Technical efficiency, productivity change and environmental degradation

Halkos, George and Bampatsou, Christina

Department of Economics, University of Thessaly, Public Power Corporation S.A.

February 2017

Technical efficiency, productivity change and environmental degradation

Christina Bampatsou[1] **&** **George Halkos**[2]
[1] *Public Power Corporation S.A.*
[2] *Laboratory of Operations Research,*
Department of Economics, University of Thessaly
c.bampatsou@gmail.com, halkos@econ.uth.gr

Abstract
This study deals with the nonparametric frontier analysis in the case of the EU 28 countries for a period spanning from 1993 to 2012. It provides statistical inference about the radial output based measure of technical efficiency under the assumption of Constant Returns to Scale (CRS) and it performs scale analysis that allows determining the nature of scale inefficiency of each data point. Furthermore, an order-α approach is developed for determining partial frontiers. Both traditional Malmquist-Luenberger and bootstrapped Malmquist productivity indexes between 1993 and 2012 are constructed. Analysis of productivity change by decomposing the Total Factor Productivity Index into Efficiency Change and Technical Change is performed showing respectively whether productivity gains derive mainly from improvements in efficiency or are mostly the result of technological progress.

Keywords: Data envelopment analysis; Environmental Economics; Carbon emissions; Eco-Efficiency; Total factor productivity index.

JEL Codes: O11; O57; Q01; Q40; Q43; Q48; Q50; Q58; R15.

1. Introduction

Data Envelopment Analysis (hereafter DEA) has been widely used in evaluating technical and allocative efficiency of Decision Making Units (DMUs) in terms of relating inputs with outputs (Lovell, 1993 and Seiford, 1996, 1997). DEA relies on a linear programming method to define technical efficiency (TE) levels, under constant (Charnes *et al.*, 1978) or variable (Banker *et al.,* 1984) returns to scale.

An important point to note is that DEA method as a non-parametric technique, cannot distinguish between noise and inefficiency. Several methods to cope with the usual misspecification and measurement problems due to statistical noise and outlier DMUs have been proposed (see among others Wilson, 1993, 1995; Simar, 2003; Simar and Wilson, 1998).

Various applications of DEA and of the Malmquist Productivity Index are utilized to calculate the performance of different DMUs over time in the presence of undesirable outputs. The latter are in the form of environmental degradation either as damages in the nature or pollutants' emissions (see among others Kortelainen, 2008; Halkos and Tzeremes, 2009, 2011; Mahlberg *et al.*, 2011; Apergis *et al.*, 2015; Long *et al.*, 2015; Halkos and Polemis, 2016).

However, the research on production function under the lines of sustainable development, taking into consideration the impact of energy consumption (exhaustible resources) and environmental degradation (CO_2 emissions[1]) is very limited in terms of bias correction using the smoothed homogeneous bootstrap. Therefore, this study aims to cover this gap and to provide more reliable and useful results for decision-makers.

Specifically we aim here to derive estimators of production frontiers, which represent the optimal combinations of inputs (labor, capital and energy) and outputs

[1] For details on climate change issues see among others Halkos (2011, 2015), Halkos and Skouloudis (2015) and Halkos and Tsilika (2014, 2016, 2017).

(GDP, CO_2 emissions) through an order-α approach and consistent bootstrap procedures in order to consider the sensitivity of distance functions and thus efficiency. To overcome the usual specification and measurement problems of DEA methodology our paper uses the latest advances of DEA analysis as has been introduced by Daraio and Simar (2005, 2007a, b), Jeong *et al.* (2010) in combination with the inferential approach introduced by Simar and Wilson (1998, 2000a, b).

For this reason we estimate and provide statistical inference in nonparametric output oriented frontier models where all outputs are scaled by the same proportion. Hence, radial technical efficiency measures are calculated (Fare, 1988; Fare and Lovell, 1994; Fare *et al.*, 1994a). Furthermore, we follow Simar and Wilson (1998, 2000a,b, 2002) by performing statistical inference regarding the radial technical efficiency measures via bootstrap technique.

After a very brief review of the existing relative literature in section 2, the remaining of this article is organized as follows. Section 3 presents the empirical methodology and the formulation of the proposed models. Section 4 contains the empirical findings. The final section concludes commenting on the derived results.

2. Data and methodology

For our purpose we use a data set of the EU 28 countries, for a period spanning from 1993 to 2012 in order to introduce the radial measure of non parametric frontier analysis. As inputs labor, capital and energy are used while we utilize GDP as desirable and CO_2 emissions as undesirable outputs. More specifically, we compute Radial (Debreu-Farrell) output-based measures of technical efficiency under the assumption of CRS, NIRS, and VRS technology. As next step, we perform statistical inference about the radial measure of technical efficiency and compute bias-correction using the smoothed homogeneous bootstrap which means that all DMUs in the sample should be similar in terms of technology and characteristics. Furthermore, we perform scale analysis of each data point.

In our analysis the order-α approach is introduced for determining more robust to extreme values partial frontiers compared to traditional full frontiers. More specifically, as Daraio and Simar (2007) claim, partial frontiers do not include all data points but just a fraction of them. For the partial frontiers specification, Bădin et al. (2012) and Mastromarco and Simar (2014) are followed. A median quartile $(\alpha = 0.5)$ is applied instead of calculating the extreme quartiles $(\alpha = 0.9, \alpha = 0.95)$. According to Bădin et al. (2012) median values of α allow us to explore the influence of environmental variables on efficiencies' distribution (technological catch-up) (Figure 2).

In the last part of our study, we perform analysis of productivity change during the whole period under consideration (see equations 1, 2 and 3) and also between the first (1993) and final (2012) years (see equations 1.1, 2.1 and 3.1) of available data, by decomposing the Total Factor Productivity Index (TFPCH) into Efficiency Change and Technical Change, for both Malmquist-Luenberger and bootstrapped Malmquist index.

2.1 The model for the determination of Malmquist-Luenberger productivity index

The Malmquist-Luenberger productivity index (ML) is employed to estimate productivity growth when an undesirable output, in the form of CO_2 emissions in our case, is included in the production model for directly reducing the creation of undesirable output and increasing the production of desirable output. Relying on Chung et al. (1997) the output-oriented Malmquist-Luenberger productivity index in the case of undesirable output is identified as:

$$TFPCHL_{t,t+1} = \left\{ \frac{[1+\vec{D}_{o,t+1}(x_t, y_t, b_t; y_t, -b_t)]}{[1+\vec{D}_{o,t+1}(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1})]} \times \frac{[1+\vec{D}_{o,t}(x_t, y_t, b_t; y_t, -b_t)]}{[1+\vec{D}_{o,t}(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1})]} \right\}^{\frac{1}{2}} \quad (1)$$

$$TFPCHL_{1993,2012} = \left\{ \frac{[1+\vec{D}_{o,2012}(x_{1993}, y_{1993}, b_{1993}; y_{1993}, -b_{1993})]}{[1+\vec{D}_{o,2012}(x_{2012}, y_{2012}, b_{2012}; y_{2012}, -b_{2012})]} \times \frac{[1+\vec{D}_{o,1993}(x_{1993}, y_{1993}, b_{1993}; y_{1993}, -b_{1993})]}{[1+\vec{D}_{o,1993}(x_{2012}, y_{2012}, b_{2012}; y_{2012}, -b_{2012})]} \right\}^{\frac{1}{2}} \quad (1.1)$$

The $TFPCH_L$ index may be decomposed into efficiency ($EFFCH_L$) and technical changes ($TECHCH_L$). This can expressed as:

$$EFFCHL_{t,t+1} = \left[\frac{[1+\vec{D}_{o,t}(x_t, y_t, b_t; y_t, -b_t)]}{[1+\vec{D}_{o,t+1}(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1})]} \right] \quad (2)$$

$$EFFCHL_{1993,2012} = \left[\frac{[1+\vec{D}_{o,1993}(x_{1993}, y_{1993}, b_{1993}; y_{1993}, -b_{1993})]}{[1+\vec{D}_{o,2012}(x_{2012}, y_{2012}, b_{2012}; y_{2012}, -b_{2012})]} \right] \quad (2.1)$$

$$TECHCHL_{t,t+1} = \left\{ \frac{[1+\vec{D}_{o,t+1}(x_t, y_t, b_t; y_t, -b_t)]}{[1+\vec{D}_{o,t}(x_t, y_t, b_t; y_t, -b_t)]} \times \frac{[1+\vec{D}_{o,t+1}(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1})]}{[1+\vec{D}_{o,t}(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1})]} \right\}^{\frac{1}{2}} \quad (3)$$

$$TECHCHL_{1993,2012} = \left\{ \frac{[1+\vec{D}_{o,2012}(x_{1993}, y_{1993}, b_{1993}; y_{1993}, -b_{1993})]}{[1+\vec{D}_{o,1993}(x_{1993}, y_{1993}, b_{1993}; y_{1993}, -b_{1993})]} \times \frac{[1+\vec{D}_{o,2012}(x_{2012}, y_{2012}, b_{2012}; y_{2012}, -b_{2012})]}{[1+\vec{D}_{o,1993}(x_{2012}, y_{2012}, b_{2012}; y_{2012}, -b_{2012})]} \right\}^{\frac{1}{2}} \quad (3.1)$$

The values of the Malmquist-Luenberger index and its components, can be greater, equal or smaller than 1. If the Malmquist-Luenberger index is greater than one then there is an improvement in productivity (productivity gains). If it is equal to 1 then productivity remains unchanged, and if it is smaller than 1 then productivity declines (productivity loss).

2.2 The model for the determination of Bootstrapped Malmquist productivity index

In this case the output-based Malmquist Productivity Index between 1993 and 2012 for data point k makes use of the output distance function which is the reciprocal of the Debreu-Farrell measure of technical efficiency (Caves et al. 1982; Fare et al. 1994a) and is defined as follows:

$$\text{TFPCHb}_{1993,2012}^{k,o} = \left\{ \frac{F^o(y_{1993}^k, x_{1993}^k, y_{1993}, x_{1993} \middle| CRS)}{F^o(y_{2012}^k, x_{2012}^k, y_{1993}, x_{1993} \middle| CRS} \times \frac{F^o(y_{1993}^k, x_{1993}^k, y_{2012}, x_{2012} \middle| CRS)}{F^o(y_{2012}^k, x_{2012}^k, y_{2012}, x_{2012} \middle| CRS} \right\}^{\frac{1}{2}} \quad (4)$$

The TFPCH_b index may be decomposed into efficiency (EFFCH_b) and technical change (TECHCH_b). This can expressed as:

$$\text{TFPCHb}_{1993,2012}^{k,o} = \frac{F^o(y_{1993}^k, x_{1993}^k, y_{1993}, x_{1993} \middle| CRS)}{F^o(y_{2012}^k, x_{2012}^k, y_{2012}, x_{2012} \middle| CRS} \\ \times \left\{ \frac{F^o(y_{2012}^k, x_{2012}^k, y_{2012}, x_{2012} \middle| CRS)}{F^o(y_{2012}^k, x_{2012}^k, y_{1993}, x_{1993} \middle| CRS} \times \frac{F^o(y_{1993}^k, x_{1993}^k, y_{2012}, x_{2012} \middle| CRS)}{F^o(y_{1993}^k, x_{1993}^k, y_{2012}, x_{2012} \middle| CRS} \right\}^{\frac{1}{2}} \quad (5)$$

The first component in (5) measures the contribution of EFFCH_b index to total factor productivity change, while the second component in (5) measures the contribution of TECHCH_b index to total factor productivity change.

Like the Malmquist-Luenberger index, the bootstrapped Malmquist index also specifies productivity increases (reductions) if its values are higher (lower) than one.

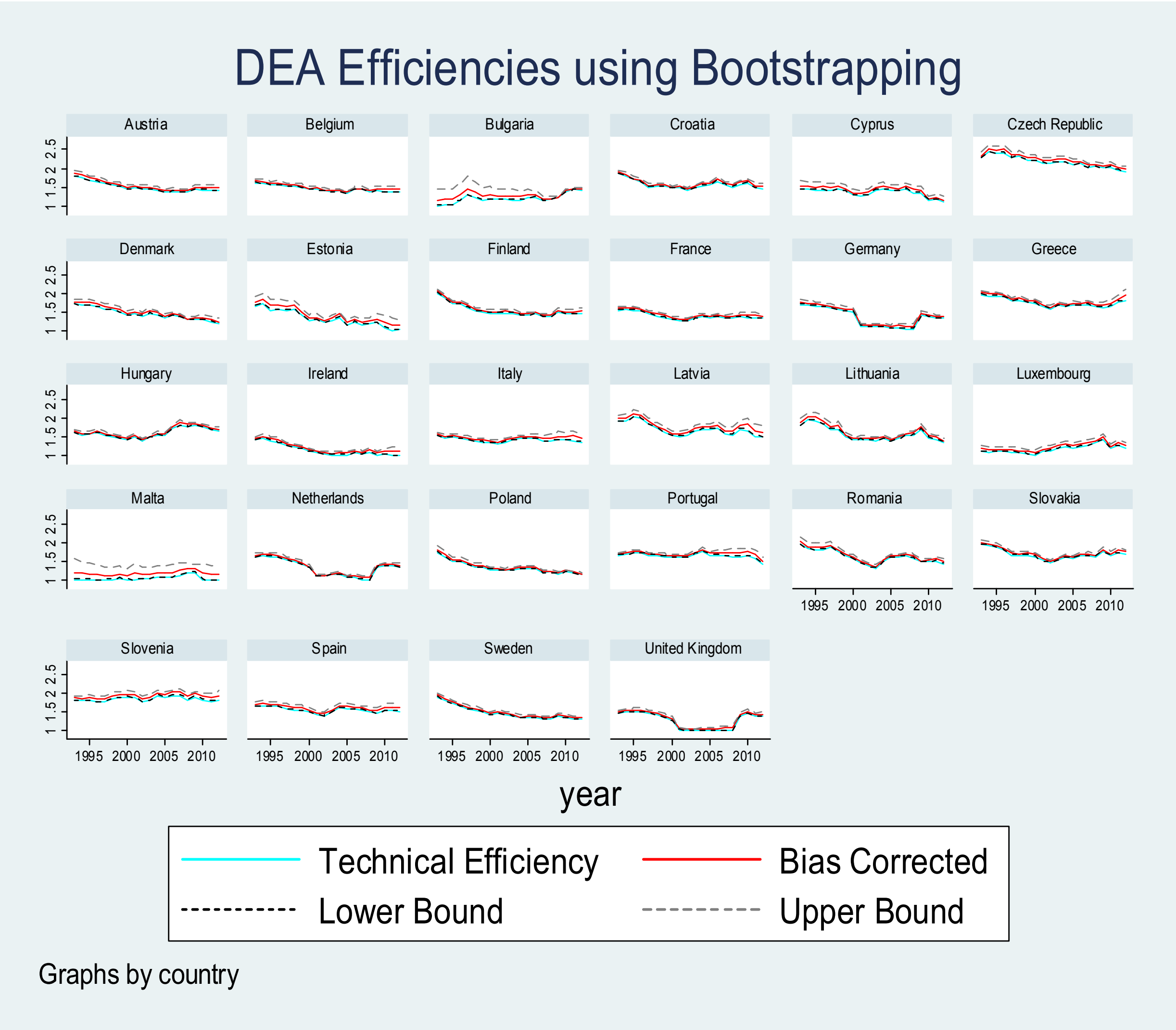
3. Results

First of all, we need to know what type of bootstrap to employ. We perform therefore the nonparametric test of independence. We run the test[2] for all returns to scale assumption for output based frontier models. More specifically we compute Radial (Debreu-Farrell) output-based measures of technical efficiency under the assumption of CRS, NIRS, and VRS technology

[2] P-value of H_0 that T4n = 0 (Ho that radial (Debreu-Farrell) output-based measure of technical efficiency under assumption of CRS technology and mix of outputs are independent) = 0.0010: hat{T4n} = 0.0052 is statistically greater than 0 at the 5% significance level.

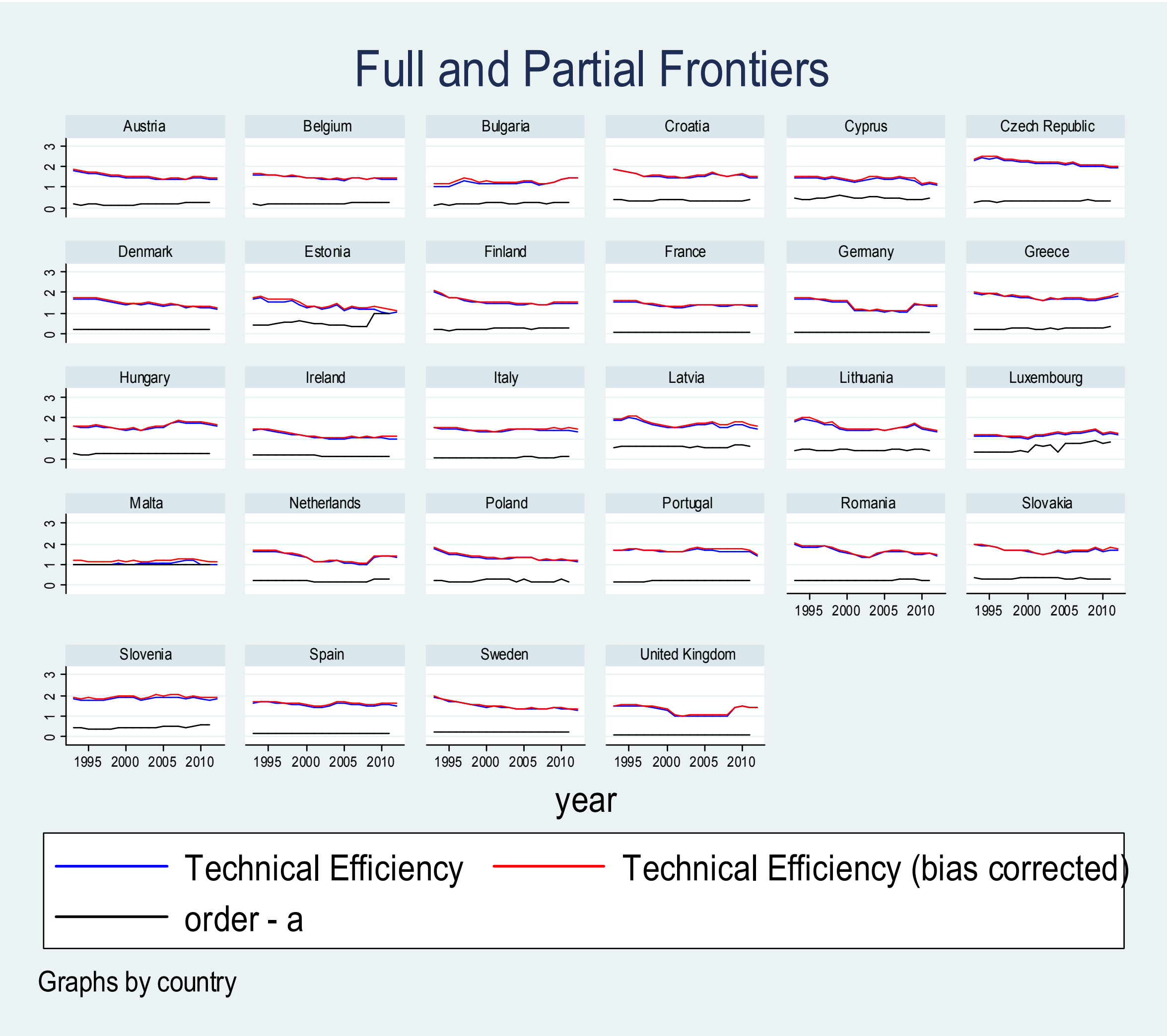
The results indicate that output-based measure of technical efficiency, under the assumption of constant returns to scale is independent of the mix of outputs. Therefore, the smoothed homogeneous bootstrap can be used under assumption of CRS technology.

Figure 1: DEA Efficiencies using Bootstraping



Subsequently, we perform statistical inference about the radial measure of technical efficiency and compute bias-correction using the smoothed homogeneous bootstrap with 999 replications. In this regard we manage to show that ignoring this bias, the obtained output-oriented efficiency measures are biased downwards (Figure 1). In addition, partial frontier approach enables us to reduce the sensitivity to outliers by enveloping just a subsample of observations (Figure 2). As derived from the empirical analysis, full frontiers which are sensitive to outliers, exceed partial frontiers in all countries (Figure 2).

Figure 2: Full and partial frontiers



In the next step of our analysis (Table 1), we perform nonparametric test[3] of returns to scale and analysis of scale efficiency.[4] We provide the results using the

[3] The binomial test requires bootstrap replications for each of K data points independently.

[4] The full Table of technical efficiency, bias-corrected measure, bias, variance, three times the ratio of bias squared to variance, lower bounds, and upper bounds of the 95% confidence interval in variables is available on request.

homogeneous bootstrap procedure, in order to provide inference with regards to the underlying technology and to perform scale analysis of each data point.

The *P*-value of the null hypothesis that the technology is constant returns to scale (vs VRS) using homogeneous smoothed bootstrap is *0.0000* implying CRS is not an appropriate assumption. Hence, nonparametric test of returns to scale advises performing efficiency measurement under assumption of VRS technology. In the second stage of scale analysis, the null hypothesis that the data point is scale efficient is tested. More specifically, the *p*-value of the null hypothesis that the technology is NIRS (vs VRS) using homogeneous smoothed bootstrap is *0.9990* implying NIRS is an appropriate assumption. Taking into account that not all data points are scale efficient, it is determined where the reason for scale inefficiency is operating under decreasing returns to scale (DRS) (Table 1).

As already mentioned previously, the values of the TFPCH index and its components, can be greater, equal or smaller than 1. If the TFPCH index is greater than one, then there is an improvement in productivity (productivity gains). Greece, France, Croatia, Austria, Belgium, Sweden, Czech Republic, Romania, Slovakia, United Kingdom, Italy, Portugal, Finland, Denmark, Netherlands, Ireland, Latvia, Lithuania, Poland, Cyprus, Germany and Estonia are countries that have productivity gains (Table 2).

Subsequently, taking into account the relationships that have been recorded in the literature regarding the TFPCH indicators, an attempt is made to a further deepening and recording of the driving forces of total factor productivity index for DMUs under consideration (Table 2).

If the TFPCH Index is equal to 1, then the productivity remains unchanged, and if it is smaller than 1, then the productivity declines (productivity loss). Bulgaria, Malta, Spain, Hungary, Slovenia, Luxembourg are countries that have productivity loss (Table 2).

Table 1: Scale analysis

Period	Country	Scale analysis
1993-2012	Austria, Belgium, Croatia, Czech Republic, Finland, Greece, Hungary, Italy, Lithuania, Slovakia, Slovenia, Spain, Sweden	scale inefficient due to DRS
1993-1996	Bulgaria	scale efficient
1997-2006		scale inefficient due to DRS
2007-2009		scale efficient
2010-2012		scale inefficient due to DRS
1993-2012	Cyprus, Luxembourg, Malta	scale efficient
1993-2007	Denmark	scale inefficient due to DRS
2008-2009		scale efficient
2010-2012		scale inefficient due to DRS
1993-1994	Estonia	scale efficient
1995		scale inefficient due to DRS
1996-1998		scale efficient
1999-2004		scale inefficient due to DRS
2005-2012		scale efficient
1993-2011	France, Poland	scale inefficient due to DRS
2012		scale efficient
1993-2000	Germany	scale inefficient due to DRS
2001-2012		scale efficient
1993-1999	Ireland	scale inefficient due to DRS
2000		scale efficient
2001		scale inefficient due to DRS
2002-2012		scale efficient
1993-2006	Latvia, Portugal	scale inefficient due to DRS
2007-2009		scale efficient
2010-2012		scale inefficient due to DRS
1993-2000	Netherlands, United Kingdom	scale inefficient due to DRS
2001-2008		scale efficient
2009-2012		scale inefficient due to DRS
1993-2008	Romania	scale inefficient due to DRS
2009		scale efficient
2010-2012		scale inefficient due to DRS

Table 2[5]: Annual means of Malmquist index and its components by country

Periods	DMU	TFPCH	EFFCH	TECHCH
1993-2012	Bulgaria	0.96091	0.994337	0.966438
1993-2012	Malta	0.983883	1	0.983883
1993-2012	Spain	0.989091	0.985051	1.005753
1993-2012	Hungary	0.99257	0.992035	1.002045
1993-2012	Slovenia	0.997359	0.99282	1.006876
1993-2012	Luxembourg	0.999675	0.991577	1.007863
1993-2012	Greece	1.00056	0.982628	1.019463
1993-2012	France	1.001311	0.99211	1.010741
1993-2012	Croatia	1.001347	1.001366	1.001472
1993-2012	Austria	1.002141	0.99422	1.009706
1993-2012	Belgium	1.004953	0.990474	1.015569
1993-2012	Sweden	1.007587	1.007757	1.002287
1993-2012	Czech Republic	1.009166	0.998157	1.013545
1993-2012	Romania	1.009623	1.015849	0.995441
1993-2012	Slovakia	1.009815	1.011344	1.000554
1993-2012	United Kingdom	1.010347	0.990286	1.018845
1993-2012	Italy	1.011508	0.985645	1.02765
1993-2012	Portugal	1.011833	0.988324	1.027685
1993-2012	Finland	1.013775	1.006183	1.009614
1993-2012	Denmark	1.014421	1.002003	1.014774
1993-2012	Netherlands	1.01716	0.997019	1.019332
1993-2012	Ireland	1.01914	1	1.01914
1993-2012	Latvia	1.019197	1.002317	1.019215
1993-2012	Lithuania	1.019395	1.019796	1.000729
1993-2012	Poland	1.023849	1.019849	1.005668
1993-2012	Cyprus	1.02464	1.005092	1.01964
1993-2012	Germany	1.025792	1.000451	1.024266
1993-2012	Estonia	1.036956	1.011382	1.026486

If EFFCH>TECHCH, then the productivity change (gains or loss) is primarily the result of an improvement in efficiency, (Bulgaria, Malta, Sweden, Romania, Slovakia, Lithuania, Poland), while if EFFCH<TECHCH, then the productivity change (gains or loss) is mainly the result of technological progress (Spain, Hungary, Slovenia, Luxembourg, Greece, France, Croatia, Austria, Belgium, Czech Republic, United Kingdom, Italy, Portugal, Finland, Denmark, Netherlands, Ireland, Latvia, Cyprus, Germany, Estonia) (Table 2).

[5] The full table of year by year changes in Malmquist index and its components is available on request.

Table 3: Measures of technical efficiency and Malmquist Productivity Index

Country	TE_{1993b}	TE_{2012b}	$TFPCH_b$	$TFPCH_L$	$EFFCH_b$	$EFFCH_L$	$TECHCH_b$	$TECHCH_L$
Austria	1.111823	1.267533	1.260291	1.16996	0.877155	0.868221	1.436793	1.347531
Belgium	1.085484	1.317985	1.178599	1.065507	0.823593	0.81668	1.431045	1.304679
Bulgaria	1	1.115806	0.535425	0.50693	0.896213	0.882371	0.597431	0.574508
Croatia	1.295411	1.282463	1.313151	1.315722	1.010096	1.009042	1.300026	1.303932
Cyprus	1.077754	1	1.222395	1.268424	1.077754	1.08197	1.134206	1.172327
Czech Republic	1.563827	1.661482	1.219347	1.170768	0.941224	0.928135	1.295491	1.261417
Denmark	1.123238	1.112242	1.376608	1.362747	**1.009886**	**0.987479**	1.363132	1.380024
Estonia	1.186267	1	1.367701	1.486885	1.186267	1.189435	1.152945	1.250077
Finland	1.41822	1.310985	1.301844	1.372126	1.081797	1.11435	1.203408	1.231324
France	1.024401	1.208891	1.186716	1.062855	0.847389	0.827602	1.400438	1.284254
Germany	1.092617	1.12648	1.226605	1.198423	0.969939	0.962742	1.264621	1.244804
Greece	1.24157	1.774565	1.283452	1.074356	0.699648	0.707354	1.834426	1.518836
Hungary	1.184647	1.408362	1.116799	1.025342	0.841153	0.839384	1.327701	1.221537
Ireland	1	1	1.41426	1.409457	1	1	1.41426	1.409457
Italy	1	1.344389	1.272612	1.080112	0.743833	0.740494	1.710885	1.458634
Latvia	1.337135	1.341451	1.279301	1.275107	0.996783	0.998811	1.28343	1.276624
Lithuania	1.495029	1.058859	1.103026	1.309852	1.411925	1.408391	0.781222	0.930034
Luxembourg	1	1.183519	**1.028494**	**0.944118**	0.844938	0.844937	1.217243	1.11738
Malta	1	1	0.782136	0.782136	1	1	0.782136	0.782136
Netherlands	1.09497	1.183299	1.186709	1.153454	0.925353	0.938122	1.282439	1.229533
Poland	1.418112	1	1.213723	1.465337	1.418112	1.418114	**0.855873**	**1.0333**
Portugal	1.077208	1.408164	1.331941	1.166861	0.764974	0.774557	1.74116	1.506491
Romania	1.623105	1.247027	1.19237	1.357458	1.301579	1.290622	**0.916095**	**1.051786**
Slovakia	1.470049	1.222324	1.164338	1.279538	1.202667	1.197798	**0.96813**	**1.068241**
Slovenia	1.287015	1.519904	1.122025	1.029927	0.846773	0.846167	1.32506	1.217164
Spain	1.053035	1.424126	1.229081	1.063455	0.739426	0.749856	1.66221	1.418212
Sweden	1.263382	1.116478	1.273631	1.36305	1.131577	1.146992	1.125536	1.18837
United Kingdom	1.024228	1.277092	1.164351	1.055725	0.802001	0.806692	1.451809	1.308714

TE_{1993b}: Measure of technical efficiency under the assumption of CRS in 1993 by using the non parametric bootstrap method

TE_{2012b}: Measure of technical efficiency under the assumption of CRS in 2012 by using the non parametric bootstrap method

$TFPCH_b$: Bootstrapped Malmquist productivity index

$TFPCH_L$: Malmquist-Luenberger productivity index

$EFFCH_b$: Efficiency change by using the non parametric bootstrap method

$EFFCH_L$: Malmquist-Luenberger Efficiency change

$TECHCH_b$: Technical change by using the non parametric bootstrap method

$TECHCH_L$: Malmquist-Luenberger Technical change

DEA being deterministic lacks statistical power and is by construction highly sensitive to outliers and measurement errors. In our study we employ the bootstrap procedure and therefore we are able to overcome the main limits of the DEA procedure. In this context we examine the different results (Table 3) between deterministic and bootstrapped Malmquist.

More specifically, in the case of Luxembourg we observe that bootstrapped Malmquist productivity index is 1.028494 and therefore the productivity has increased between 1993 and 2012, while at the same time the Malmquist-Luenberger productivity index with a value of 0.944118 indicates productivity loss. In Slovakia, Romania and Poland we observe that the index of technical change by using the non parametric bootstrap method is less than 1 and therefore the technology has deteriorated between 1993 and 2012, while at the same time the Malmquist-Luenberger technical change index with values greater than 1 indicates an improvement in technology. In the case of Denmark, we observe that the index of Efficiency change by using the non parametric bootstrap method is 1.009886 and therefore the efficiency has increased between 1993 and 2012, while at the same time the Malmquist-Luenberger Efficiency change index with a value of 0.987479 indicates efficiency loss.

From table 3[6] we observe that productivity of Austria, Belgium, Czech Republic, France, Germany, Greece, Hungary, Italy, Latvia, Luxembourg, Netherlands, Portugal, Slovenia, Spain, United Kingdom has increased as a result of technological progress while productivity has fallen for Bulgaria and Malta. In Bulgaria, the main reason for decreased productivity was loss both in efficiency and technology. In Malta, efficiency change leaves the TFPCHb unchanged, but technology has deteriorated to such an extent that the entire productivity has decreased. In Ireland, on the contrary efficiency change

[6] The full table of technical efficiency, output based measure of scale efficiency, as well as indicator variables if statistically scale efficient and the nature of scale inefficiency are available on request.

leaves the TFPCHb unchanged, but technology has improved to such an extent that the entire productivity has increased.

We also observe that productivity of Lithuania, Poland, Romania and Slovakia has increased as a result of efficiency progress, while in the case of Croatia, Cyprus, Denmark, Estonia, Finland and Sweden the main reason for increased productivity was gain both in efficiency and technology.

Examining the cases of Bulgaria, Luxembourg and Italy we observe that they were on the frontier in 1993 but moved away from the 2012 frontier. On the contrary, Poland, Cyprus and Estonia were inefficient in 1993 but in 2012 they define the frontier. Malta and Ireland were on the frontier in both 1993 and 2012. Finally we observe that the remaining countries, Lithuania, Hungary, Slovenia, Slovakia, United Kingdom, Belgium, Netherlands, France, Romania, Czech Republic, Germany, Spain, Austria, Sweden, Latvia, Greece, Finland, Croatia, Portugal, Denmark, were inefficient in both 1993 and 2012.

4. Conclusions

This study applies a non-parametric frontier method by using bootstrap techniques to correct the biased estimators of DEA in productivity and efficiency analysis of the EU 28 countries in the presence of undesirable output in the form of carbon dioxide emissions for the time period of 1993 to 2012.

Concerning the methodologies applied to cope with the misspecification and measurement problems mentioned the latest advances of DEA analysis have been used. In this context, we manage to show that ignoring bias can lead to an underestimation of the inefficiency of DMUs (Figure 1). In addition, we show that the determination of partial frontiers can improve estimates of productivity in a production frontier that is usually biased upwards (Figure 2). Furthermore, by investigating the scale efficiency of EU 28 it is determined where the reason for scale inefficiency is operating under decreasing returns to scale (DRS) (Table 1).

Finally, we perform analysis of productivity change between 1993 and 2012, by decomposing both Malmquist-Luenberger and bootstrapped Malmquist index into Efficiency Change and Technical Change. The detailed decomposition of the Total Factor Productivity Index (TFPCH) offers additional insights for policy implications, representing the driving forces of productivity gains or losses for the entire EU 28 (Tables 2, 3). The decomposition of total factor productivity index into efficiency and technical changes may provide policy makers with the appropriate framework in understanding whether productivity gains are obtained mostly from efficiency enhancements or are generally derive from technological progress.

References

Apergis, Nicholas, Goodness C. Aye, Carlos Pestana Barros, Rangan Gupta, and Peter Wanke. (2015). Energy efficiency of selected OECD countries: A slacks based model with undesirable outputs, *Energy Economics,* **51**: 45-53.

Bădin, L., Daraio, C. and Simar, L. (2012). How to measure the impact of environmental factors in a nonparametric production model?, *European Journal of Operational Research*, **223:** 818–833

Banker, R. D., A. Charnes, and W. W. Cooper (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science,* **30**: 1078–1092.

Caves, D., Christensen, L. and Diewert, W.E. (1982). The economic theory of index numbers and the measurement of input, output, and productivity, *Econometrica*, **50**: 1393–1414

Charnes, A., Cooper, W.W. and Rhodes E. (1978) Measuring efficiency of decision making units, *European Journal of Operational Research*, **2(6):** 429–444.

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

Daraio, C. and Simar, L. (2005) Introducing environmental variables in nonparametric frontier models: A probabilistic approach, *Journal of Productivity Analysis*, **24(1):** 93–121.

Daraio, C. and Simar, L. (2007a) *Advanced robust and nonparametric methods in efficiency analysis*, New York: Springer.

Daraio, C. and Simar, L. (2007b) Conditional nonparametric frontier models for convex and nonconvex technologies: a unifying approach, *Journal of Productivity Analysis*, **28(1):** 13-32.

Efron, B. (1979). Bootstrap methods: Another look at the Jackknife. *Annals of Statistics*, **7**: 1-26.

Efron, B, and Tibshirani, R.J. (1993). *An introduction to the bootstrap*. Chapman and Hall, London.

Fare, R. (1988). *Fundumentals of Production Theory*. Berlin: Springer.

Fare, R., and C. A. K. Lovell. (1994). Measuring the technical efficiency of production. *Journal of Economic Theory,* **19**: 150–162.

Färe, Rolf., Shawna Grosskopf, and C. A. Knox Lovell. (1994a). *Production Frontiers*, Cambridge: Cambridge University Press.

Halkos G. (2011). Environment and economic development: determinants of an EKC hypothesis," MPRA Paper **33262**, University Library of Munich, Germany.

Halkos G.E. (2015). Climate change actions for sustainable development, *International Journal of Innovation and Sustainable Development*, **9(2):** 118-136.

Halkos G, Tzeremes N. (2009) Exploring the existence of Kuznets curve in countries' environmental efficiency using DEA window analysis. *Ecological Economics*, **68**: 2168-2176.

Halkos, G. and Tzeremes, N. (2011). Does the Kyoto Protocol Agreement Matters? An Environmental Efficiency Analysis, MPRA, Paper No. **30652**, May 2011

Halkos, G. and Polemis, M. (2016). The good, the bad and the ugly? Balancing environmental and economic impacts towards efficiency, MPRA Paper **72132**, University Library of Munich, Germany.

Halkos G. and Skouloudis A. (2015). Exploring corporate disclosure on climate change: Evidence from the Greek business sector, MPRA Paper **64566**, University Library of Munich, Germany.

Halkos G.E. and Tsilika K.D. (2014). Analyzing and visualizing the synergistic impact mechanisms of climate change related costs. *Applied Mathematics and Computation*, 246: 586-596.

Halkos G.E. and Tsilika K.D. (2016). Climate change impacts: Understanding the synergetic interactions using graph computing, MPRA Paper **75037**, University Library of Munich, Germany.

Halkos G.E. and Tsilika K.D. (2017). Climate change effects and their interactions: An analysis aiming at policy implications. *Economic Analysis and Policy,* **53**: 140-146.

Jeong, S.O., Park, B.U. and Simar, L. (2010) Nonparametric conditional efficiency measures: asymptotic properties, *Annals of Operational Research*, **173(1):** 105-122.

Kortelainen, M., (2008). Dynamic environmental performance analysis: A Malmquist index approach, *Ecological Economics*, **64(4):** 701–715.

Kumar S, Khanna M. (2009) Measurement of environmental efficiency and productivity: a cross-country analysis. *Environment and Development Economics,* **14**: 473–495.

Long, Xingle, Xicang Zhao, and Faxin Cheng. (2015). The comparison analysis of total factor productivity and eco-efficiency in China's cement manufactures, *Energy Policy,* **81**: 61-66.

Lovell, C.K., (1993). Production frontier and productive efficiency. In: Fried, H.O., Lovell, C.K., Schmidt, S.S. (Eds.), The Measurement of Productive Efficiency. Techniques and Applications. Oxford University Press, Oxford, pp. 3–67.

Mahlberg, Bernhard, Mikulas Luptacik and Biresh K. Sahoo (2011). Examining the drivers of total factor productivity change with an illustrative example of 14 EU countries, *Ecological Economics*, **72:** 60-69.

Mastromarco, C., Simar, L. (2014). Effect of FDI and time on catching-up: new insights from a conditional nonparametric frontier analysis, *Journal of Applied Econometrics*, 30(5): 826-847.

Seiford, L.M., (1996). Data envelopment analysis: the evolution of the state-of-the-art (1978–1995). *Journal of Productivity Analysis,* **7(2/3)**: 99–138.

Seiford, L.M., (1997). A bibliography for data envelopment analysis (1978–1996). *Annals of Operation Research,* **73**: 393–438.

Simar, L. and P. W. Wilson (1998). Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models. *Management Science,* **44**: 49–61.

Simar, L. and Wilson, P.W. (2000a) A general methodology for bootstrapping in nonparametric frontier models, *Journal of Applied Statistics*, **27(6)**: 779–802.

Simar, L. and Wilson, P.W. (2000b) Statistical inference in nonparametric frontier models: the state of the art, *Journal of Productivity Analysis*, **13(1)**: 49–78.

Simar, L. and P. W. Wilson (2002). Non-Parametric Tests of Returns to Scale. *European Journal of Operational Research,* **139**: 115–132.

Simar, L. (2003). Detecting outliers in frontier models: a simple approach, *Journal of Productivity Analysis*, **20**: 391–424.

Taskin F, Zaim O. (2001) The role of international trade on environmental efficiency: a DEA approach. *Economic Modelling*, **18**:1-17.

Wilson, P. W. (1993), Detecting outliers in deterministic nonparametric frontier models with multiple outputs, *Journal of Business and Economic Statistics,* **11**: 319–323.

Wilson, P. W. (1995), Detecting influential observations in data envelopment analysis, *Journal of Productivity Analysis,* **6**: 27–45.

Zaim O, Taskin F. (2000) A Kuznets curve in environmental efficiency: an application on OECD countries. *Environmental and Resource Economics,* **17**: 21–36.

Zaim O. (2004) Measuring environmental performance of state manufacturing through changes in pollution intensities: a DEA framework. *Ecological Economics,* **48**: 37–47.

Zofio JL, Prieto AM (2001) Environmental efficiency and regulatory standards: the case of CO_2 emissions from OECD industries. *Resource and Energy Economics,* **23**: 63–83.