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Ranking National Innovation Systems according to their technical efficiency

Monica Mihaela Matei[a]*, Anamaria Aldea[b]

[a]The Bucharest Academy of Economic Studies, 6 Romana Square, Bucharest010374, Romania
[b]The Bucharest Academy of Economic Studies, 6 Romana Square, Bucharest 010374, Romania

Abstract

The purpose of this study is to measure and compare the performance of the National Innovation Systems using the information available in IUS 2011 database. In order to fulfill this purpose, the variables describing the innovation process included in this database are used to estimate the technical efficiency of the EU27 Member States as well as Croatia, Iceland, Norway, Switzerland and Turkey.
Thus the efficiency of the decision making units represented by National Innovation Systems is estimated using a nonparametric frontier model: data envelopment analysis (DEA). Statistical inference for DEA estimators is based on bootstrap, a very well-known resampling method. Ranking the countries provide an interesting insight into the innovation system classification.

Keywords: Innovation system, efficiency, data evelopment analysis, ranking;

1. Introduction

The new economic strategy of the European Union for the coming decade is called Europe 2020 and its main objective isto help countries to go out of the crisis and prepare the EU economy for the future. One of the objectives of the Europe 2020 Strategy is to develop a smart growth by improving EU's performance in education, knowledge and innovation.

European Commission assumption is that Innovation can be translated into new goods and services that create growth and jobs and thus innovation becomes one of the most important pillars of European economy.

One concrete action that has been initiated is the development of a tool intended to help assessing the innovation performance in EU Member States. This tool is known as Innovation Union Scoreboard (IUS) and includes innovation indicators which capture the performance of the national innovation systems and trend analyses for the EU 27 Member States as well as for Croatia, Iceland, the Former Yugoslav Republic of Macedonia, Norway, Serbia, Switzerland and Turkey (Innovation Union Scoreboard, 2011).

The purpose of this study is to measure and compare the performance of some National Innovation Systems (NIS) using the information available in IUS 2011 database. In order to fulfil this purpose, the variables describing the innovation process included in this database are used to estimate the NIS`s efficiency bytransforming innovation inputs into innovation outputs. Therefore, the analysis presented in this paper is based on a systemic approach of the

*Monica MihaelaMatei. Tel.: +040728230514
E-mail address: matei.monicamihaela@gmail.com

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innovation process meaning we try to capture the interactions among the actors involved in the process and how their inputs are translating into outputs.

According to Buesa (2002) a system of innovation can be defined as the set of institutional and business organizations which, within a specific geographical area, interact with the aim of allotting resources to performing activities geared to generating and spreading knowledge which supports the innovations. These are the basis of economic development.

The analysis presented in this paper is based on a nonparametric approach. Thus the efficiency of the decision making units represented by National Innovation Systems is estimated using a nonparametric frontier model: Data Envelopment Analysis (DEA). Statistical inference for DEA estimators is based on bootstrap, a very well-known resampling method. We consider that different policies and strategies may be developed for each country,based on this ranking. .

2. Prior work

Fritsch (2002) developed a stochastic approach assuming a functional form for a knowledge production function and his results showed a strong impact of the number of private sector R&D employees on the number of patents.

There are also studies developed in this field that use nonparametric methods for the estimation of innovation systems efficiency. Most of them deal with regional innovation systems. For instance, Kutvonen (2007), used a DEA model in order to identify best practice cases of regional innovation policies and he draw the conclusion that DEA provides means for benchmarking regional policies in different areas. Ta-Wei Pan et. all (2010) measure the performance of national innovation systems in Europe and Asia which applies Data Envelopment Analysis models and their results show that Asian countries are generally better performers than European countries (). Theyaslo proved that DEA isuseful to estimate efficiency of the innovation systems.

3. Methodology

The nonparametric approach in the field of efficiency estimation develops Koopmans definition of technical efficiency and linear programming models known as envelopment models. According to Koopmans: “an input-output vector is technically efficient if and only if, increasing any output or decreasing any input is possible only by decreasing some other output or increasing some other input” (Koopmans, 1951). The envelopment models are based on the following principle: the inefficiency of a decision making unit is given by the distance to an “efficient frontier” estimated using only the information regarding the quantities of inputs used and the quantities of outputs produced by a sample of decision making units.

Technical efficiency is a concept related to the production frontier and depending on the orientation chosen it shows if:

- Either a producer fails to produce the maximum possible amount of available inputs (output orientation);
- Or the producer is able to use a minimum amount of inputs needed to achieve the desired output (input orientation).

Thus,by analyzing technical efficiency, one can choose between output maximization and input minimization. In this paper we use an output oriented model that requires solving the following maximization problem for every decision making unit that uses inputs$x \in R_{+}^{p}$to produce outputs $y \in R_{+}^{q}$ (Daraio and Simar, 2007):

$$\hat{\lambda}(x,y) = max\{\lambda | \lambda y \leq \sum_{i=1}^{n} \gamma_i y_i \,; x \geq \sum_{i=1}^{n} \gamma_i \, x_i, \sum_{i=1}^{n} \gamma_i = 1, \gamma_i \geq 0, i = 1, \dots, n\} \quad (1)$$

wherethe only information we have is the sample $\chi = \{(x_i, y_i), i = 1, \dots n\}$, meaning we know the inputs and the outputs for n producers or decision making units.

The main advantages of using envelopment models are given by the following aspects:

- Allow multiple input/output modeling;
- Do not require specifying a functional form of the production function.

The major disadvantage is given by the deterministic nature of these nonparametric models which causes problems in making statistical inference. One of the solutions found to eliminate this disadvantage is based on bootstrap techniques (Simar, Wilson 2000). Bootstrap is a resampling technique that does not require the introduction of parametric assumptions and can be used to estimate the statistical inference tools (standard deviation, bias, confidence intervals) when the distribution of estimators is unknown or when the sample size is reduced. The basic principle of this technique is the following one: a sufficient number of bootstrap samples are extracted with replacement,from the original sample and the statistic of interests is estimated on each new sample. Finally, the values obtained for this statistic indicate a certain empirical distribution based on which confidence intervals can be built. In the context of DEA models the bootstrap technique has to be adapted to their particular characteristics and this is why a homogeneous bootstrap is used (Simar, Wilson, 1998). In this case the generation is based on a smooth estimate $\hat{f}(\cdot,\cdot)$ of the joint pdf on (x,y). The basic idea in this algorithm is to create a bootstrap sample by projecting each observation (x_i, y_i) onto the estimated frontier, and then projecting this point away from the frontier randomly.

4. Empirical results

4.1. Data description

In order to estimate NIS technical efficiency, first we have to select the inputs and the outputs that characterizethe innovation system of a country. In this study we used some of the variables included in IUS 2011 database. The inputs (Table 1) selected to describe NIS capture: the availability of educated workforce, the quality of the research system, collaboration efforts among firms and public sector and intellectual assets.

Table 1. Inputs variables

Variable	Code	Definition (according to IUS 2011)
New doctorate graduates (ISCED 6) per 1000 population aged 25-34	I_1	Number of doctorate graduates (ISCED6) per population between 25 and 34 years
International scientific co-publications per million population	I_2	Number of scientific publications with at least one co-author based abroad (where abroad is non-EU for the EU27) per total population
Public R&D expenditures as % of GDP	I_3	R&D expenditures in the government sector and the higher education sector as % of Gross Domestic Product
Business R&D expenditures as % of GDP	I_4	All R&D expenditures in the business sector as a % of Gross Domestic Product
Public-private co-publications per million population	I_5	Number of public private co-authored research publications per total population
PCT patents applications per billion GDP (in PPS€)	I_6	Number of patent applications filed at European Patent Office divided by Gross Domestic Product in Purchasing Power Parity Euros
Community trademarks per billion GDP (in PPS€)	I_7	Number of new community trademarks applications divided by Gross Domestic Product in Purchasing Power Parity Euros

Given that we want to measure economically useful new knowledge, the outputs chosen in this analysis are related to employment and exports capturing the ability to commercialize the results of innovation (Table 2).The output variables describe the economic effects of the innovation measured by labor market quality and value of exports. Thedescriptive statistics computed for input/ output variables show that our decision making units are not very homogeneous. This heterogeneity is caused mainly by input variables related to public-private co-publications or to patents applications. There are countries like Denmark, Sweden, Switzerland with a very high number of research publication resulted from public-private collaboration but there are countries like Turkey, Latvia, Bulgaria where the number of such publications is even 130 times lower. Such differences are also registered for the number of patents. The degree of variation is not so high for the output variables. In this case the variation coefficients are less than 40%. The variable with the greatest dispersion is O_3 which measures the value of knowledge intensive services exports. Ireland is the country with the largest share of knowledge – intensive services in total service exports and Greece has the lowest share.

Table 2 Output variables

Variable	Code	Definition (according to IUS 2011)
Employment in knowledge-intensive activities (manufacturing and services) as % of total employment	O_1	Number of employed persons in knowledge intensive activities in business industries (activities where at least 33% of employment has a higher education degree) as a % of total employment
Medium and high-tech product exports as % total product exports	O_2	Value of medium and high tech exports as % total product exports
Knowledge-intensive services exports as % total service exports	O_3	Exports of knowledge intensive services (transport services, communications services, insurance services, financial services, computer services, research and development, architectural, engineering services) value as % total service exports

The Input/output variables presented in Table 1 and Table 2 are selected from a list of 25 indicators included in IUS 2011 database. In the report prepared by the Maastricht Economic and Social Research Institute on Innovation and Technology (Innovation Union Scoreboard 2011, 2011) the information available in this database is used to measure the innovation performance through a composite score calculated as an average of the 25 variables describing the innovation. According to this measurement the member states fall into four performance groups:

- *Innovation leaders* are countries whose performance is well above that of EU27 average. Denmark, Finland, Germany and Sweden are in this group.
- *Innovation followers* are countries that show performance close to that of EU27 average: Austria, Belgium, Cyprus, Estonia, France, Ireland, Luxembourg, Netherlands, Slovenia and UK.
- *Moderate innovators* are countries whose performance is below that of EU27 average: Czech Republic, Greece, Hungary, Italy, Malta, Poland, Portugal, Slovakia and Spain.
- *Modest innovators* are: Romania, Bulgaria, Latvia, and Lithuania because their performance is well below that of EU27 average.

The study developed in this paper aims to investigate whether those countries considered innovation leaders are both technically efficient.

4.2. Reducing dimensionality

In order to estimate technical efficiency we useDEA which is a nonparametric method. The curse of dimensionality is typical for nonparametric techniques and it is reflected by the rates of convergence. These rates are very low if the number of inputs and outputs is large and if the sample size is not large enough. Given that our sample size is only 31 and that we cannot increase it in order to increase the rates of convergence, we choose to aggregate the input/outputs variable to reduce the dimensionality.

Given the high correlation levels we found among the input variables we used an aggregation procedure described by Daraio and Simar (2007). Our final purpose was to find a factor *I* calculated as a linear combination of all inputs:

$I = \sum_{i=1}^{7} v_i\, I'(2)$

where $I_i^{'}$ is the input variable I_i divided by its mean. We also denoted by X the matrix of these new scaled inputs. The weights v_i are given by an eigenvector of the matrix $X'X$ corresponding to its largest eigenvalue denoted λ_1.The factor *I* was computed using the weights: $v = (0.34\ 0.38\ 0.31\ 0.39\ 0.44\ 0.43\ 0.33\ )'$

The correlation coefficients (Table 3) between *I* and the original variables are high showing that this factor represents well the inputs I_i. Also the percentage of inertia which is explained by this first factor given by the ratio

$\lambda_1/(\sum_{i=1}^{7}\lambda_i)$ is 0.88 indicating that most of the information contained in the original variables is well summarized by I.

Table 3Correlations between original input variables and aggregated input

Correlation	I_1	I_2	I_3	I_4	I_5	I_6	I_7
I	0.69	0.93	0.80	0.95	0.93	0.93	0.62

In the output space, we used the same method and we obtained the factor O by aggregating the variablesO_1, O_2, O_3. The weights used in aggregation are given by the vector $u = (0.58\ \ 0.57\ \ 0.59)'$.

The correlations between the factor O and the original variables are given in *Table 6*, indicating loss of information contained invariable O_2. But the percentage of inertia explained by the first factor is 0.95 showing that the information is well summarized by the factor O.

Table 4Correlations between original output variables and aggregated output

Correlation	O_1	O_2	O_3
O	0.82	0.50	0.80

We managed to reduce the dimensionality with the cost of losing some information contained in the original variables. Figure 1 shows the cloud of points representing the countries in our sample.

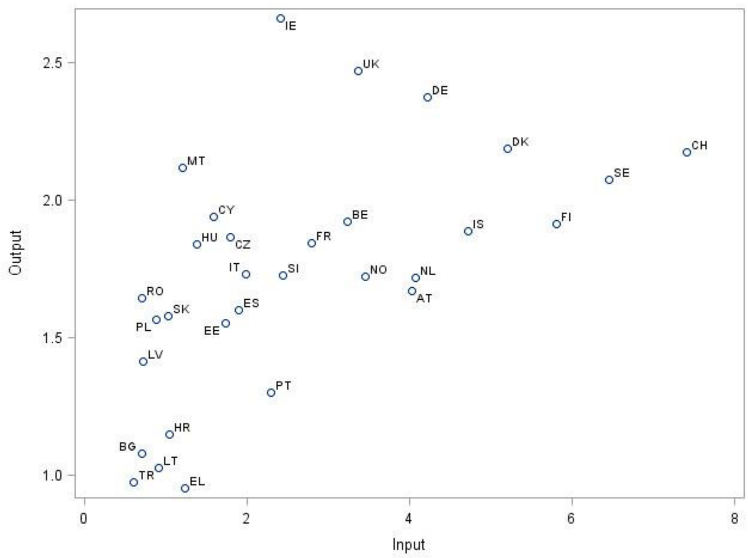

Figure1. Decision making units

4.3. Efficiency estimates

In order to estimate the efficiency scores for the 31 national innovation systems we used an output oriented DEA model assuming variable returns to scale. The results are presented in the following and are returned from a routine in FEAR (Frontier Efficiency Analysis with R) which implements the bootstrap method of Simar and Wilson (1998). The bias estimates and the 95% confidence intervals were produced using 2000 bootstrap replications. Figure 2 displays the original efficiency estimates as well as the bias corrected estimates and the 95% confidence intervals for DEA estimators for each decision making unit. Given that FEAR command returned Farrell efficiency estimates all the scores are greater than or equal to 1. The DEA estimator definition (1) shows that the higher the efficiency scores the more inefficient the decision making unit is. In our sample there are four countries which first received an efficiency score equal to one: Malta, Romania, Turkey and Ireland. But DEA estimators are biased and in consequence our analysis doesn't stop after determining the point estimates - we also estimated the bias of DEA estimators and 95% confidence intervals. The original efficiency estimates lie outside the estimated confidence intervals – in Figure2 the orange dots are below green lines showing that the original estimates are biased. Thence we trust bias corrected scores instead of the original ones and our ranking is built on these scores.

As it can be seen from Figure 2, Malta has the most efficient innovation system and it is followed by Ireland and UK. Even if countries like Romania or Turkey have original efficiency scores equal to one, after the bias correction they ranked 4th and 6th.

The results presented here prove that a point estimate of the efficiency score equal to one does not always mean 100% efficiency. The best example is that of Turkey: although its efficiency score equals one the wide confidence interval determines a large uncertainty about the true value of the score.

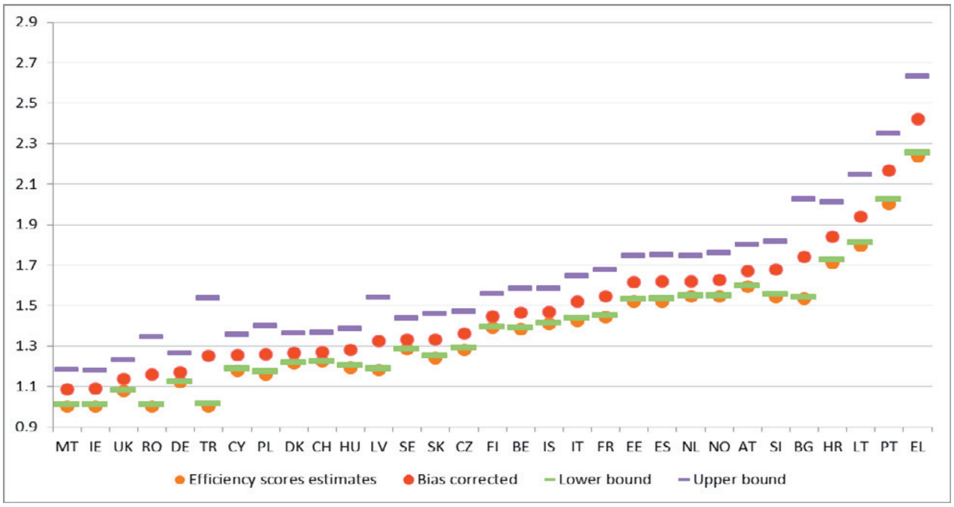

Figure 2. DEA and Bootstrap results

Comparing the hierarchy obtained from the efficiency analysis with the IUS performance groups we conclude that the innovation leaders are not also technically efficient when transforming innovation inputs in innovation outputs. Countries from the innovators followers and moderate innovators groups come in at the first, second and third position as the most efficient of our sample. These countries will not be able to increase to much the level of their outputs given their innovation inputs. In the opposite situation are countries like Greece, Portugal and Lithuania which are very inefficient meaning that their exports and employment could increase given their human resources and their research system. Therefore policymakers should develop different policies and strategies for these countries.

5. Conclusions

The results presented in this paper show that by using envelopment techniques and bootstrap we could offer an alternative method of performance evaluation in the innovation field. After comparing our results with those presented in IUS reports of the European Commission we can conclude that innovation leaders do not always have the most efficient innovation systems as well as modest innovators are not necessarily inefficient in transforming innovation inputs into outputs of innovation

We think that due to the complexity of the innovation process, the development and the implementation of innovation relatedpoliciesmust take into accountarange of measuresbothqualitativeandquantitative. Therefore taking into account the IUS classification and our efficiency results we conclude that Ireland, UK and Germany may be considered best practices in terms of innovation policies. This remark is based on the fact that their performance measured in IUS report is above that of EU27 average and also their efficiency scores are among the smallest.

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References

Bădin, L. and L. Simar (2009). A Bias-Corrected Nonparametric Envelopment Estimator of Frontiers, *Econometric Theory*, 25, 5, 1289-1318

Buesa, M., Heijs, J., Ramirez, Pellitero, M., Baumert, T. (2006). Regional systems of innovation and the knowledge production function: The Spanish case, Technovation , 26, 463-472.

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

Efron, B., Tibshirani, R., (1993). *An introduction to the bootstrap*, CRC Press.

Fritsch M. (2002). Measuring the Quality of Regional Innovation Systems: A Knowledge Production Function Approach, *International Regional Science Review*, Volume: 25, Issue: 1, Pages: 86-101.

Koopmans,T.C. (1951). *An Analysis of Production as an Efficient Combination of Activities*, in Koopmans T.C. (Ed).

Kutvonen, A. (2007). *Ranking Regional innovation policies: DEA based benchmarking in a European setting*, Research Report 193.

Simar, L. , P.W. Wilson (1998). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models, Management Science 44, 49–61.

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

Ta-Wei Pan, Shiu-Wan Hung, Wen Min LU (2010). DEA performance measurement of the national innovation system in Asia and Europe, *Asia-Pacific Journal of Operational Research*,Vol 27, No. 3,pp 369-392.

Wilson, P. (2008). FEAR: A software Package for Frontier Analysis with R, *Socio Economic Planning Sciences*, Vol.42, No. 4, pp 247-254.