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THE RENEWABLE ENERGY DEVELOPMENT: A NONPARAMETRIC EFFICIENCY ANALYSIS

Anamaria ALDEA[1]
Anamaria CIOBANU[2]
Ion STANCU[3]

Abstract

The paper's main objective is to examine the efficiency of renewable energy development in the EU using 2009 national data. We apply nonparametric techniques to determine efficiency estimators that provide an insight into the quality of renewable energy policy and its impact on the EU countries. We use nonparametric techniques to determine the DEA efficiency estimates and a bootstrap algorithm that corrects the efficiency estimates and also provides confidence intervals for the bias-corrected efficiency estimates. Moreover, our analysis reveals the energy policy impact by country on the development of renewable energy markets. The implications of the results are discussed in relation to the current developments in the EU renewable energy market and recent policy initiatives.

Keywords: efficiency estimates, non-parametric techniques, bootstrap algorithm, DEA, renewable energy

JEL Classification: C14, C38, Q01, Q20

1. Background

Despite several initiatives to promote renewable energy development in the EU countries, little research has been carried out to investigate the efficiency of these policies. There is an increasing need for a comparative analysis of the effectiveness of the reforms made by these countries in the renewable energy market. In order to measure the efficiency in the EU renewable energy market, we used non-parametric techniques to compute efficiency estimates for EU countries' renewable energy markets, based on extensive international research and on personal interpretation of the efficiency of the energy sector.

[1] Department of Economic Informatics and Cybernetics, Academy of Economic Studies, E-mail: anamaria_aldea@csie.ase.ro
[2] Department of Finance, Academy of Economic Studies, E-mail: anamaria.ciobanu@fin.ase.ro
[3] Department of Finance, Academy of Economic Studies, E-mail: ion.stancu@fin.ase.ro

Empirical data for 2009 regarding the indicators used in the models were collected from the European Commission. We employ the Data Envelopment Analysis (DEA) technique to obtain efficiency estimates. In addition, we use Bootstrap estimation methods to obtain more accurate estimates. Due to the sample size, we use an aggregate input that is meant to reduce the dimensions and avoid the curse of dimensionality.

The remainder of the paper is organized as follows. A brief overview of the literature in Section 2 places this study in the larger research context. The methodology is described in Section 3, and in Section 4 we present the data and variables of the models. The results are discussed in Section 5, followed by a brief conclusion.

2. Literature review

Measuring efficiency using parametric and non-parametric techniques is increasingly popular among researchers from different fields, as well as among practitioners. The applications can be made for different areas of research, such as: economics, social science, technology, etc. There are two ways to measure efficiency: parametric and nonparametric approaches. Because they are more flexible compared to the parametric approaches, we considered the non-parametric techniques and we combined them with the last years' algorithms as bootstrapping the confidence intervals.

In recent years, data envelopment analysis (DEA) has gained large popularity in energy and environmental research (see, for example, Lins *et al*., 2012; La Rovere *et al*., 2010; Fare *et al*., 2004; Boyd *et al*., 2002; Zaim, 2004; Arcelus and Arocena, 2005; Picazo-Tadeo *et al*., 2005 and Zhou *et al*., 2007). In the field of measuring the efficiency of energy utilities when environmental regulations are imposed, we can cite the research made by Korhonen and Syrjanen (2003), Agrell and Bogetoft (2005) and Hattori *et al*. (2005).

One of the key elements of the energy market restructuring and development is the electric power distribution. For this reason, studies using non-parametric techniques were elaborated in order to identify the technical efficiency of the electric power distribution industry, e.g. Edvardsen and Førsund (2003), Jamasb and Pollitt (2003) and Giannakis *et al*. (2005). The emerging market of renewable energy is not covered in many studies regarding the efficiency of its development and this research attempts to fill in the gap in the literature regarding the efficiency measuring of the policies implemented to support the development of the EU renewable energy market.

3. Methodology

The efficiency analysis of the EU renewable energy sector uses nonparametric techniques in order to determine the efficiency estimates. The steps of this analysis are the following: first, we apply Data Envelopment Analysis (DEA); second, we use the bootstrap estimation algorithm in order to determine bias-corrected efficiency estimates and, third, a reduction in the dimensional space together with the bootstrap algorithm to obtain better information. Factor analysis is also employed as a prior step of this investigation. The DEA techniques presented in this paper were defined by the work of Coelli *et al*. (2005), which represents the guidebook for our applications.

Data Envelopment Analysis (DEA) is commonly used to evaluate the efficiency of a number of decision units (firms, countries, sectors, etc.). Coelli (1995), among many others, indicated that the DEA approach has one main advantage in estimating the efficiency scores: in contrast to parametric analysis (e.g., Cobb-Douglas function) it does not require to assume a functional form to specify the relationship between inputs and outputs.

DEA uses linear programming in order to construct a non-parametric frontier over the data set. All observed points lie below or on the frontier and efficiency measures are computed relative to this frontier. Farrell (1957) was the first to use a non-parametric approach to define a production frontier. A linear programming problem is solved for each firm in a sample of *N* firms. Each problem has as solution an efficiency score taking values between zero and unit (Aldea and Ciobanu, 2011).

For our study of the energy sector, we use an output orientation model under the VRS (Variable Returns to Scale) assumption, based on the following specification[4]:

$$\begin{aligned}
&\max_{\phi,\lambda} \phi \\
&-\phi Y_i + Y\lambda \geq 0 \\
&X_i - X\lambda \geq 0 \\
&N1'\lambda = 1 \\
&\lambda \geq 0
\end{aligned}$$

where: *Y* is the output matrix, *X* is the input matrix, Y_i is the i^{th} column of matrix Y and represents the outputs vector of firm/unit *i*, X_i is the input vector of firm *i,* and N1 is an $N \times 1$ vector of unit values. The optimum solution for output orientation is $1 \leq \phi \leq \infty$.[5] The term $\phi - 1$ represents the proportional increase in outputs that must be achieved by the firm *i* using the same amount of inputs. The term $1/\phi$ defines the technical efficiency score that varies between zero and unit.

Bootstrap algorithm for DEA estimators

We shall briefly explain the bootstrap algorithm for DEA estimators as in Aldea and Vidican (2007a, b and 2009) and Aldea and Ciobanu (2011).

In 1979, Efron introduced the bootstrap procedure in order to analyze not only the efficiency scores but also how sensitive they were to the sampling variation. The basic idea is how to simulate repeatedly or replicate the data generating a process and how to apply the initial estimator to each simulated sample. In the end, the final estimators replicate the sampling distribution of the original estimation.

In Simar and Wilson (2000a, 2007), the general principles of the bootstrap algorithm are fully explained. In this paper, we only briefly explain the bootstrap method, using the same denotation as Simar and Wilson (2007). The bootstrap procedure is used to

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[4] *Defined by Coelli* et al. *(2005) in Chapter 6.*

[5] *Initially, Φ is the efficiency score defined by Farrell (1957) for an output-oriented model with CRS assumption.*

replicate finite sample data[6] X_n generated by the initial data generation process (P) by a number of replicas (B) that tend to infinity. Doing so, there will be two worlds: the real and the bootstrap world. In the bootstrap world, the algorithm constructs a world similar to the real one but the estimators from the real world become here the true ones, which include the data generation process ($\hat{P}$) over the production set ($\hat{\Psi}$) and the efficiency measure $\hat{\lambda}_{VRS}(x,y)$ (variables returns to scale are assumed). A new data set X_n^* will be obtained in the bootstrap world from the estimator of the data generation process in the real world ($\hat{P}$), which is now known. For each point in the bootstrap world, a new estimator $\hat{\lambda}_{VRS}(x,y)$ is obtained. This way, the new estimator $\hat{\lambda}^*_{VRS}(x,y)$ from the bootstrap world is an estimator of the estimator from the true world $\hat{\lambda}_{VRS}(x,y)$, based on the sample generated in the bootstrap world X_n^*. The B samples generated by the use of $\hat{P}$ and the application of the original estimator to these bootstrap samples will find a set of pseudo estimates $\hat{\lambda}_{VRS,b}(x,y)$, where $b = 1,...,B$. The distributions of these bootstrap values will lead to a Monte Carlo approximation of the sampling distributions $\hat{\lambda}_{VRS}(x,y)$ conditioned by $\hat{P}$. By the law of large numbers, B replicas must tend to infinity such as these approximations have errors that tend to zero. Also, the sample size should tend to infinity for the bootstrap to be consistent. Simar and Wilson (2007) suggest B=2000 replicas so that the confidence intervals provide a good approximation.

In 1998, Simar and Wilson presented a bootstrap procedure based on confidence intervals. Their idea was to use bootstrap estimates of the bias in order to correct the bias of the DEA estimators. Their algorithm, which we apply in this paper, is based on bootstrapping confidence intervals, bias corrections and smoothing techniques (Aldea and Ciobanu, 2011).

Briefly, using Simar and Wilson (1998 and 2007b), the steps to follow when we implement the homogenous bootstrap algorithm are:

Step 1. Compute the efficiency estimates $\hat{\lambda}_i = \hat{\lambda}_i(x_i, y_i),\ i = 1,2,...,n$ based on the initial selection $X_n = \{(x_i, y_i),\ i = 1,2,...,n\}$;

Step 2. Select a bandwith *h*;

Step 3. The set $D_{2n} = \{\hat{\lambda}_1, \hat{\lambda}_2, ..., \hat{\lambda}_n, (2-\hat{\lambda}_1), (2-\hat{\lambda}_2), ..., (2-\hat{\lambda}_n)\}$ is defined and $\beta_1^*, \beta_2^*, ..., \beta_n^*$ are generated by drawing with replacement;

Step 4. $\varepsilon_1^*, \varepsilon_2^*, ..., \varepsilon_n^*$ are drawn indipendenlty from the kernel function K(); compute: $\beta_i^{**} = \beta_i^* + h\varepsilon_i,\ i = 1,2,...,n$,

[6] *We use the same denotation as Simar and Wilson (2007).*

Step 5. Compute β_i^{***} as the standardized value of β_i^{**} ($i=1,2,...,n$), using $\beta_i^{***}=\overline{\beta^*}+\frac{\beta_i^{**}-\overline{\beta^*}}{(1+h^2\sigma_K^2\sigma_\beta^2)^{1/2}}$, where $\overline{\beta^*}=n^{-1}\sum_{i=1}^n\beta_i^*$ is the sample mean of the β_i^*, and $\sigma_\beta^2=n^{-1}\sum_{i=1}^n(\beta_i^*-\overline{\beta^*})^2$ is the sample variance of the β_i^* and σ_K^2 is the variance of the probability density function used for the kernel function . These values are later used to compute the new efficiency estimates

$$\lambda_i^* = \begin{cases} 2-\beta_i^{***} \ for\ \beta_i^{***}<1 \\ \beta_i^{***}\ otherwise \end{cases};$$

Step 6. Define the bootstrap sample $X_n^*=\left\{(x_i,y_i^*),i=1,2,...,n\right\}$,

where $y_i^*=\lambda_i^*\hat{\lambda}_i^{-1}y_i$;

Step 7. Apply DEA technique to the generated set $X_n^*=\left\{(x_i,y_i^*),i=1,2,...,n\right\}$ used as a reference set and compute the new efficiency estimates $\hat{\lambda}^*(x,y)$;

Step 8. Repeat Steps 3-7 for B times until we get the bootstrap estimates $\left\{\hat{\lambda}_b^*(x,y),\ b=1,2,...,B\right\}$.

The bias is explained by: $BIAS(\hat{\lambda}_{VRS}(x,y))\equiv E(\hat{\lambda}_{VRS}(x,y))-\lambda(x,y)$ (which is a negative number).

Using the bootstrap estimates $\left\{\hat{\lambda}_b^*(x,y),\ b=1,2,...,B\right\}$, the bias of the estimator $\hat{\lambda}_{VRS}(x,y)$ can be estimated by the following relation:

$$BIAS(\hat{\lambda}_{VRS}(x,y))=B^{-1}\sum_{b=1}^{B}\hat{\lambda}_{VRS,b}^*(x,y)-\hat{\lambda}_{VRS}(x,y)$$

The new estimator $\hat{\hat{\lambda}}_{VRS}(x,y)$ corrected with the previously explained bias is:

$$\hat{\hat{\lambda}}_{VRS}(x,y)=\hat{\lambda}_{VRS}(x,y)-BIAS(\hat{\lambda}_{VRS}(x,y))=2\hat{\lambda}_{VRS}(x,y)-B^{-1}\sum_{b=1}^{B}\hat{\lambda}_{VRS,b}^*(x,y)$$

The standard deviation in Tables 1 and 2 used for a 95% confidence interval is the sample variance of the bootstrap values $\hat{\lambda}_{VRS,b}^*(x,y)$, computed as $\hat{\sigma}^2=B^{-1}\sum_{b=1}^{B}\left[\hat{\lambda}_{VRS,b}^*(x,y)-B^{-1}\sum_{b=1}^{B}\hat{\lambda}_{VRS,b}^*(x,y)\right]^2$ that provides an estimate of the variance of $\hat{\lambda}_{VRS}(x,y)$ - the output-oriented efficiency estimator.

One of the recurrent problems of the efficiency analysis is given by the small size of the sample. The “curse” of dimensionality shows that if we work with small samples the efficiency estimates are better than the real ones and that is enough reason to question their reliability. If this is the case, one option is to reduce the dimensions by aggregating the inputs and/or the outputs in order to get a two dimensional space: one input-one output. Mouchart and Simar (2002) show how we should proceed in order to obtain the aggregated input (which is also our case). The main idea is to make a linear combination of the inputs and we get an aggregated input that also includes the information given by all the initial inputs (see Mouchart and Simar, 2002, for further information).

4. Data

The analysis is made from the perspective of efficiency of the measures to support the sustainable development of renewable energy market in each EU country, and we employ two models described below:

- The EIDG Model uses one output (effectiveness indicator for energy from RES) and three inputs (energy intensity of the economy, energy dependency, the greenhouse gas intensity of energy consumption) and
- The EIG Model uses one output (effectiveness indicator for energy from RES) and an aggregated input based on two of the previous inputs (energy intensity of the economy and the greenhouse gas intensity of energy consumption).

The database used includes 27 countries. We defined several inputs and outputs for each model, which are presented as follows: the output, namely the effectiveness indicator for energy from RES is estimated as a ratio of the share of renewable energy in gross final energy consumption in 2009 to the target level of this indicator for 2020. For this indicator, we collected data from EurObserv’ER. In order to reflect sustainable development of the renewable energy market and by considering the data availability constraint we selected as inputs of the models the following indicators, available in the EUROSTAT database: energy intensity of the economy, energy dependency, the greenhouse gas intensity of energy consumption.

5. Results

We computed the DEA efficiency estimates, DEA efficiency corrected-estimates and bootstrap 95%- confidence intervals using FEAR 1.15 (designed by Paul W. Wilson[7], Clemson University, U.S.), which is a library that runs R 2.12.0.

R 2.12.0 is a software package that can be used to manipulate and compute data, as well as graphic representations. The software package is a synthesis of the new data analysis methods and it employs the S language that writes most of the functions used.

[7] *FEAR 1.15, designed by Paul W. Wilson, Clemson University, U.S.A. is a software library that can be linked to the R package.*

FEAR 1.15 is a software library that can be connected to R 2.12.0. The FEAR routines allows the user to compute the DEA efficiency estimates for technical, allocative and total efficiency assuming different returns to scale (constant, variable or non-increasing).

As a previous step of the investigation, we use the Factor Analysis and 73% of the initial data are recuperated. Two factors are computed and a graphic representation is shown in Annex 1. As one may see in Annex 1, we should focus our analysis on countries like Malta, the Netherlands and Bulgaria.

5.1. DEA estimates and Factor Analysis

We performed the multistage DEA output-oriented model with variable returns to scale (VRS) that generated efficiency estimates for the 27 countries used in the sample.

5.1.1. The EIDG Model

The VRS output-oriented DEA model generated average efficiency estimates for the 27 countries, taking on values between 0.020 and 1, with an average of 0.75 over the period of time considered – 2009. Although the sample average is not very high, the limited number of DMUs (decision making unit) might be a reason for the high variation in the efficiency estimates. We found 11 countries with unit efficiency estimates: the Czech Republic, Denmark, Estonia, Ireland, Latvia, Hungary, the Netherlands, Austria, Romania and Sweden. Due to the sample size, this large number of efficient countries was expected.

This result is justified for countries like Estonia, Latvia, Austria, Romania, and Sweden, which reached the highest renewable energy share in the gross final energy consumption in 2009 as compared to the target of this indicator for 2020. This evolution was accompanied by a decrease in their energy dependence, energy intensity of the economy, the greenhouse gas intensity of energy consumption.

There is only one country with a relative high efficiency estimate: Belgium – 0.86. This country could increase the outputs by almost 14% with the available resources. Other countries with relatively high efficiency estimates are Portugal – 0.81 and Finland – 0.82.

On the opposite side, the least efficient countries are Malta (0.0206), Luxembourg (0.257) and the UK (0.266).

5.1.2. The EIG Model

Other studies also argue that the DEA results are more meaningful when there are enough DMUs to allow for a more varied comparison relative to the number of variables (outputs and inputs). However, when there are no more available data, the only option that we have is the dimensional reduction in the initial input space.

By using an aggregated input, we rerun the analysis and obtain different and better results than those of the previous model. The average efficiency for the new model is 0.693, which is not very different from the average of the first model, as it was expected to be. We also notice that the number of efficient countries is much lower: only 4 (Latvia, Hungary, the Netherlands and Sweden), as compared to 11 countries in the first model. As we can see, these 4 countries are among the efficient countries found by the first model.

Among the countries with high efficiency estimate we find Estonia– 0.94, Austria – 0.98, Romania – 0.95 and Finland – 0.82 (these countries were among the efficient ones in the EIDG Model). The least efficient countries are Malta (0.206), Luxemburg (0.257) and the UK (0.195). More information about these efficiency estimates are obtained using the following bootstrap corrected-efficiency estimates.

5.2 Bootstrap on the DEA estimators

Using FEAR 1.15 package that implements Simar and Wilson's (1998) bootstrap procedure, 2000 bootstrap samples are generated in order to estimate the confidence intervals for the distance functions that measure the technical efficiency. With the DEA routine we computed the Farrel output distance functions under variable returns to scale assumptions. We applied the bootstrap procedure for the DEA VRS efficiency estimates for one year (2009) to both EIDG Model and EIG Model for the reduced space.

Table 1 displays the results obtained with FEAR 1.15 showing the original efficiency estimates, the bias-corrected estimates and the 95% confidence intervals. As we can see, the bias is large relative to the variance in each case, so we prefer the bias-corrected estimates to the original estimates. The original estimates are placed outside the estimate confidence intervals – the last two columns, but the bias-corrected efficiency estimates are inside the interval. The table shows that no DMU is actually placed on the frontier.

Table 1

The EIDG Model, output bias-corrected efficiency estimates (B=2000)

DMU	VRS Efficiency estimates	VRS-Corrected Efficiency estimates	Bias	Standard Deviation	Lower Bound	Upper Bound
DMU01	0.8663	0.7402	-0.19656	0.013406	0.6153	0.8550
DMU02	0.7525	0.6987	-0.10233	0.00391	0.6333	0.7472
DMU03	1	0.7627	-0.31119	0.054953	0.5052	0.9860
DMU04	1	0.7639	-0.30908	0.052928	0.5052	0.9851
DMU05	0.5567	0.4914	-0.23864	0.016978	0.4380	0.5526
DMU06	1	0.7921	-0.26251	0.022759	0.6474	0.9869
DMU07	1	0.7600	-0.31578	0.0514	0.5052	0.9837
DMU08	0.5581	0.4860	-0.26594	0.025281	0.4143	0.5513
DMU09	0.6907	0.6269	-0.14744	0.007402	0.5612	0.6859
DMU10	0.6662	0.5738	-0.24177	0.015187	0.4934	0.6549
DMU11	0.5704	0.5114	-0.20235	0.013855	0.4520	0.5644
DMU12	0.5676	0.5008	-0.23519	0.013636	0.4446	0.5599
DMU13	1	0.8374	-0.19423	0.007504	0.7439	0.9833
DMU14	0.7628	0.7124	-0.09278	0.003449	0.6506	0.7588
DMU15	0.2577	0.2339	-0.39466	0.059159	0.2086	0.2565
DMU16	1	0.7759	-0.28883	0.034847	0.5827	0.9848
DMU17	0.020619	0.0191	-3.74049	6.747292	0.0173	0.0206
DMU18	1	0.7601	-0.31566	0.054742	0.5052	0.9860

DMU	VRS Efficiency estimates	VRS-Corrected Efficiency estimates	Bias	Standard Deviation	Lower Bound	Upper Bound
DMU19	1	0.8074	-0.23857	0.015303	0.6874	0.9856
DMU20	0.6197	0.5354	-0.2541	0.017782	0.4718	0.6114
DMU21	0.8144	0.7489	-0.10747	0.004708	0.6745	0.8102
DMU22	1	0.8560	-0.16827	0.008024	0.7340	0.9838
DMU23	0.701	0.6375	-0.14207	0.006562	0.5767	0.6966
DMU24	0.7628	0.7219	-0.07424	0.002692	0.6639	0.7604
DMU25	0.8247	0.7475	-0.12527	0.004682	0.6792	0.8182
DMU26	1	0.8141	-0.22842	0.013526	0.6942	0.9854
DMU27	0.2665	0.2276	-0.64193	0.202288	0.1832	0.2629

Source: Own calculations.

By analyzing Table 1, we find quite significant differences between the efficiency estimates and the bias-corrected efficiency estimates for the analyzed year. The latter are much lower. The average efficiency for the new model is 0.634. We see that the 11 countries that were initially efficient are no longer after bootstrapping was applied. The unit efficiency countries have now much lower efficiency estimates. For instance, Denmark has now a 0.76 efficiency estimate. Among the most efficient countries we find: Latvia (0.83), Austria (0.80), Romania (0.85) and Sweden (0.81). The corrected efficiency estimates for Portugal and Finland are now almost similar: 0.748 and 0.747, respectively.

The least efficient countries are the same, but their efficiency estimates are even lower. The previous inefficient countries have a much lower efficiency score: Malta – 0.019 and UK – 0.22.

A similar analysis is made for the EIG Model and Table 2 displays the results obtained with FEAR 1.15 showing the original efficiency estimates, the bias-corrected estimates and the 95% confidence intervals.

Table 2

The EIG Model, output bias-corrected efficiency estimates (B=2000)

DMU	VRS Efficiency estimates	VRS-Corrected Efficiency estimates	Bias	Standard Deviation	Lower Bound	Upper Bound
DMU01	0.7507	0.630597	-0.25371	0.018285	0.5350	0.7328
DMU02	0.7525	0.719923	-0.06013	0.00245	0.6636	0.7515
DMU03	0.7434	0.664383	-0.15999	0.009347	0.5841	0.7339
DMU04	0.6804	0.626574	-0.12626	0.005202	0.5705	0.6759
DMU05	0.5567	0.521795	-0.12016	0.006515	0.4763	0.5549
DMU06	0.9466	0.847812	-0.12309	0.003665	0.7640	0.9335
DMU07	0.5439	0.460352	-0.33368	0.033387	0.3953	0.5344
DMU08	0.5289	0.470429	-0.235	0.018449	0.4137	0.5211
DMU09	0.6907	0.644803	-0.10306	0.004345	0.5888	0.6872
DMU10	0.6011	0.539664	-0.18939	0.013876	0.4749	0.5937

DMU	VRS Efficiency estimates	VRS-Corrected Efficiency estimates	Bias	Standard Deviation	Lower Bound	Upper Bound
DMU11	0.536	0.504625	-0.116	0.006442	0.4635	0.5346
DMU12	0.4965	0.433016	-0.29529	0.020433	0.3837	0.4860
DMU13	1	0.877144	-0.14006	0.004951	0.7754	0.9793
DMU14	0.7628	0.72818	-0.06233	0.0025	0.6704	0.7617
DMU15	0.2577	0.246266	-0.18017	0.021346	0.2268	0.2573
DMU16	1	0.842728	-0.18662	0.009668	0.7258	0.9789
DMU17	0.020619	0.019749	-2.13529	3.230367	0.0182	0.0206
DMU18	1	0.736076	-0.35856	0.055187	0.5052	0.9769
DMU19	0.9816	0.882405	-0.11452	0.005029	0.7779	0.9688
DMU20	0.6082	0.556879	-0.15153	0.006899	0.5068	0.6024
DMU21	0.8144	0.762068	-0.08432	0.003084	0.6953	0.8112
DMU22	0.9587	0.913374	-0.05176	0.001642	0.8408	0.9572
DMU23	0.701	0.666002	-0.07496	0.00319	0.6121	0.6995
DMU24	0.7628	0.727573	-0.06347	0.002545	0.6704	0.7616
DMU25	0.8247	0.773516	-0.08024	0.00294	0.7067	0.8224
DMU26	1	0.893923	-0.11866	0.003215	0.8070	0.9855
DMU27	0.1958	0.186041	-0.26791	0.040742	0.1710	0.1954

Source: Own calculations.

The average efficiency for the corrected efficiency estimates is 0.625; lower than before the bootstrap efficiency estimates were computed. We can see in Table 2 that the countries that were efficient have by almost 30% lower efficiency estimates, such as: the Netherlands (with unit efficiency estimate) has a 0.73 corrected efficiency estimate, Latvia – 0.877, Hungary – 0.842 and Sweden – 0.893. But, as we can see, Estonia, Romania and Austria are now placed among the high efficient countries, though not unit efficient. The UK, Malta and Luxembourg are the least efficient countries, with efficiency estimates even lower than before.

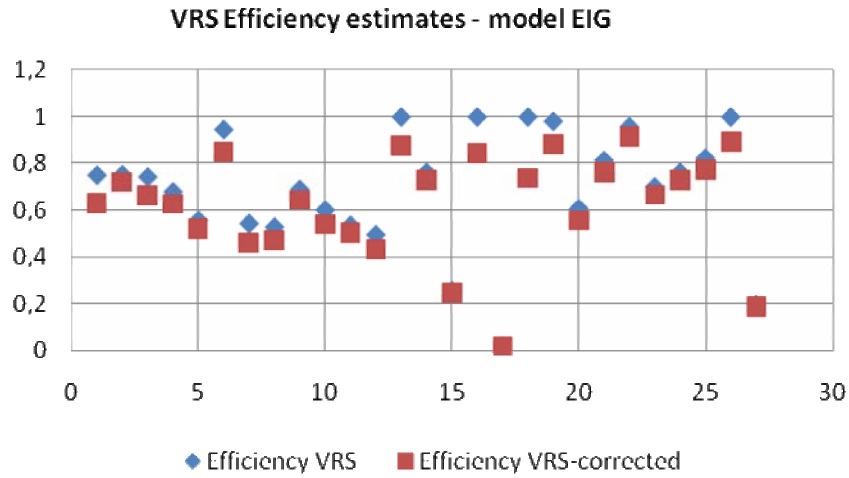
These results are similar to those obtained for 2008 available data (Aldea and Ciobanu, 2011). Countries such as Latvia, Hungary, the Netherlands, Estonia, Romania, and Bulgaria have improved their efficiency by comparison with their efficiency estimates for 2008.

We can mention that the bootstrap efficiency estimates are computed as Farrel distance functions, which is no impediment because they represent the reciprocal of Shepard distance factors.

Figure 1 shows that corrected efficiency estimates are different and they vary around the initial ones.

Figure 1

Efficiency estimates and bias-corrected efficiency estimates – The EIG Model



Source: Own calculations.

Conclusions

Even considering the small sample size, we notice that the non-parametric methods used to determine efficiency estimates show interesting results. Using these techniques together with the bootstrapping algorithm make us fully understand the estimators' significance giving an insight into the evolution of renewable energy.

Furthermore, the reduction in the dimension space used to compute the efficiency estimates with the EIG Model gives us much more reliable information.

The results indicate the countries with higher efficiency in implementing the reforms in renewable energy market and their impact on indicators such as the energy intensity of the economy, energy dependence, the greenhouse gas intensity of energy consumption. The countries with high efficiency estimates can be considered as best practice examples in supporting the development of renewable energy market.

Future research requires an analysis of the environmental factors (that can be classified neither as outputs nor as inputs) of the efficiency estimators in the renewable energy based on Bădin, Daraio and Simar (2010a, b) and Bădin and Simar (2009).

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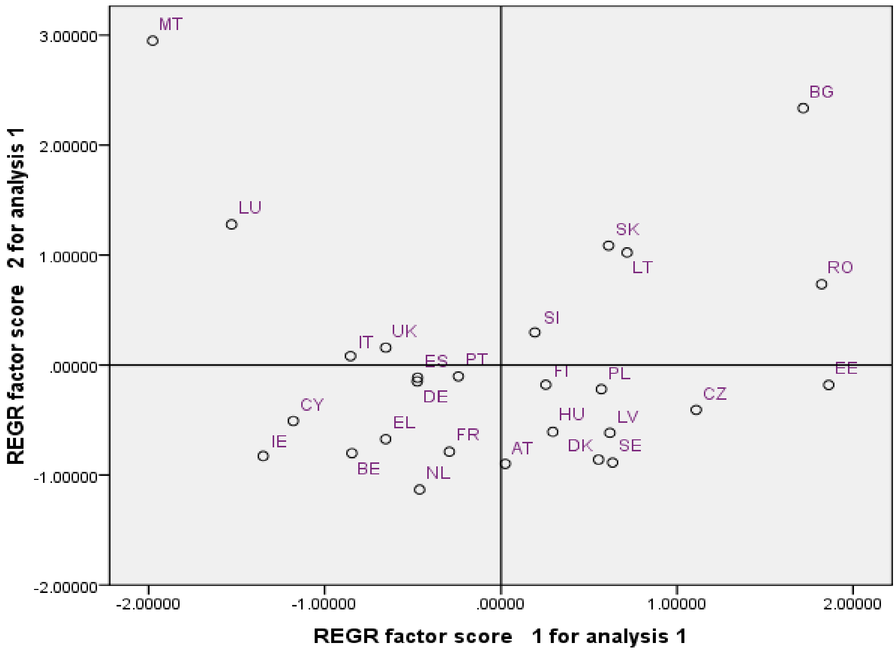
Annex 1

Variables projection for 27 countries (the EIDG Model)



Source: Own calculations.