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ANALYSIS OF RENEWABLE ENERGY DEVELOPMENT USING BOOTSTRAP EFFICIENCY ESTIMATES

Abstract. *This paper main objective is to examine the efficiency of renewable energy development in EU using national level data in 2008 and 2009. We apply nonparametric techniques to determine efficiency estimators that will give us an insight about the quality of renewable energy market. We employ Data Envelopment Analysis techniques and Bootstrap estimation methods, which allow us to obtain more precise estimations than conventional methods. Our paper is a good example of why Bootstrap algorithms should be used when we make use of finite samples and non-parametric methods to obtain efficiency estimates. We use R 2.4.0 language and FEAR 1.1 libraries in order to implement the above techniques. Moreover, our analysis has important policy relevant implications for the performance of renewable energy markets. The present paper is based on a previous work performed for a paper presented at X European Workshop in Efficiency and Productivity, France - July 2007.*

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

JEL Classification C14, C38, Q01, Q20

1. Background

The research project “Integrated System of Multi-Criteria Analysis of Investments Efficiency in the Field of Renewable Energy Exploitation to Support the Sustainable Development”, CNCSIS code: ID_1807, contract no. 799/19.01.2009, project director Anamaria Ciobanu had set interesting objectives, among which the measurement of efficiency in the renewable energy market from the perspective of sustainable development. The field of sustainable development implies a trade off between economic development, social ethics, efficient exploitation of natural resources and environment preservation. Hence, the investment decision in exploitation of renewable energy should be analyzed by taking into account the three pillars (economical, ecological and socio-cultural dimensions) that support the sustainable development of our society. As EU contries are moving forward with reforms in the renewable energy market, there is an increasing need for a comparative analysis of reforms′ effectiveness. The principal issue we encounter in the measurement of efficiency in the renewable energy market is to define the term "efficiency". The project uses the non-parametric techniques to compute efficiency estimates for EU countries in renewable energy market and it is based on a large research activity in the international academics and on a personal interpretation of the efficiency of the energy sector.

We make use of aggregate data collected from European Commission over the years 2008 and 2009. We employ Data Envelopment Analysis (DEA) technique to estimate technical efficiency levels. In addition, we use Bootstrap estimation methods in order to obtain more accurate estimates. Previous of the efficiency analysis, we employ Factor Analysis in order to get more information from the initial data set.

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 for the model. The results are discussed in Section 5, followed by a brief conclusion.

2. Literature review

During the past 20 years, measuring efficiency using parametric and non-parametric techniques had become a strong research domain, gathering researchers from different fields, as well as practitioners. The large number of empirical analysis that can be done using these tools leads to different application areas. One of those is the interesting subject of measuring efficiency in energy market. Taking into consideration the large number of approaches when it comes to efficiency in energy market, the non-parametric techniques are very interesting to use, especially if they are combined with the last years algorithms as bootstrapping the confidence intervals.

DEA techniques have been widely applied to estimate efficiency and productivity by considering pollutants and to model environmental performance. See, for example, Fare et al. (2004), Boyd et al. (2002), Zaim (2004), Arcelus and Arocena (2005), Picazo-Tadeo et al. (2005) and Zhou et al. (2007). Other researchers used this technique to measure the efficiency of energy utilities when environmental regulations are imposed e.g. Korhonen and Syrjanen (2003), Agrell and Bogetoft (2005) and Hattori et al. (2005).

Electricity distribution is a key element of the energy market restructuring and development. The non-parametric techniques have been also applied in measuring the technical efficiency of the electricity distribution industry e.g. Edvardsen and Førsund (2003), Jamasb and Pollitt (2003) and Giannakis et al. (2005). As a consequence of underdeveloped market of renewable energy, literature is rare regarding studies on countries/regions efficiency in using RES.

3. Methodology

The examination of efficiency in EU renewable energy sector involved three methodological steps: 1) the Data Envelopment Analysis (DEA); 2) Bootstrap estimation methods for DEA estimates and 3) Factor Analysis. The DEA presented in this paper are 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 efficiency scores: in contrast to parametric analysis (e.g. Cobb-Douglas function), it does not require the assumption of 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[1]. 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 one.

For our study of the energy sector, we use an output orientation model, under the VRS assumption, based on the following specification[2]:

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

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 ones. The optimum solution for output orientation is $1 \leq \phi \leq \infty$.[3] 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 one.

Bootstrap algorithm for DEA estimators

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

In 1979, Efron introduced the bootstrap procedure in order to analyze not only the efficiency scores but also how sensitive they are to the sampling variation. The

[1] Farrell (1957) was the first to use a non-parametric approach to define a production frontier

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

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

basic idea is how to repeatedly simulate or replicate the data generating 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. We use the same notation as Simar and Wilson (2007). The bootstrap procedure is used to replicate finite sample data[4] 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 similar world as 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 $\hat{\theta}_{VRS}(x,y)$ (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 $\hat{\theta}_{VRS}(x,y)$ is obtained. This way, the new estimator $\hat{\theta}^*_{VRS}(x,y)$ from the bootstrap world is an estimator of the estimator from the true world $\hat{\theta}_{VRS}(x,y)$, 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 $\hat{\theta}_{VRS,b}(x,y)$, where $b = 1,...,B$. The distributions of these bootstrap values will lead to a Monte Carlo approximation of the sampling distributions $\hat{\theta}_{VRS}(x,y)$ conditioned by $\hat{P}$. By the law of large numbers, B replicas must tend to infinity in order for these approximations to have errors that tend to zero. Also, the sample size should tend to infinity in order for the bootstrap to be consistent. Simar and Wilson (2007) suggests B=2000 replicas so that the confidence intervals give 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. For a better understanding of the algorithm we suggest an extended study of Simar and Wilson's 1998 paper, "Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models".

The Factor Analysis is one of the most known statistic instruments that are very well suited for the analysis of the information contained by a sample of data (Hardle and Simar, 2007; Ruxanda, 2001). This analysis is ment to reduce the information contained in a space with multiple variables and offers bidimensional representation of the initial space. A first step is to fully understand the correlation

[4] We use the same notation as Simar and Wilson (2007).

among variables and then, to project the initial data to a reduce, bidimensional space[5]. The factor analysis was first used in the efficiency area by Deprins şi Simar (1988).

4. Data

The analysis was made from two distinct perspectives: efficiency of the measures to support the sustainable development at the level of each EU country (hence named Model DDE) and efficiency of the actions took by the authorities of each EU countries to support the development of renewable energy market, particularly with respect to wind energy (hence generically named Model REE).

Although a number of 2 variations of Model DDE and 3 variations of Model REE were performed, in the present paper we show the finding for the following final analysis:

- Model DDE uses 1 output (Effectiveness indicator for energy from RES) and 3 inputs (Energy intensity of the economy, Energy dependency, The greenhouse gas intensity of energy consumption) and
- Model REE uses 2 outputs (Wind capacity for 1000 inhabitants, Share of wind energy in gross inland energy consumption) and 3 inputs (Time to be spent for administrative permission process, Number of all permits that need to be obtained, Grid Indicator)

The data base used includes 27 countries for Model DDE and 24 countries for Model REE. We defined several inputs and outputs for each model which are presented as follows:

a) For the model DDE we have chosen as output the effectiveness indicator for energy from RES, which is estimated as a ratio between the share of renewable energy in gross final energy consumption in 2008 and the target level of this indicator for 2020. We selected the inputs in order to reflect sustainable development of the economy and by considering the data availability constraint. As consequence we have chosen from Eurostat database the values estimated for energy intensity of the economy, energy dependency, the greenhouse gas intensity of energy consumption.

b) For the model REE we have chosen as outputs wind capacity for 1000 inhabitants, share of wind energy in gross inland energy consumption, for which we gathered the data from Eurostat Energy Database. We selected the inputs in order to reflect the barriers the electricity producers encounter when implementing the wind energy investment projects. We gathered the data from the report made by European Commission about non-cost barriers to renewable energy growth in EU Member States.

[5] For further details, see Ruxanda (2001)

5. Results

In order to compute the DEA estimator as well as the bootstrap confidence intervals we use R 2.4.0 and FEAR 1.1, designed by Paul W. Wilson[6], Clemson University, U.S.A.

R 2.4.0 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 S language that writes most of the functions used.

FEAR 1.1 is a software library that can be connected to R 2.4.0. The FEAR routines allows the user to compute the DEA estimators for technical, allocative and total efficiency assuming constant, variable or non-increasing returns to scale.

5.1. DEA estimates and Factor Analysis

The multistage DEA output oriented with variable returns to scale generated high efficiency estimates for the 27 countries (Model DDE) and for 24 countries (Model REE).

5.1.1. Model DDE

The multistage DEA generated average efficiency estimates for the 27 countries, taking values between 0.022 and 1, with an average of 0.617 over 2008. We claim that such high values are mainly due to the limited number of DMUs (decision making unit). Other studies have also argued that DEA results are more meaningful when there are enough DMUs to allow a more varied comparison relative to the number of variables (outputs and inputs). We found 5 countries with unitary efficiency estimates: Denmark, Austria, Romania, Slovakia and Sweden. These countries have reached the highest level of the renewable energy share in gross final energy consumption in 2008 compared with the target level of this indicator for 2020. This evolution was accompanied by a decrease in their energy dependency, energy intensity of the economy, the greenhouse gas intensity of energy consumption. There are also several countries with high efficiency estimates (over 0.8): Estonia, Portugal and Finland. These counties could increase their outputs by almost 20% with the available resources. At the opposite side, the countries with lowest efficiency estimates are Malta (0.02), Belgium (0.275), Luxemburg (0.209), Netherlands (0.206) and UK (0.216).

Using SPSS 16.0, we make use of Factor Analysis for a better understanding of the data. After the rotation, we use 2 factors that can be explained by the *energy consumption* (factor 1) and *energy intensity* (factor 2). As it can be seen in Annex 1, we can analyze several groups of countries such as: Cyprus, Malta and Luxemburg with high values for the 1st factor (large energy consumption) and which also have low DEA estimates. Bulgaria is considered to be an outlier and another group includes Romania and Estonia.

[6] FEAR 1.1, designed by Paul W. Wilson, Clemson University, U.S.A. is a software library that can be linked to the R package.

5.1.2. Model REE

In this case, the multistage DEA generated low VRS efficiency estimates for the 24 countries, with an average of 0.289 over 2009. These low values are subject to our own choice of inputs and outputs that define the VRS efficiency estimates. Also, the low number of DMUs is a restriction to better results. We found 3 countries with unitary efficiency estimates Denmark, Sweden and Bulgaria. But only Denmark has also unitary CRS and scale efficiencies, while the other 2 have very low values for these types of efficiencies. We can conclude that Denmark is the only efficient country. This can be explained by the fact that this country has successfully implemented renewable energy market reforms that facilitate the execution of large scale renewable energy projects. There are also several countries with average efficiency estimates (over 0.6): Spain and Portugal that could increase their outputs by almost 40% with the available resources, and there are 14 countries with very low efficiency estimates (around 0.02). Romania and Slovakia are the most inefficient countries. But, the large number of inefficient countries is consistent with the low efficiency average.

For this analysis, we performed a similar Factor Analysis (see Annex 1b) to the one for Model DDE and we constructed 2 principal components after rotation that can be interpreted as the *energy output* (factor 1) and the *energy inputs* (factor 2). Using these factors, Denmark has the highest value for factor 1, which is consistent with the fact that this country is the only efficient one. Countries such as Spain, Portugal, Germany and Ireland are grouped in one cluster with high values for factor 1 and relatively good values for the 2nd factor. At the opposite side, Romania, Italy and Latvia can be included in one group that can be considered to be inefficient. As we can see, the Factor Analysis strengthens the DEA efficiency estimates.

What makes the difference between countries with high and low efficiency estimates is the stability of the administrative framework that include: a single regulatory contact point (one-stop-shoping) or only few authorities that are involved in granting the permits; short lead time for collecting all permits; authorization exemption for small RES systems. In addition, the countries with high efficiency estimates have fewer barriers linked to grid connections and access. Usually these barriers have as main reasons: the lack of grid capacity caused by the incentive to expand on economical basis only, lack of RES spatial planning, insufficient design of networks with regard to the intermittent nature of renewable energy. For this reasons in various countries (Austria, Belgium, Czech Republic, Greece, Netherlands, Portugal, Romania, Slovakia, Spain and the United Kingdom) grid connection is frequently denied. The countries with high efficiency estimates can be taken as concrete examples of best practice in supporting the development of renewable energy market.

4.2 Bootstrap on the DEA estimators

Using FEAR 1.1 package that implements Simar and Wilson's (1998) bootstrap procedure, 2000 bootstrap samples were 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 for both DDE and REE Models.

Table 1 displays the results obtained with FEAR 1.1 showing the original efficiency estimates, the bias-corrected estimates and the confidence intervals at 5% significance level. As we can observe, 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 situated outside the estimate confidence intervals – the last two columns. The explanation can be found in the bias of the original estimates, which produce bias-corrected estimates that are included in the confidence intervals. From the table we can see that no DMU is actually situated on the frontier.

Table 1: Bootstrap results for 2008: output efficiency estimates with VRS for DDE Model (B=2000)

DMU	*Efficiency VRS*	*Efficiency VRS-Corrected*	*Bias*	*Standard Deviation*	*Lower Bound*	*Upper Bound*
DMU01	0.2747	0.7106	-0.4359	0.0651	3.6765	4.6358
DMU02	0.6483	0.8065	-0.1582	0.0081	1.5586	1.9088
DMU03	0.6581	1.0176	-0.3595	0.0278	1.5712	2.1999
DMU04	1.0000	1.4457	-0.4457	0.0599	1.0274	1.9779
DMU05	0.5413	0.9184	-0.3771	0.0331	1.8858	2.5691
DMU06	0.9317	1.1337	-0.2020	0.0105	1.1022	1.5004
DMU07	0.3690	1.1540	-0.7850	0.2193	2.7748	4.4663
DMU08	0.4835	0.7497	-0.2662	0.0232	2.0891	2.6554
DMU09	0.5934	0.7759	-0.1825	0.0128	1.6970	2.1289
DMU10	0.5274	1.1317	-0.6043	0.1342	1.9311	3.2848
DMU11	0.4637	0.8187	-0.3550	0.0324	2.2114	2.8737
DMU12	0.3516	0.5928	-0.2412	0.0296	2.8563	3.4890
DMU13	0.8241	0.9621	-0.1380	0.0063	1.2228	1.5264
DMU14	0.7362	0.9045	-0.1683	0.0104	1.3688	1.7587
DMU15	0.2087	0.9135	-0.7048	0.1374	4.8692	6.2711
DMU16	0.5604	0.8138	-0.2534	0.0233	1.8011	2.3689
DMU17	0.0219	4.1672	-4.1452	8.1793	45.710	56.428
DMU18	0.2596	1.1242	-0.8646	0.1534	3.9422	5.4254
DMU19	1.0000	1.1997	-0.1997	0.0086	1.0255	1.3887
DMU20	0.6178	0.9588	-0.3410	0.0253	1.6667	2.2698
DMU21	0.8241	0.9558	-0.1317	0.0065	1.2228	1.5300
DMU22	1.0000	1.1650	-0.1650	0.0080	1.0264	1.3625
DMU23	0.6593	0.8402	-0.1809	0.0104	1.5306	1.9117
DMU24	1.0000	1.4411	-0.4411	0.0548	1.0347	1.9776
DMU25	0.8791	1.0868	-0.2077	0.0133	1.1504	1.5774
DMU26	1.0000	1.4598	-0.4598	0.0603	1.0335	1.9778
DMU27	0.2163	1.4646	-1.2483	0.4866	4.7393	7.3479

Looking at the data, we found quite significant differences between the DEA and Bootstrap estimates for the analyzed year. We can see that the DMU (here, countries) that were initially efficient are not anymore after bootstrapping. Also, the bootstrap efficiency estimates are computed as Farrel distance functions, which is no impediment because they represent reciprocal of Shepard distance factors. What is very interesting is that, in most cases they have a much lower efficiency level. For instance, all countries that were fully efficient initially (DEA estimates equal to 1) have now a decrease in efficiency, some of them with even 31% (Austria and Denmark) or 15% (Romania).

A similar analysis is made for the REE Model (See Annex 2). In Figure 1, we can also see that corrected efficiency estimates are different and they vary around the initial ones.

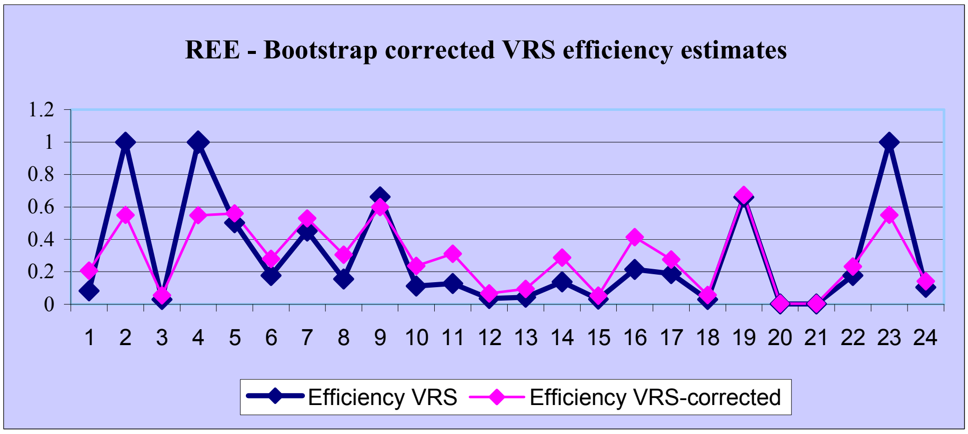

Figure 1.VRS Efficiency and VRS efficiency corrected estimates (B=2000) – Model REE

The number of countries that exhibits efficiency increases from 21 to all 24 of them because there are no more efficient countries. The initial efficiency country is no longer efficient and, as we can see, there is place for improvement in outputs with the same amount of inputs. For instance, Bulgaria which has a unitary VRS efficiency estimate is no longer efficient and requires a very large (0.45%) increase in efficiency after we compute the VRS corrected-efficiency estimates. The countries which exhibits relatively high efficiency estimates before the bootstrap corrected estimates are computed are still the same (Denmark, Sweden, Portugal, Spain and Germany) but with slightly different estimates. Slovakia and Romania still remain the least efficient countries.

CONCLUSIONS

The non-parametric methods show very interesting results when they are used to determine the efficiency estimators. But the non-parametric techniques used together with the bootstrapping algorithm make us fully understand the estimators' significance giving an insight of the evolution of renewable energy market. The results are consistent with the current evolution on this market by pointing out the countries with higher efficiency in implementing the reforms. The countries with high efficiency estimates can be considered as best practice examples in supporting the development of renewable energy market. Some policy implications are provided for decision makers. Firstly, a stable administrative framework is needed with no discretionary power allocated to the administrations and fewer authorities involved in the granting permits process. Secondly, a more clear and strong regulations for the connection and the access to the grid are needed. The whole administrative procedure for grid connection should be simplified and priority grid access should be guaranteed for renewable energy. Thirdly, the government should support the development of the new grid infrastructure.

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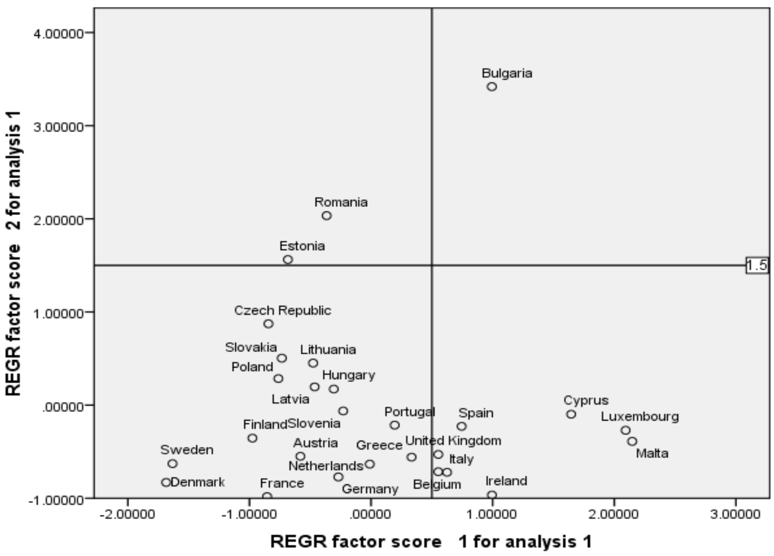
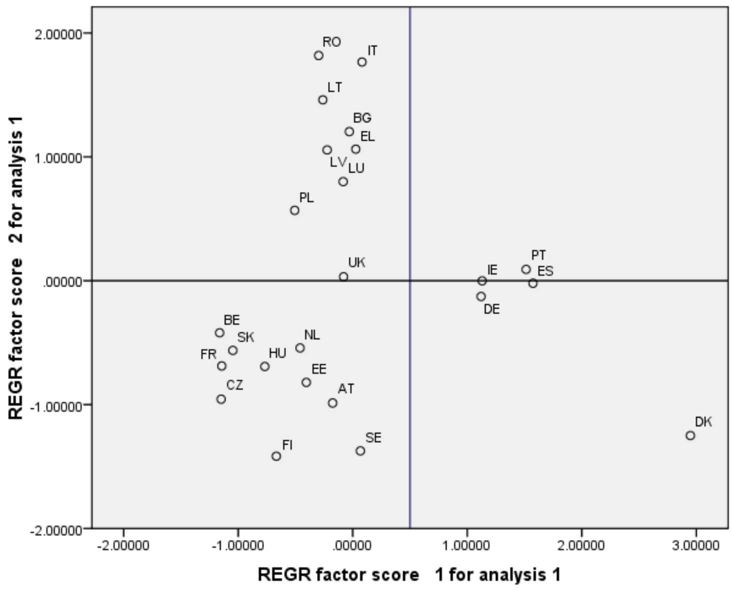
Annex 1a) Variables projections for 27 countries



Annex 1b) Variables projections for 24 countries



Annex 2 Bootstrap results for 2009: output efficiency estimates with VRS for Model REE (B=2000)

DMU	*Efficiency VRS*	*Efficiency VRS-corrected*	*Bias*	*Standard deviation*	*Lower bound*	*Upper bound*
1	0.0828	4.8403	-4.7575	5.3792	12.469	20.827
2	1	1.8126	-0.8126	0.0396	1.2156	1.9988
3	0.0293	18.207	-18.177	38.182	37.136	61.169
4	1	1.8188	-0.8188	0.0373	1.2567	1.9988
5	0.5024	1.7842	-1.2818	0.14	2.2642	3.7418
6	0.1773	3.5924	-3.4151	1.1408	6.4302	10.49
7	0.4511	1.8914	-1.4403	0.2096	2.5045	4.2227
8	0.1556	3.2703	-3.1147	1.2953	7.1197	11.418
9	0.6621	1.6645	-1.0024	0.0849	1.717	2.8543
10	0.1113	4.2432	-4.1319	3.0522	9.458	15.875
11	0.1279	3.2144	-3.0865	2.0768	8.0724	13.461
12	0.0362	15.079	-15.043	28.649	30.222	50.557

13	0.0435	10.535	-10.492	18.241	24.445	40.545
14	0.1373	3.4752	-3.3379	1.7967	7.7408	12.851
15	0.032	19.164	-19.132	33.975	34.959	58.186
16	0.2135	2.4208	-2.2073	0.7693	5.0054	8.2981
17	0.1893	3.6305	-3.4412	0.9297	6.0208	9.8658
18	0.0294	17.337	-17.307	44.042	36.127	61.394
19	0.6619	1.484	-0.8221	0.0785	1.6641	2.7522
20	0.0011	335.55	-335.55	28470	918.57	1540.8
21	0.0017	298.83	-298.83	9438	628.73	1003.8
22	0.1761	4.298	-4.1219	1.4666	6.4913	11.186
23	1	1.8168	-0.8168	0.0369	1.2202	1.9988
24	0.104	7.0257	-6.9217	4.2732	11.138	18.939