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Halkos, George and Tzeremes, Nickolaos

University of Thessaly, Department of Economics

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by

George Emm. Halkos[1] and Nickolaos G. Tzeremes

Department of economics, University of Thessaly

Abstract

This paper demonstrates an evaluation of 71 developed and under-developed countries' biodiversity performance using a methodological framework based to the new advances of Data Envelopment Analysis (DEA). By using conditional DEA, bootstrapping and kernel density estimations, efficiency levels of 71 countries are compared and analyzed. In such a way the paper by modelling and measuring countries' biodiversity performance analyses whether the countries environmental policies have been used efficiently in order to enhance biodiversity. Our empirical results indicate that there are major inefficiencies among the 71 countries in terms of their biodiversity performances which have been negatively influenced by their higher levels of population and of GDP per capita.

***Keywords*:** Biodiversity; Conditional DEA; Bootstrap techniques; Convexity test; Kernel density estimation

JEL Classification: C63, C69, O13, Q57

[1] Corresponding author: Professor George Emm. Halkos, Director, Department of Economics, University of Thessaly, Korai 43, 38333, Volos, Greece. http://www.halkos.gr. Email: halkos@econ.uth.gr. Tel.: 0030 24210 74920. FAX: 0030 24210 74772.

1. Introduction

The biological diversity (biodiversity) is a concept entailed in the modern scientific and political terminology and in daily life with various social and economic dimensions.

Biodiversity is in danger due mainly to human activities. In the second half of the 20th century, human population was doubled from 2.5 billion in 1950 to more than 6 billion in 2000. At the same time the value of economic activity increased by more than 400% over the second half of last century (Delong 2003). The area of natural habitat has been reduced for a number of reasons such as conversion of lands to agriculture, over-harvesting of fish, air and water pollution, climate change, urban development, increasing sequence of fires in forests, etc. For these reasons the current rates of species extinction have been dramatically increased.

Threats to the natural habitat are in general lower in the developed countries compared to the tropical developing countries where much of the biodiversity resides. One of the main concerns of the environmental social sciences is the deep understanding of the social and economic forces that change the environment. Scholars have contributed to global biodiversity loss research by paying attention to the relevance and context of species in threat to the interdisciplinary community (Hoffman 2004; Naidoo and Adamowicz 2001). Due to data limitations and reliability cross national comparisons have tackled basically the loss of land-based species like birds and mammals. The studies mentioned only partially capture the cumulative effects of human activity on global diversity.

For the first time this paper by introducing the term 'biodiversity efficiency' tries to capture 71 countries' biodiversity performances by employing the latest advances of conditional DEA techniques as has been extensively analysed by Daraio and Simar (2005a; 2005b; 2007). DEA methodology has been used by several authors in order to measure environmental 'efficiency'. Kao et al. (1993) (measuring the efficiency of forest management) and Alsharif et al. (2008) (measuring the efficiency of supply systems) emphasise the benefits of DEA application on environmental management. In addition, several authors have been based on DEA methodology in order to measure environmental performance/ efficiency (Färe et al., 1999; Färe et al., 2003; Färe et al., 2004; Tyteca, 1996, 1997; Zaim and Taskin, 2000; Taskin and Zaim, 2000; Jung et al., 2001; Halkos and Tzeremes, 2009).

However this paper goes a step further and instead of providing measurement techniques and applications of environmental performance directly, examines countries' biodiversity performances taking into account four external factors which according to environmental literature seem to influence countries' biodiversity levels. These factors are: countries' population (in thousands), per capita CO_2 emissions, per capita Gross Domestic Product and the GINI index of income inequality. In addition, this paper provides for the first time an illustrative application of how the latest advances on non parametric techniques can been used in order for the policy makers to be able to measure biodiversity performance and be able to account and measure external influences on that performance measures. Moreover, it raises several issues regarding the 'proper' adoption of DEA models in order for the decision maker to implement DEA modelling regardless the problem facing. For instance 'scale' and 'convexity' issues have been tackled using the bootstrap technique. In addition, the estimators have been tested for bias and have been corrected appropriately. However, as stated, the main argument in efficiency measurement literature is the issue of environmental (or external) factors which influence the efficiency measurement of the decision making unit. In that respect this study employs conditional measurements of efficiency, using different smoothing techniques. Hence, by creating new conditional and unbiased estimators we provide strong evidences of countries' biodiversity performance levels conditioned to the factors affecting them the most.

The structure of this study is the following. Section 2 presents the data used, while section 3 discusses analytically the proposed non parametric techniques. Section 4 refers to the empirical results derived and the last section concludes the paper.

2. Data

One of the most commonly used methods of describing biodiversity of an area is the count of species that reside in this area. Obviously a complete enumeration of all species even in a simple square metre is impossible, as the vast majority of living organisms remains unknown. At the same time there are cases of existence of different definitions for species creating different estimates of their richness. Additional problems arise in the analysis of the geographical distribution of the various species, the change of these distributions in time etc. The huge variety of living creatures is ranked in multiple levels (from genes to ecosystems) making their complete enumeration extremely difficult and in many case infeasible. Therefore, in our study we use secondary data subtracted from World Resources Database (World Resource Institute, 2005).

Table 1: Descriptive statistics of the inputs, external factors and the output used in the analysis.

Inputs/ Output	**AgrProd (Input)**	**ProtAreas (Input)**	**EnergIntens(Input)**	**WSE(Output)**
Averages	118,676	14,244	290,465	96,519
Max	198,000	72,300	942,000	99,697
Min	54,000	0,400	98,000	73,467
Std	28,541	13,592	207,171	4,162
External Variables	**GDPC (Z_1)**	**GINI (Z_2)**	**Popul (Z_3)**	**CO2 (Z_4)**
Averages	8938,915	40,725	1009,798	222,859
Max	33939,000	60,700	36820,000	5584,800
Min	501,000	19,500	1,306	1,100
Std	9004,694	9,580	4648,123	695,718

In this study we use economic and environmental data in order to calculate biodiversity performance of a sample of 71 countries. In that respect we need to clarify the inputs/ outputs used. Table 1 provides descriptive statistics of the variables used. Specifically as inputs a number of variables are used such as:

1) Total agricultural production index (1999-2001=100) (AgrProd). According to several authors the high exposure of agricultural production in fertilisers, pesticides, herbicides and to frequent crop rotation has resulted in into hostile habitat for many species, which in turn have caused a decline of biodiversity on those areas (Pimentel et al. 1992; Wagner and Edwars, 2001; Grashof-Bokdam and van Langevelde, 2004; Billeter et al. 2008).

2) Energy intensity in all economics sectors (toe per million $) (EnergIntens). Energy consumption due to its influence in environmental temperature levels has a direct impact on biodiversity (Hutchinson, 1959; Wright, 1983; Allen et al., 2002; Huston et al. 2003).

3) National protected areas (total number) in every country (ProtAreas). According to Mcneely (1994) protected areas are essential to the conservation of biological diversity and human welfare.

Traditional biodiversity metrics such as Shannon's or Simpson's index (Simpson, 1949; Margalef, 1958) have been widely used in ecology. However, recent approaches suggest that measurement needs to have a reference state in order to capture the magnitude of change (Bucklandet al., 2005; Loh et al., 2005; Nielsen et al., 2007). Lamb et al. (2009) suggest that his kind of indexes can be applied as common metric and thus changes in biodiversity intactness can be examined. Another issue regarding those indexes is the ecological state variables of richness and diversity, but according to Magurran, (2004) they retain only a small portion of the available information which describes biodiversity. Based on the same notion this study uses one output in a form of a weighted species enrichment (WSE) ratio. It has a simplistic form and is calculated by the number of species known minus those which are endangered. The species used contain full data on reptiles, mammals, fish, birds and plants for each country. More analytically the index can be constructed as:

$$WSE = \frac{\sum_{i=1}^{n}(kij - tij)}{\sum_{i=1}^{n} kij} x \ \ 100 \qquad (1),$$

where k= the number of known species, i = the country for which the species are reported, j = is a particular specie category (i.e. plants) and t = the number of threaten species. The higher the values of index the higher will be the country's specie enrichment.

According to van Strien et al. (2009) biodiversity measures need to reflect changes in general rather than the ups and downs of particular species or species groups. Thus it is essential to know how external 'uncontrollable' environmental drivers influence the specific set of species monitored (directly or indirectly). As such we use four other variables as external factors in order to establish their influence on countries' biodiversity performance. These are the data provided for population (in thousands) (Popul), the per capita CO_2 emissions (in tons CO_2 per million \$) (CO2), the per capita Gross Domestic Product (GDPC) and the GINI index of income inequality (0= perfect equality). The data used in our study refer to the year 2004 for existing species and 2003 for endangered species. Our sample consists of 71 countries[2]. Table 1 presents the descriptive statistics of all the variables used and as can be realised there are many disparities among the countries under consideration.

[2] The countries used are the ones with full record (no missing values).

This can be justified due to the fact that the sample consists under develop and developed countries. This can be easily observed when looking at the values of standard deviations of the external variables, which are in our main interest when evaluating their influence on countries' biodiversity performance.

3. Methodology

3.1 Performance measurements

The first DEA estimator was introduced by Farrell (1957) to measure technical efficiency. However DEA became more popular when was introduced by Charnes et al. (1978) to estimate Ψ and allowing constant returns to scale (CCR model). The production set Ψ constraints the production process and is the set of physically attainable points (x, y) :

$$\Psi = \left\{ (x, y) \in \Re_{+}^{N+M} \middle| x \ \ can \ \ produce \ \ y \right\} \qquad (2),$$

where $x \in \Re_{+}^{N}$ is the input vector and $y \in \Re_{+}^{M}$ is the output vector. Later, Banker et al. (1984) introduced a DEA estimator allowing for variable returns to scale (BCC model). The CCR model uses the convex cone of $\hat{\psi}_{FDH}$ to estimate Ψ, whereas the BCC model uses the convex hull of $\hat{\psi}_{FDH}$ to estimate Ψ. In this paper we use input oriented models since the decision maker through different governmental policies have greater control over the inputs compared to the outputs used. Following the notation by Simar and Wilson (2008), the CCR model developed by Charnes et al. (1978) can be calculated as:

$$\hat{\Psi}_{CRS} = \left\{ \begin{array}{l} (x, y) \in \Re^{N+M} \middle| y \leq \sum_{i=1}^{n} \gamma_i y_i ; x \geq \sum_{i=1}^{n} \gamma_i x_i \ \ for \ \ (\gamma_1, \ldots \gamma_n) \\ such \ \ that \ \ \gamma_i \geq 0, i = 1, \ldots n \end{array} \right\} \qquad (3).$$

The BBC model developed by Banker et al. (1984) allowing for variable returns to scale can then be calculated as:

$$\hat{\Psi}_{VRS} = \begin{Bmatrix} (x,y) \in \Re^{N+M} \middle| y \leq \sum_{i=1}^{n} \gamma_i y_i ; x \geq \sum_{i=1}^{n} \gamma_i x_i \quad for \quad (\gamma_1, \ldots \gamma_n) \\ such \quad that \quad \sum_{i=1}^{n} \gamma_i = 1; \ \gamma_i \geq 0, i = 1, \ldots n \end{Bmatrix} \tag{4}$$

Finally the FDH estimator $\hat{\psi}_{FDH}$ which is the free disposal hull of the observed sample X_n and developed by Deprins et al. (1984) can be expressed as:

$$\begin{aligned} \hat{\Psi}_{FDH} &= \left\{ (x,y) \in \Re^{N+M} \middle| y \leq y_i, x \geq x_i, (x_i, y_i \in X_n \right\} \\ &= \bigcup_{(x_i, y_i) \in X_n} \left\{ (x,y) \in \Re_{+}^{p+q} \middle| y \leq y_i, x \geq x_i \right\} \end{aligned} \tag{5}$$

3.2 Bias correction using the bootstrap technique

According to Simar and Wilson (1998, 2000, 2008) DEA estimators were shown to be biased by construction. They introduced an approach based on bootstrap techniques (Efron 1979) to correct and estimate the bias of the DEA efficiency indicators. Therefore, 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 reputations. 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 $\hat{\theta}^{*}_{DEA,b}(x,y)$ need to be calculated. The calculation of the variance of the bootstrap values is illustrated below:

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

According to Simar and Wilson (2008) we need to avoid the bias correction illustrated in (7) unless:

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

Finally, the $(1-\alpha)\ x\ 100$ - percent bootstrap confidence intervals can be obtained for $\theta(x,y)$ as:

$$\frac{1}{\hat{\delta}_{DEA}(x,y) - nc^{*}_{1-a/2}} \le \theta(x,y) \le \frac{1}{\hat{\delta}_{DEA}(x,y) - nc^{*}_{a/2}} \qquad (10).$$

Furthermore, using the methodology proposed by Badin and Simar (2004) we obtain a bias corrected FDH estimator:

$$\hat{x}^{\vartheta}_{n_y}(y) = x^{y}_{(1)} - \sum_{i=1}^{n_y-1}(1-\frac{i}{n_y})^{n_y}(x^{y}_{i+1} - x^{y}_{(i)}) \qquad (11),$$

the first term is the FDH estimator and the second term is the bias correction. According to Badin and Simar (2004) this estimator is a symmetric version of the order-m minimum input function proposed by Cazals, Florens and Simar (2002). Another approach is also provided by Jeong and Simar (2006) producing an algorithm for a linearized version of FDH (LFDH) offering in such a way a bias-corrected estimator.

3.3 Testing for returns to scale and convexity

According to Simar and Wilson (2002) bootstrap techniques can be used in order to test for the adoption of results between the Constant Returns to Scale (CRS) against the Variable Returns to Scale (VRS) such as: $H_0 : \Psi^{\theta}$ is globally CRS against $H_1 : \Psi^{\theta}$ is VRS. The test statistic mean of the ratios of the efficiency scores is then provided by:

$$T(X_n) = \frac{1}{n}\sum_{i=1}^{n}\frac{\hat{\theta}_{CRS,n}(X_i, Y_i)}{\hat{\theta}_{VRS,n}(X_i, Y_i)} \quad (12).$$

Then the *p-value* of the null-hypothesis can be obtained as:

$$p - value = prob(T(X_n) \leq T_{obs} | H_0 \quad is \quad true)$$

(13) where T_{obs} is the value of T computes on the original observed sample X_n .Then this *p-value* can be approximated by the proportion of bootstrap values of T^{*b} less the original observed value of T_{obs} such as:

$$p - value \approx \sum_{b=1}^{B}\frac{\mathrm{I}\left(T^{*b} \leq T_{obs}\right)}{B} \quad (14).$$

According to Daraio and Simar (2005a) a similar statistical test can be created for testing convexity between the DEA and FDH estimators. Then the null hypothesis of convexity will be rejected if the test statistic is too small. According to Daraio and Simar, bootstrap techniques (introduced by Simar and Wilson 1998, 2000) and are the only way to perform these tests when evaluating the appropriate *p-values*. Therefore, we use for the first time a similar approach as described previously in such a way that $H_0 : \Psi^{\theta}$ is globally CRS against $H_1 : \Psi^{\theta}$ is FDH. The test statistic mean of the ratios of the efficiency scores is then provided by:

$$T(X_n) = \frac{1}{n}\sum_{i=1}^{n}\frac{\hat{\theta}_{CRS,n}(X_i, Y_i)}{\hat{\theta}_{FDH,n}(X_i, Y_i)} \quad (15).$$

Then the *p*-value can be calculated following equations (13) and (14). If the *p-value* is too small then the FDH estimator need to be adopted against the DEA estimator since the convexity hypothesis is not true for the original observed sample X_n.

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

In order to analyse the effect of external variables (population, GDP per capita, GINI index and CO_2) on the efficiency scores obtained we follow the probabilistic approach developed by Daraio and Simar (2005b, 2007). 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:

$$\theta(x, y|z) = \inf\left\{ \theta \middle| F_X(\theta x|y, z) > 0 \right\} \quad (16), \text{ where}$$

$Fx(x|y,z) = \Pr ob(X \leq x|Y \geq y, Z = z)$. Daraio and Simar then suggested a kernel estimator defined as follows:

$$\hat{F}_{X|Y,Z,n}(x|y,z) = \frac{\sum_{i=1}^{n} I(x_i \leq x, y_i \geq y) K((z - z_i)/h)}{\sum_{i=1}^{n} I(y_i \geq y) K((z - z_i)/h)} \quad (17), \text{ where}$$

K(.) is the Epanechnikov kernel and *h* is the bandwidth of appropriate size[3]. Therefore, we obtain a conditional DEA efficiency measurement defined as:

$$\hat{\theta}_{DEA}(x, y|z) = \inf\left\{ \theta \middle| \hat{F}_{X|Y,Z,n}(\theta x|y, z) > 0 \right\} \quad (18).$$

Then in order to establish the influence of an environmental variable on the efficiency scores obtained a scatter of the ratios $\frac{\hat{\theta}_n(x, y|z)}{\hat{\theta}_n(x, y)}$ against Z (in our case as mentioned

[3] For the calculation of bandwidth we used the two stage data driven approach suggested by Daraio and Simar (2007, p.110). Furthermore, we have used kernel with compact support (Epanechnikov) as suggested by Daraio and Simar (2005b).

there are four external factors) and its smoothed nonparametric regression lines would help us to analyse the effect of Z on the efficiency scores. If this regression is increasing it indicates that Z is unfavourable to the efficiency of the prefectures whereas if it is decreasing then it is favourable.

Table 2: Efficiency scores, biased corrected estimates, confidence intervals and $\hat{\theta}_n(x,y|z)-\hat{\theta}_n(x,y)$ differences of the different external factors.

Countries	CRS	Bias_Corrected	BIAS	Std	Lower bound	Upper bound	GDPC (Z_1)	GINI(Z_2)	Popul(Z_3)	CO2(Z_4)
Bangladesh	1,000	0,838	-0,194	0,013	0,704	0,990	-0,817	-0,221	0,000	0,000
Morocco	1,000	0,877	-0,140	0,005	0,776	0,989	-0,469	-0,196	-0,415	-0,052
Tajikistan	1,000	0,876	-0,142	0,004	0,796	0,990	-0,875	-0,228	-0,775	-0,702
Tunisia	1,000	0,810	-0,234	0,020	0,674	0,990	-0,330	-0,089	0,000	-0,303
Ukraine	1,000	0,828	-0,208	0,013	0,712	0,990	-0,254	-0,337	0,000	0,000
Uruguay	1,000	0,814	-0,229	0,018	0,682	0,989	0,000	0,000	-0,936	-0,265
Romania	0,994	0,930	-0,069	0,001	0,874	0,983	-0,292	-0,513	-0,518	-0,035
Japan	0,991	0,963	-0,030	0,000	0,926	0,987	0,009	-0,588	-0,116	0,009
Italy	0,974	0,935	-0,043	0,001	0,892	0,967	-0,010	-0,545	-0,301	0,026
Ireland	0,973	0,845	-0,156	0,009	0,720	0,963	0,027	-0,287	-0,913	0,027
Slovakia	0,971	0,862	-0,130	0,003	0,788	0,959	0,029	-0,525	-0,803	-0,385
El Salvador	0,960	0,883	-0,090	0,003	0,799	0,952	-0,468	0,040	-0,020	-0,610
Germany	0,957	0,848	-0,134	0,007	0,735	0,947	-0,021	-0,512	-0,156	-0,005
Russian Federation	0,954	0,875	-0,094	0,003	0,791	0,943	0,001	0,046	0,046	0,046
United Kingdom	0,953	0,922	-0,035	0,000	0,887	0,947	-0,037	-0,250	-0,249	0,047
Armenia	0,950	0,900	-0,058	0,001	0,861	0,941	-0,649	-0,049	0,049	-0,888
Switzerland	0,932	0,873	-0,072	0,001	0,835	0,924	0,059	-0,397	-0,743	-0,396
Costa Rica	0,919	0,816	-0,137	0,006	0,725	0,910	-0,024	0,081	0,081	-0,704
Portugal	0,919	0,878	-0,052	0,001	0,834	0,910	-0,112	-0,318	-0,665	-0,126
Poland	0,917	0,807	-0,150	0,005	0,720	0,907	-0,120	-0,389	-0,269	-0,063
Colombia	0,900	0,837	-0,084	0,002	0,782	0,891	-0,214	0,100	-0,282	-0,228
Greece	0,893	0,845	-0,063	0,001	0,794	0,885	-0,104	-0,395	-0,627	-0,019
Azerbaijan	0,886	0,816	-0,096	0,004	0,733	0,876	-0,479	-0,201	-0,647	-0,411
Panama	0,878	0,846	-0,044	0,000	0,810	0,872	-0,350	0,011	-0,853	-0,681
Dominican Rep	0,874	0,837	-0,051	0,001	0,786	0,871	-0,349	-0,028	-0,669	-0,515
France	0,870	0,834	-0,049	0,001	0,792	0,864	-0,022	-0,388	-0,225	-0,008
Senegal	0,856	0,819	-0,053	0,001	0,782	0,849	-0,731	-0,122	-0,613	-0,772
Turkey	0,828	0,748	-0,129	0,007	0,659	0,822	-0,262	-0,133	-0,209	0,172
Peru	0,822	0,734	-0,146	0,006	0,662	0,813	-0,212	0,144	-0,320	-0,318
Denmark	0,817	0,748	-0,113	0,002	0,715	0,807	0,043	-0,497	-0,734	-0,319
Israel	0,809	0,776	-0,053	0,001	0,746	0,802	-0,062	-0,210	-0,667	-0,311
Spain	0,802	0,763	-0,065	0,001	0,716	0,796	-0,065	-0,356	-0,314	0,012
South Africa	0,793	0,747	-0,078	0,001	0,702	0,784	-0,104	0,140	-0,250	0,109
Zimbabwe	0,784	0,730	-0,094	0,001	0,693	0,774	-0,509	0,120	-0,477	-0,492
Guatemala	0,780	0,740	-0,070	0,001	0,705	0,773	-0,393	0,124	-0,518	-0,525
Paraguay	0,770	0,727	-0,077	0,002	0,675	0,764	-0,390	0,128	-0,658	-0,633
Philippines	0,768	0,709	-0,108	0,003	0,660	0,760	-0,323	0,081	-0,112	-0,049
Kyrgyzstan	0,738	0,690	-0,095	0,002	0,646	0,730	-0,494	-0,303	-0,683	-0,527
Thailand	0,729	0,708	-0,041	0,000	0,684	0,725	-0,281	-0,128	-0,192	-0,132
Canada	0,726	0,696	-0,060	0,001	0,668	0,719	0,095	-0,363	-0,299	0,193
Bulgaria	0,721	0,603	-0,270	0,020	0,541	0,712	-0,183	-0,398	0,147	-0,298

Mexico	0,718	0,668	-0,104	0,005	0,603	0,714	-0,227	0,200	-0,101	0,197
Algeria	0,714	0,637	-0,170	0,012	0,555	0,708	-0,320	-0,241	-0,308	-0,010
Korea, Rep	0,712	0,669	-0,089	0,003	0,615	0,707	-0,057	-0,357	-0,236	0,272
Malaysia	0,702	0,667	-0,074	0,002	0,622	0,697	-0,122	0,020	-0,361	-0,199
United States	0,696	0,672	-0,051	0,001	0,650	0,691	0,090	-0,111	0,000	0,065
Australia	0,693	0,619	-0,171	0,004	0,590	0,684	0,035	-0,253	-0,382	0,068
Cote d'Ivoire	0,689	0,665	-0,052	0,001	0,642	0,685	-0,583	-0,202	-0,407	-0,563
Brazil	0,680	0,630	-0,118	0,004	0,584	0,675	-0,091	0,240	0,006	0,056
Uzbekistan	0,672	0,557	-0,307	0,026	0,481	0,664	-0,430	0,086	-0,240	-0,070
Indonesia	0,667	0,629	-0,090	0,002	0,602	0,661	-0,424	-0,308	-0,020	-0,071
Chile	0,667	0,618	-0,118	0,003	0,580	0,661	-0,111	0,120	-0,414	-0,014
Cameroon	0,663	0,625	-0,092	0,002	0,588	0,656	-0,546	0,002	-0,409	-0,624
Honduras	0,652	0,621	-0,076	0,001	0,597	0,645	-0,471	0,066	-0,526	-0,561
Pakistan	0,640	0,615	-0,063	0,001	0,585	0,636	-0,520	-0,332	-0,055	-0,069
Nicaragua	0,638	0,619	-0,050	0,001	0,596	0,635	-0,491	0,103	-0,564	-0,568
Kenya	0,633	0,591	-0,112	0,002	0,560	0,624	-0,576	-0,012	-0,214	-0,442
Egypt	0,618	0,584	-0,096	0,002	0,550	0,613	-0,362	-0,334	-0,147	0,065
Ecuador	0,612	0,596	-0,045	0,001	0,574	0,609	-0,386	-0,078	-0,395	-0,356
Bolivia	0,602	0,582	-0,058	0,001	0,554	0,600	-0,453	-0,063	-0,452	-0,412
Trinidad and Tobago	0,596	0,554	-0,129	0,005	0,505	0,590	-0,048	-0,067	-0,594	-0,320
Jordan	0,575	0,538	-0,121	0,006	0,491	0,570	-0,309	-0,183	-0,524	-0,337
Venezuela	0,574	0,546	-0,090	0,002	0,517	0,571	-0,227	0,078	-0,243	-0,102
Nepal	0,570	0,528	-0,139	0,004	0,502	0,566	-0,507	-0,155	-0,279	-0,526
Jamaica	0,570	0,535	-0,116	0,002	0,508	0,563	-0,296	-0,115	-0,561	-0,374
Mozambique	0,563	0,509	-0,190	0,005	0,480	0,558	-0,534	-0,121	-0,319	-0,548
Ghana	0,557	0,478	-0,296	0,022	0,422	0,551	-0,422	-0,049	-0,290	-0,449
Zambia	0,536	0,449	-0,360	0,035	0,392	0,531	-0,513	0,160	-0,311	-0,526
Vietnam	0,530	0,484	-0,182	0,010	0,437	0,525	-0,409	-0,145	-0,104	-0,108
Tanzania, United Rep	0,519	0,462	-0,238	0,017	0,416	0,512	-0,507	-0,040	0,209	-0,500
Nigeria	0,491	0,460	-0,135	0,007	0,423	0,487	-0,454	0,080	-0,027	-0,178
Averages	*0,777*	*0,715*	*-0,115*	*0,005*	*0,661*	*0,770*	*-0,282*	*-0,140*	*-0,340*	*-0,244*
Std	*0,154*	*0,137*	*0,069*	*0,007*	*0,128*	*0,152*	*0,233*	*0,210*	*0,273*	*0,277*
Max	*1,000*	*0,963*	*-0,030*	*0,035*	*0,926*	*0,990*	*0,095*	*0,240*	*0,209*	*0,272*
Min	*0,491*	*0,449*	*-0,360*	*0,000*	*0,392*	*0,487*	*-0,875*	*-0,588*	*-0,936*	*-0,888*

4. Empirical results

Following the methodology proposed by Simar and Wilson (2002) this paper tests the model for the existence of returns to scale (analysed previously). In our application we have three input factors and one output and we obtained for this test a p-value of 0,98 > 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[4]. Furthermore, we obtained a similar statistical test for assuming convexity on the results obtained and thus to choose between the CCR and FDH estimates (bias corrected). In a process analysed previously we obtained a p-value of 0,77 > 0,05 (with B=2000) hence, we cannot reject the null hypothesis of CRS.

Overall, the tests indicate that the proper estimates for measuring countries' biodiversity performances are obtained by the CCR model. The efficiency results obtained using the methodology proposed are presented in table 2. Analytically, table 2 presents the efficiency scores of the 71 countries, the biased corrected efficiency scores and the 95-percent confidence internals: lower and upper bound obtained by B=2000 bootstrap replications using the algorithm described previously. As reported the biodiversity efficient countries (i.e. efficient score =1) are reported to be Bangladesh, Marocco, Tajikistan, Tunisia, Ukraine and Uruguay. Whereas countries with higher scores (i.e. more than 0,8) are reported to be Romania, Japan, Italy, Ireland, Slovakia, El Salvador, Germany, Russian Federation, the United Kingdom, Armenia, Switzerland, Costa Rica, Portugal, Poland, Colombia, Greece, Azerbaijan, Panama, Dominican Rep, France, Senegal, Turkey, Peru, Denmark, Israel and Spain. Finally, the countries with the lowest performance (<0,6) are Trinidad and Tobago, Jordan, Venezuela, Nepal, Jamaica, Mozambique, Ghana, Zambia, Vietnam, Tanzania United Rep. and Nigeria. However, these results obtained from biased CCR indicators and as explained previously following expression (9) the biased corrected results need to be adopted for our analysis. According to the biased corrected efficiency measures the countries with the higher biodiversity efficiency scores (i.e. > 0,8) are reported to be Japan, Italy, Romania, the United Kingdom, Armenia, El Salvador, Portugal,

[4] All the results obtained from BCC and FDH models are available upon request.

Morocco, Tajikistan, Russian Federation, Switzerland, Slovakia, Germany, Panama, Greece, Ireland, Bangladesh, Colombia, Dominican Rep, France, Ukraine, Senegal, Costa Rica, Azerbaijan, Uruguay, Tunisia and Poland. Furthermore, the countries with poor performance (i.e. <0.6) are Trinidad and Tobago, Venezuela, Jordan, Jamaica, Nepal, Mozambique, Vietnam, Ghana, Tanzania United Rep., Nigeria and Zambia. Adopting the methodology proposed before we created four conditional CCR biodiversity efficiency estimators taking into account the influence of the four external variables used (i.e. population, GDPC, GINI and CO_2).

Table 3: Descriptive statistics of the conditional DEA estimates

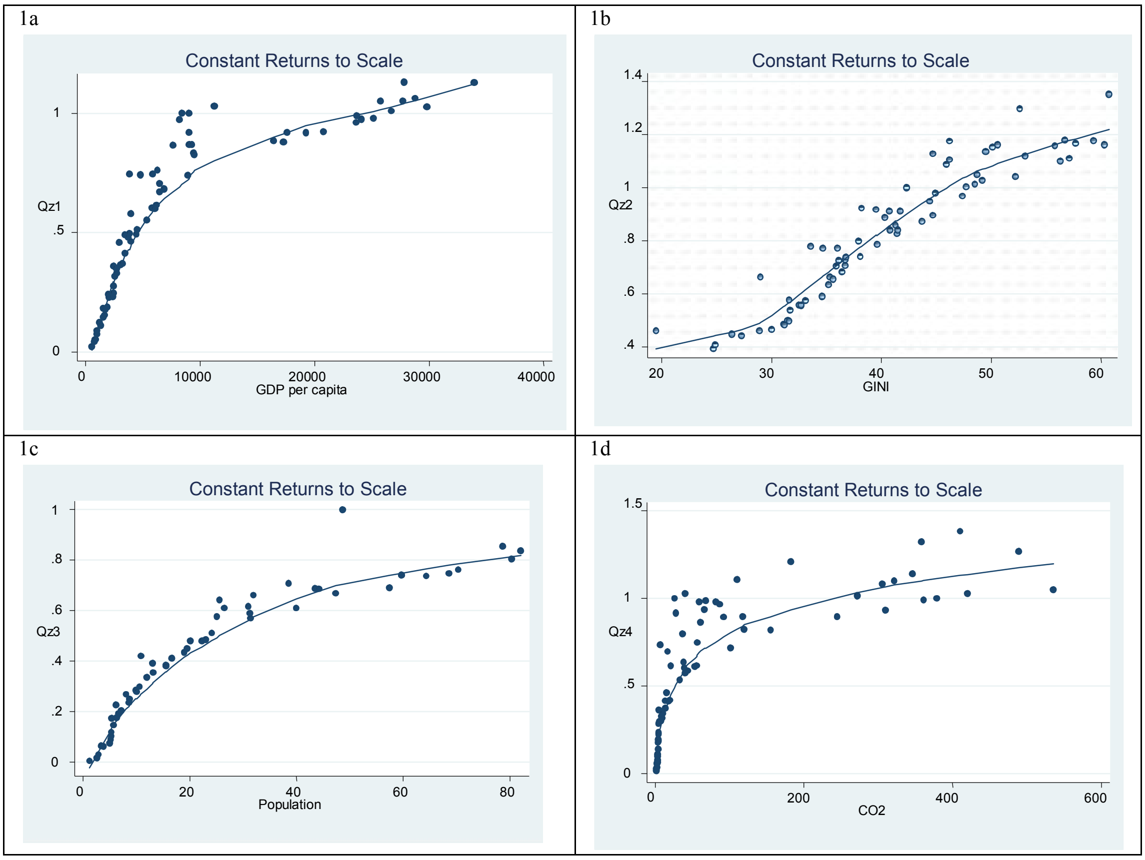
	θ(x,y|z1)	θ(x,y|z2)	θ(x,y|z3)	θ(x,y|z4)	θ(x,y|z1)/θ(x,y)	θ(x,y|z2)/θ(x,y)	θ(x,y|z3)/θ(x,y)	θ(x,y|z4)/θ(x,y)
Averages	0,495	0,637	0,436	0,533	0,605	0,831	0,558	0,664
Max	1,000	1,000	1,000	1,000	1,131	1,352	1,404	1,382
Min	0,011	0,284	0,002	0,010	0,022	0,392	0,004	0,018
Std	0,309	0,210	0,289	0,329	0,333	0,255	0,339	0,381

Table 3 provides the descriptive statistics of the several conditional DEA estimators used[5]. As can be realised the highest influence on countries biodiversity performance is due to countries' population. The original average value of the efficiency scores (Table 2) was 0,777 (for the biased efficiency scores) and 0,715 (for the unbiased efficiency scores). However taking into account the influence of the countries' populations, the average value of the efficiency score has been decreased to the level of 0,436 (Table 3). Similarly the next higher effect has been made by the countries' levels of GDP per capita. The influence of GDP per capita on countries' biodiversity performance has decreased the average efficiency scores to 0,495. Accordingly the levels of countries' CO_2 have decreased countries' efficiency scores to an average value of 0,533. However, the GINI index doesn't seem to have such a dramatic influence on countries' biodiversity performance compared to the other three

[5] The analytical results of the conditional DEA estimators are available upon request.

variables examined. The same conclusions can be obtained when analysing the descriptive statistics of the ratios of conditional DEA to the original DEA estimates $\theta(x,y|z)/\theta(x,y)$.

Figure 1: Examining the effect of the external variables on countries' biodiversity performance



As described previously figure 1 illustrates the effect of the three external variables on countries' biodiversity performance. As can be realised by the graphs (1a-d) the four factors have a negative effect on countries' performances. However, one of the interesting points of this study is to analyse the effect of the four factors on a country to country basis. For that reason the result of the efficiency levels of $\theta(x,y)$ - $\theta(x,y|z)$ are presented on Table 2 according to the external factors. Analysing the results on Table 2 we can observe that GDP per capita has a positive influence on several countries' biodiversity performances. These countries are Canada, the United

States, Switzerland, Denmark, Australia, Slovakia, Ireland and Japan. However, for some countries GDP per capita has a negative impact. The highest negative impact levels on countries' biodiversity performances (> -0,5) have been reported for Nepal, Tanzania United Rep, Zimbabwe, Zambia, Pakistan, Mozambique, Cameroon, Kenya, Cote d'Ivoire, Armenia, Senegal, Bangladesh and Tajikistan.

Furthermore, when we are looking at the effect of income inequality (GINI) on countries biodiversity performance we realise that it has a small positive effect on countries' performance. These countries are Brazil, Mexico, Zambia, Peru, South Africa, Paraguay, Guatemala, Chile, Zimbabwe, Nicaragua, Colombia, Uzbekistan, Costa Rica, Philippines, Nigeria, Venezuela, Honduras, Russian Federation, El Salvador, Malaysia, Panama and Cameroon. However, income inequality has a negative effect on countries' performance with the highest negative results (> -0,5) to be reported for Denmark, Germany, Romania, Slovakia, Italy and Japan.

Population appears to have a small positive impact on six countries' biodiversity performances (Tanzania United Rep, Bulgaria, Costa Rica, Armenia, Russian Federation and Brazil), however, on the rest of the countries it appears to have a negative impact. The countries which appear to be affected the most (i.e. >-0,7) are Denmark, Switzerland, Tajikistan, Slovakia, Panama, Ireland and Uruguay. Finally, for the case of CO_2 it can be realised that in the majority of cases the influence is negative. Specifically, the highest negative influence (>-0,5) is reported for Tanzania United Rep, Dominican Rep, Guatemala, Nepal, Zambia, Kyrgyzstan, Mozambique, Honduras, Cote d'Ivoire, Nicaragua, El Salvador, Cameroon, Paraguay, Panama, Tajikistan, Costa Rica, Senegal and Armenia.

5. Conclusions

Strien et al. (2009) have provided a typology of biodiversity indicators relative to their link with their environmental factors based on the typology introduced by Gregory et al. (2005). As such this study provides a composite indicator of measuring countries' biodiversity performance and can be characterised as 'type 4' indicators. These kinds of indicators show how biodiversity is responding to environmental factors in general, rather than looking how specific species or species groups are doing. As such, to our knowledge, for the first time, this study uses conditional DEA, bootstrap techniques and kernel density estimations for 71 countries in order to measure their biodiversity performances. By obtaining among others, the efficiency scores and the optimal ratios levels for inefficient countries this study provides raw policy models for biodiversity performance evaluation. Following Hamilton's (2005) remarks regarding biodiversity's theoretical limitations of measurement and its usefulness in a sociological and political perspective, this paper provides a real example of how new advances in DEA methodology can be used for providing a methodological framework creating biodiversity indicators taking into account different environmental factors. In addition, the methodological tests adopted revealed that the convexity proved to be a vital issue of the construction of unbiased DEA estimators. Moreover, when we test for scale efficiencies it appeared that such a hypothesis would led us to biased estimations.

As such, the empirical results reveal that GDP per capita, income inequalities, levels of CO_2 and population level have an overall negative effect on countries' biodiversity performance. However, countries' population level is the dominant threat of countries' biodiversity performance followed up by GDP per capita and income inequalities. More analytically, it appears that GDP per capita has a positive effect on developed countries' biodiversity performance but a negative effect on under develop and developing countries. From the other hand income inequalities have a negative effect on developed countries' biodiversity performance and a positive effect on under develop and developing countries. The results reveal, that CO_2, population, income inequalities and GDP per capita have different impact on developed, under develop and developing countries and therefore environmental policies must be adopted and implemented accordingly.

Due to the fact that the main concerns of the environmental social sciences is the deep understanding of the social and economic forces that change the environment the methodological approach applied in this paper can be a vital tool for shaping and evaluating environmental policies.

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