	0.170	-1.403	0.280	0.146	0.210
Austria	0.131	0.106	-1.761	0.618	0.091	0.124	Latvia	0.441	0.302	-1.042	0.104	0.262	0.394
Azerbaijan	0.394	0.328	-0.510	0.045	0.286	0.375	Lithuania	0.353	0.264	-0.955	0.105	0.230	0.324
Bahrain	0.412	0.337	-0.539	0.057	0.289	0.394	Luxembourg	0.323	0.264	-0.689	0.051	0.236	0.298
Bangladesh	0.169	0.138	-1.305	0.216	0.122	0.159	Malaysia	0.237	0.191	-1.026	0.154	0.165	0.221
Belarus	0.298	0.262	-0.450	0.040	0.236	0.287	Malta	0.288	0.214	-1.196	0.158	0.187	0.266
Belgium	0.200	0.173	-0.798	0.189	0.148	0.194	Mexico	0.293	0.238	-0.799	0.237	0.192	0.286
Benin	0.220	0.175	-1.191	0.275	0.147	0.209	Morocco	0.151	0.111	-2.382	0.687	0.095	0.139
Bolivia	0.704	0.497	-0.590	0.060	0.416	0.663	Mozambique	0.409	0.319	-0.686	0.097	0.270	0.394
Botswana	0.244	0.185	-1.316	0.196	0.160	0.222	Namibia	0.254	0.201	-1.040	0.223	0.169	0.245
Brazil	0.280	0.195	-1.573	0.336	0.165	0.261	Nepal	0.432	0.316	-0.847	0.068	0.277	0.392
Bulgaria	0.273	0.234	-0.616	0.054	0.211	0.261	Netherlands	0.160	0.133	-1.243	0.447	0.113	0.155
Cambodia	0.243	0.190	-1.153	0.232	0.161	0.232	New Zealand	0.196	0.162	-1.068	0.145	0.144	0.183
Cameroon	0.288	0.229	-0.891	0.125	0.197	0.271	Nigeria	0.264	0.212	-0.913	0.204	0.178	0.254
Canada	0.153	0.112	-2.388	0.757	0.096	0.143	Norway	0.147	0.119	-1.569	0.475	0.102	0.138
Chile	0.228	0.202	-0.562	0.070	0.181	0.221	Oman	0.363	0.310	-0.468	0.048	0.271	0.350
China	1.000	0.605	-0.652	0.040	0.527	0.894	Pakistan	0.776	0.608	-0.357	0.022	0.512	0.723
Colombia	0.240	0.208	-0.644	0.084	0.183	0.230	Panama	1.000	0.644	-0.552	0.022	0.588	0.909
Congo	0.278	0.207	-1.240	0.143	0.181	0.253	Paraguay	0.675	0.466	-0.662	0.056	0.399	0.633
Costa Rica	0.291	0.229	-0.920	0.107	0.201	0.268	Peru	0.194	0.144	-1.765	0.372	0.125	0.178
Croatia	0.335	0.232	-1.323	0.177	0.202	0.300	Philippines	0.445	0.380	-0.381	0.027	0.335	0.424
Cuba	0.274	0.226	-0.775	0.111	0.196	0.262	Poland	0.151	0.117	-1.947	0.614	0.100	0.141
Cyprus	0.775	0.559	-0.496	0.042	0.473	0.728	Portugal	0.214	0.189	-0.619	0.090	0.168	0.208
Czech Republic	0.254	0.226	-0.484	0.064	0.200	0.248	Qatar	0.196	0.120	-3.243	0.994	0.106	0.177
Denmark	0.218	0.186	-0.780	0.124	0.163	0.209	Romania	0.138	0.114	-1.530	0.469	0.098	0.131

Dominican Republic	0.090	0.056	-6.652	5.206	0.048	0.083	Russian Federation	0.226	0.177	-1.231	0.458	0.143	0.219
Ecuador	0.356	0.306	-0.462	0.041	0.270	0.342	Saudi Arabia	0.329	0.284	-0.481	0.071	0.243	0.319
Egypt	0.758	0.591	-0.374	0.020	0.507	0.703	Senegal	0.216	0.167	-1.381	0.216	0.145	0.199
El Salvador	1.000	0.621	-0.610	0.030	0.556	0.894	Singapore	0.665	0.526	-0.397	0.030	0.441	0.619
Eritrea	0.539	0.403	-0.623	0.058	0.344	0.505	Slovak Republic	0.131	0.100	-2.318	0.590	0.087	0.118
Estonia	0.265	0.221	-0.765	0.117	0.192	0.255	Slovenia	0.281	0.246	-0.500	0.056	0.219	0.272
Ethiopia	0.370	0.295	-0.683	0.069	0.256	0.345	South Africa	0.441	0.364	-0.480	0.050	0.309	0.416
Finland	0.443	0.369	-0.449	0.042	0.317	0.423	Spain	0.185	0.140	-1.721	0.697	0.116	0.177
France	0.161	0.117	-2.340	0.913	0.098	0.150	Sri Lanka	0.277	0.238	-0.584	0.078	0.209	0.269
Georgia	0.738	0.541	-0.494	0.028	0.470	0.669	Sudan	0.231	0.178	-1.272	0.191	0.156	0.212
Germany	0.184	0.132	-2.160	0.918	0.110	0.176	Sweden	0.191	0.166	-0.809	0.172	0.144	0.185
Ghana	0.313	0.231	-1.140	0.167	0.199	0.291	Switzerland	0.229	0.197	-0.693	0.143	0.169	0.221
Greece	0.175	0.151	-0.925	0.188	0.132	0.169	Syrian Arab Republic	0.449	0.375	-0.437	0.036	0.328	0.429
Guatemala	0.457	0.365	-0.555	0.051	0.314	0.430	Thailand	0.298	0.259	-0.497	0.072	0.224	0.289
Haiti	0.633	0.510	-0.382	0.038	0.423	0.614	Togo	0.040	0.024	-16.310	25.072	0.021	0.036
Honduras	0.327	0.256	-0.846	0.091	0.222	0.305	Trinidad and Tobago	0.878	0.586	-0.567	0.047	0.498	0.835
Hungary	0.160	0.132	-1.317	0.245	0.116	0.150	Tunisia	0.280	0.234	-0.700	0.076	0.208	0.267
Iceland	0.268	0.196	-1.377	0.155	0.172	0.240	Ukraine	0.406	0.348	-0.413	0.037	0.302	0.391
India	0.102	0.072	-4.162	1.932	0.062	0.095	United Arab Emirates	0.311	0.272	-0.454	0.048	0.240	0.299
Indonesia	0.219	0.173	-1.212	0.309	0.145	0.207	United Kingdom	0.209	0.160	-1.456	0.568	0.131	0.202
Ireland	0.430	0.359	-0.459	0.045	0.308	0.409	USA	1.000	0.607	-0.648	0.042	0.526	0.916
Israel	0.218	0.188	-0.725	0.079	0.169	0.208	Uruguay	0.408	0.287	-1.038	0.094	0.251	0.363
Italy	0.166	0.126	-1.924	0.835	0.104	0.159	Uzbekistan	0.902	0.618	-0.509	0.028	0.544	0.823
Jamaica	0.846	0.571	-0.569	0.029	0.512	0.760	Venezuela	0.278	0.232	-0.718	0.108	0.199	0.265
Japan	0.156	0.105	-3.065	1.464	0.089	0.146	Yemen	0.322	0.265	-0.676	0.089	0.228	0.308
Jordan	0.347	0.250	-1.110	0.139	0.217	0.321	Zambia	0.400	0.300	-0.837	0.093	0.257	0.366

Descriptive Statistics

	CRS	**BC**	**BIAS**	**STD**	**LB**	**UB**
Mean	0.360	0.273	-1.207	0.498	0.236	0.336
Std	0.229	0.153	1.690	2.432	0.133	0.208
Min	0.040	0.024	-16.310	0.020	0.021	0.036
Max	1.000	0.673	-0.357	25.072	0.588	0.916

Figure 1: Kernel density functions of countries' environmental efficiencies derived from unconditional and conditional CRS and biased corrected CRS DEA models using Gaussian Kernel and the appropriate bandwidth



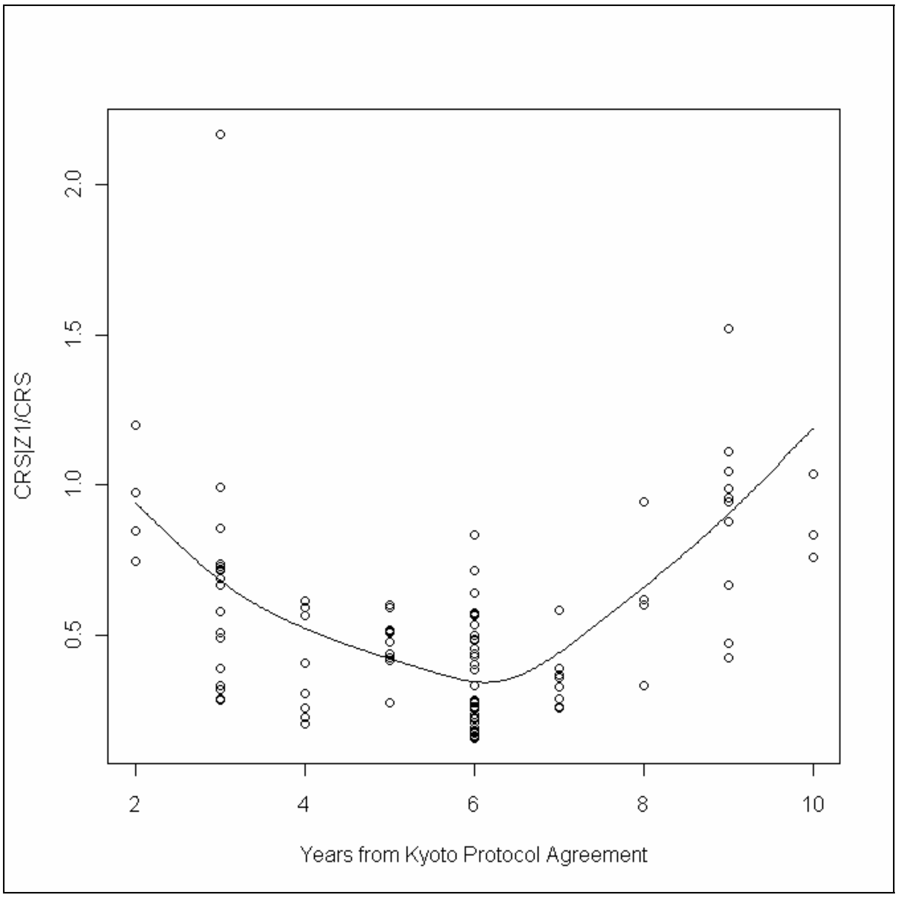
Furthermore, figure 2 provides a graphical representation of the effect of the number of years countries have signed the Kyoto protocol agreement (in order to take measures to limit emissions and promote adaptation to future climate change impacts) since 2007 (the year the environmental efficiency is computed) on countries' environmental efficiency. For this task we use the 'Nadaraya-Watson' estimator, which is the most popular method for nonparametric kernel regression proposed by Nadaraya (1965) and Watson (1964) (see equation 17). For the calculation of bandwidth we have used least-squares cross-validation criterion (LSCV) which is a fully automatic data-driven approach (Hall et al. 2004; Li and Racine 2004, 2007)

As such figure 2 illustrates the nonparametric estimate of the regression function using the conditional and unconditional biased corrected CRS environmental efficiency estimates. Figure 2 illustrates the effect of 'z' under CRS assumption. When the regression is decreasing, it indicates that 'z' factor is favourable to environmental efficiency. In our case figure 2 illustrates a decreasing nonparametric regression line up to a point (six years) indicating that the environmental variable (the years since the Kyoto protocol agreement was signed) act as substitutive input in the production process of countries' environmental efficiency. Therefore, it provides the opportunity to "save" in the activity of production.

But after the six years it appears that the regression line has a steeper and increasing shape indicating a highly negative effect on countries environmental efficiencies. This result clearly indicates that countries adopt the agreement for a certain time period (in our case up to six years) trying to improve their environmental performances by reducing their CO_2 emissions. However, after a certain time point countries are not complying with the KPA and in turn their higher economic growth rates are not followed by relative reductions on their CO_2 emissions having a negative effect on their environmental efficiencies.

Figure 2 about here

Figure 2: The global effect of Kyoto protocol agreement on countries' carbon dioxide environmental efficiency.



5. Conclusions

This paper applies an efficiency analysis in a sample of 110 countries in order to establish the effect of KPA on their environmental efficiencies in CO_2 emissions. Then by applying an inferential approach on DEA efficiency scores the paper measures countries' environmental efficiency for the year 2007. Biased corrected results and 95% confidence intervals have been produced indicating major environmental inefficiencies among countries. At a second stage of the analysis our paper verifies the effect of KPA on countries' environmental efficiencies by calculating their conditional environmental measures. The biased corrected conditional results reveal that when the time period since a country has signed the KPA is taken into account their environmental efficiency scores decrease.

In order to observe the effect more closely in a third step the paper uses nonparametric regression in order to reveal the effect of the agreement and countries' compliance to CO_2 reductions. The results reveal that countries are complying with KPA in the first six years, which in turn has a positive effect on their environmental efficiencies. However after that period it appears that countries avoid complying with the actions imposed by the agreement or they are unable to adjust accordingly the reductions of CO_2 emissions on their economies' growth rates which in turn have an immediate negative effect on their environmental efficiencies.

Finally, our study provides evidence of how the new advances and recent developments in efficiency analysis can be applied in an input-output analysis for an effective evaluation of environmental policies providing a vital tool to policy makers for analysing environmental related problems.

Appendix

A1: Countries used in our analysis

Albania, Algeria, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahrain, Bangladesh, Belarus, Belgium, Benin, Bolivia, Botswana, Brazil, Bulgaria, Cambodia, Cameroon, Canada, Chile, China, Colombia, Congo, Costa Rica, Croatia, Cuba, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Eritrea, Estonia, Ethiopia, Finland, France, Georgia, Germany, Ghana, Greece, Guatemala, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Korea Republic, Kuwait, Kyrgyzstan, Latvia, Lithuania, Luxembourg, Malaysia, Malta, Mexico, Morocco, Mozambique, Namibia, Nepal, Netherlands, New Zealand, Nigeria, Norway, Oman, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russian Federation, Saudi Arabia, Senegal, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, Sudan, Sweden, Switzerland, Syrian Arab Republic, Thailand, Togo, Trinidad and Tobago, Tunisia, Ukraine, United Arab Emirates, United Kingdom, USA, Uruguay, Uzbekistan, Venezuela, Yemen and Zambia

A2: A synoptic illustration of the bootstrapped based algorithm introduced by Simar and Wilson (1998, 2000)

Step 1: Transform the input-output vectors using the original efficiency estimates $\left\{\hat{\theta}_{in,}\ i=1,...,n\right\}$ as $\left(\hat{x}_i^{\,l}, y_i\right) = \left(x_i \cdot \hat{\theta}_{in}, y_i\right)$

Step 2: Generate smoothed resampled pseudo-efficiencies γ_i^* as follows:

2.1 Given a set of estimated efficiencies $\left\{\hat{\theta}_{in}\right\}$, use the "rule of thump" [42, p.47-48] to obtain the bandwidth parameter h as $h = 0.9n^{1/5}\min\left\{\hat{\sigma}_{\hat{\theta}}, R_{13}/1.34\right\}$, where $\hat{\sigma}_{\hat{\theta}}$ = the standard deviation of $\left\{\hat{\theta}_{in}\right\}$ and R_{13} is the interquartile range of the empirical distribution of $\left\{\hat{\theta}_{in}\right\}$.

2.2 Generate $\left\{\delta_i^*\right\}$by replacing, with replacement, from the empirical distribution of $\left\{\hat{\theta}_{in}\right\}$of the estimated efficiencies.

2.3 Generate the sequence $\left\{\tilde{\delta}_i^*\right\}$ using:

$$\tilde{\delta}_i^* = \begin{cases} \delta_i^* + h\varepsilon_i^* & \text{if} \quad \delta_i^* + h\varepsilon_i^* \le 1 \\ 2 - (\delta_i^* + h\varepsilon_i^*) & \text{otherwise} \end{cases}$$

where ε_i^* is drawn i.i.d. from a standard normal distribution.

2.4 Generate the smoothed pseudo-efficiencies $\{\gamma_i^*\}$ using the following formula:
$\gamma_i^* = \bar{\delta}_i^* (\tilde{\delta}_i^* - \bar{\delta}_i^*) / \sqrt{1 + h^2 / \hat{\sigma}_{\hat{\theta}}^2}$, where $\bar{\delta}_i^* = \sum_{i=1}^{n} \delta_i^* / n$ which is the average of the resampled original efficiencies.

Step 3: Let the pseudo-data be given by

$$\left(x_i^*, y_i^*\right) = \left(\hat{x}_i^l / \gamma_i^*, y_i \right)$$

Step 4: Estimate the bootstrap efficiencies using the pseudo-data as:

$$\hat{\theta}_{in}^{SW*} = \min_{\theta, z} \left\{ \theta : y_i \leq Yz, \theta x_i \geq X^* z, \sum_{i=1}^{n} z_i = 1, z \in R_+^n \right\}$$

Step 5 Repeat steps (2)-(4) **B** times to create a set of **B** bank specific bootstrapped efficiency estimates $\hat{\theta}_{in}^{SW*b}$ $, i = 1,...,n, b = 1,..,B$, According to Simar and Wilson [33, 34] a proper B = 2000 replications.

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