An efficiency approach to innovation process

Monica Mihaela Matei

1National Scientific Research Institute for Labour and Social Protection, Bucharest, The Bucharest Academy of Economic Studies
e-mail: matei.monicamihaela@gmail.com

Abstract

The main goal of this paper is to model innovation phenomenon on national level using Data envelopment Analysis (DEA) technique. We want to evaluate the innovation performance of 31 countries from the point of view of technical efficiency. Given that the innovation process is one of the main drivers for sustained economic growth, it is obvious that we need innovation policies based on rigorous quantitative analysis. We think that ranking countries according to their innovation performance may represent a useful tool for the policy makers and we present here an evaluation based on the information provided by European Innovation Scoreboard (EIS) which is one of the instruments designed to understand the sources and patterns of innovative activity. The efficiency scores obtained from a DEA model show that the countries considered innovation leaders, because their innovation performance reflected by Summary Innovation Index is well above that of EU average, are not also technically efficient when transforming innovation inputs into innovation outputs.

Keywords: innovation, technical efficiency, DEA

1. Introduction

Innovation is a complex phenomenon which has a systematic nature. National Innovation system is a concept defined by Freeman as “the network of institutions in the public and private sectors whose activities and interactions initiate, import, modify and diffuse new technologies” (Freeman 1995) and by Lundvall “as the elements and relationships which interact in the production, diffusion and use of new, and economically useful, knowledge located within or rooted inside the borders of a nation state” (Lundvall, 1992).

The main goal of this paper is to model innovation phenomenon on national level using Data envelopment Analysis (DEA) technique. We want to evaluate the innovation performance of 31 countries from the point of view of technical efficiency. Koopmans definition for technical efficiency is: “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”.

Given that the innovation process is one of the main drivers for sustained economic growth, it is obvious that we need innovation policies based on rigorous quantitative analysis. We think that ranking countries according to their innovation
performance may represent a useful tool for the policy makers. As previous researchers have shown, DEA provides means for benchmarking national policies in different areas. In his study, Antero Kutvonen (Kutvonen, 2007) showed that a transnational comparison of regional policies developed with a DEA model provides meaningful insights to regional policy development that policymakers can act on. Another conclusion drawn in his paper is that DEA model identifies best practice cases of regional innovation policies.

There is also a recent study (Ta-Wei Pan et al., 2010) which applies the data envelopment analysis approach for the evaluation of the operating performance of the National Innovation Systems (NIS) in 33 Asian and European countries. The analysis was developed on data extracted from the World Competitiveness Yearbook (2004,2006) and World Development Indicators (2004). The results obtained from a DEA input oriented model indicate that the Asian group is a better performer than European group.

We present here an evaluation based on the information provided by European Innovation Scoreboard (EIS) 2009 which is one of the instruments designed to understand the sources and patterns of innovative activity. The indicators capturing the inputs of the innovation process refer to: science, engineering, social sciences and humanities doctorate graduates, participation in life long learning, public R&D expenditures, private credit, business R&D expenditures, public-private co-publications. The indicators of EIS capturing the outputs of the process refer to: employment in medium-high and high-tech manufacturing, medium and high-tech manufacturing exports. We have included time lags between inputs and outputs considering that it takes time before inputs transfer into outputs. In our study we introduce a bootstrap algorithm developed by Simar and Wilson (1999) and we compute not only point estimates for the efficiency scores but also 95% confidence intervals and bias corrected efficiency scores. Also, by using this algorithm we managed to test the type of the returns to scale of the production process.

2. Methodology

Like we said before, our final purpose is to evaluate the performance of a certain number of countries from the point of view of technical efficiency. The countries included in EIS are the producers or the decision making units, and they use inputs \( x \in \mathbb{R}^p \) to produce outputs \( y \in \mathbb{R}^q \).

In the process of efficiency estimation, the only information we have is the sample \( \chi = \{(x_i, y_i), i = 1, \ldots, n\} \), meaning we know the inputs and the outputs for \( n \) producers.

Having the inputs and the outputs for every unit, the production set is defined as follows (Daraio, 2007):

\[
\psi = \{ (x, y) | x \in \mathbb{R}^p, y \in \mathbb{R}^q, \text{is feasible} \} \tag{1}
\]

In the efficiency measurement the upper boundary of \( \psi \), also referred to as production frontier is of interest because units that are technical efficient operate on it. The production frontier is defined by (Daraio, 2007):

\[
\psi^F = \{ (x, y) \in \psi | (\theta x, y) \notin \psi, \forall \theta < 1, (x, \lambda y) \notin \psi, \forall \lambda > 1 \} \tag{2}
\]
Also, $\psi$ can be defined in terms of its sections, using the input requirement set or the output correspondence set. The input requirement set consist of all input vectors that can produce the output vector $y \in \mathbb{R}^q$. The output correspondence set consists of all output vectors that can be produced by a given input vector $x \in \mathbb{R}^p$. Choosing one of these sections means we choose an input oriented model or an output oriented model. The presentation in this section refers to the output oriented models.

In that case, the production frontier is defined by (Daraio, 2007):

$$\psi^3 = \{(x, y) \in \psi \mid (\theta x, y) \in \psi, \forall 0 < \theta < 1, (x, \lambda y) \in \psi, \forall \lambda > 1\}$$  \hspace{1cm} (3)

The most known nonparametric estimator of efficiency frontiers is DEA (Data Envelopment Analysis) estimator. It is nonparametric and this means it does not need the specification of a functional form for the frontier. DEA employs linear programming techniques to estimate the production frontiers. Like we said before, efficiency computations are made relative to the frontier or envelopment surface. There are two basic types of envelopment surfaces in DEA, referred to as constant returns to scale and variable returns to scale (Simar et al., 2008):

$$\hat{\psi}_{VRS} = \left\{(x, y) \in \mathbb{R}^{p+q} \mid y \leq \sum_{i=1}^{n} \gamma_i y_i; x \geq \sum_{i=1}^{n} \gamma_i x_i; \text{for} \ (\gamma_1, \ldots, \gamma_n), \sum_{i=1}^{n} \gamma_i = 1; \gamma_i \geq 0, i = 1, \ldots, n\right\}$$  \hspace{1cm} (4)

This estimator is referred as $\hat{\psi}_{VRS}$ because it allows for variable returns to scale. In the constant returns to scale situation the equality constrained $\sum_{i=1}^{n} \gamma_i = 1$ is dropped:

$$\hat{\psi}_{CRS} = \left\{(x, y) \in \mathbb{R}^{p+q} \mid y \leq \sum_{i=1}^{n} \gamma_i y_i; x \geq \sum_{i=1}^{n} \gamma_i x_i; \text{for} \ (\gamma_1, \ldots, \gamma_n), \gamma_i \geq 0, i = 1, \ldots, n\right\}$$  \hspace{1cm} (5)

The estimator of the output efficiency score for a given $(x_0, y_0)$ is obtained by solving the following linear program:

$$\hat{\lambda}_{VRS}(x_0, y_0) = \max \left\{\lambda \mid \hat{\lambda} y_0 \leq \sum_{i=1}^{n} \gamma_i y_i; x_0 \geq \sum_{i=1}^{n} \gamma_i x_i; \lambda \geq 0; \sum_{i=1}^{n} \gamma_i = 1; \gamma_i \geq 0; i = 1, \ldots, n\right\}$$  \hspace{1cm} (6)

We solve the linear program described above when we choose a VRS model. When using a DEA CRS model to estimate the score the linear program becomes:

$$\hat{\lambda}_{CRS}(x_0, y_0) = \max \left\{\lambda \mid \hat{\lambda} y_0 \leq \sum_{i=1}^{n} \gamma_i y_i; x_0 \geq \sum_{i=1}^{n} \gamma_i x_i; \lambda \geq 0; \gamma_i \geq 0; i = 1, \ldots, n\right\}$$  \hspace{1cm} (7)

Thus, before estimating technical efficiency, we need to know whether the technology is one of constant return to scale. The return to scale is one of the properties of the boundary of the production set. The less restrictive model for RTS is the varying return to scale situation (VRS) where the returns are allowed to be eventually locally increasing, then constant and finally non-increasing.

We use a procedure proposed by Simar and Wilson (2002) in order to test the type of the return to scale (Simar et al., 2008).

The test hypotheses are:
\[ H_0 : \psi^\beta \text{ is globally CRS} \]
\[ H_1 : \psi^\beta \text{ is VRS} \quad (8) \]

It is known that VRS estimators are consistent whatever being the hypothesis on return to scale and that CRS are consistent only if the null hypothesis is true. If the return to scale is constant then CRS and VRS estimators of the efficiency scores are very similar. This represents the justification for the test statistic that will be used in the process of establishing if null hypothesis is rejected or accepted is the following:

\[ T(\chi_n) = \frac{1}{n} \sum_{i=1}^{n} \frac{S_{\text{CRS}}(x_i, y_i)}{S_{\text{VRS}}(x_i, y_i)}, \quad (9) \]

where \( \hat{S}_{\text{CRS}} = (\hat{\lambda}_{\text{CRS}})^{-1} \) and \( \hat{S}_{\text{VRS}} = (\hat{\lambda}_{\text{VRS}})^{-1} \).

Also, given that \( \hat{S}_{\text{CRS}} \leq \hat{S}_{\text{VRS}} \), the null hypothesis will be rejected if the test statistics is too small.

The p-value of the null hypothesis is then obtained by computing:

\[ p-value = \Pr_{\text{null}}(T(\chi_n) \leq T_{\text{obs}} \mid H_0 \text{ is true}) \]

where \( T_{\text{obs}} \) is the value of \( T \) computed on the original observed sample \( \chi \).

In order to compute this probability, we use a bootstrap algorithm. Naïve bootstrap involves, simulating \( B \) pseudo samples \( \chi^{*,b}_n \) of size \( n \) under the null (using the CRS estimate of the frontier for generating the pseudo samples), and for each bootstrap sample computing the value \( T^{*,b} = T(\chi^{*,b}_n) \). The p-value is then approximated by the proportion of bootstrap samples with values \( T^{*,b} \) less than the original observed value \( T_{\text{obs}} \):

\[ p-value = \frac{1}{B} \sum_{b=1}^{B} \mathbb{1}(T^{*,b} \leq T_{\text{obs}}) \quad (10) \]

In the boundary estimation framework, the naïve bootstrap is not consistent (Kneip et al, 2008). Kneip, Simar and Wilson proved the consistency of two approaches also based on bootstrap. The first, known as subsampling is based on drawing pseudo samples of size \( m \) smaller than \( n \) and the second one is known as smoothing technique because the generation is based on a smooth estimate \( \hat{f}(.,.) \) of the joint pdf on \( (x,y) \). In order to approximate the probability p-value we used the second one by implementing the homogeneous bootstrap algorithm developed by Simar and Wilson (Simar et. Al, 2008) 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.

Because one can not stop the analysis after determining the point estimates, the bootstrap algorithm can be used to give estimates of bias as well as of standard error and confidence intervals.
3. Data description

In order to investigate the innovation process from a DEA point of view we used 7 inputs and 2 outputs. The indicators describing the inputs are (EIS 2009):

$I_1$: S&E and SSH doctorate graduates per 1000 population aged 25-34. The numerator of this indicator is the number of science, engineering, social sciences and humanities graduates at second stage of tertiary education, and the denominator is the population between 24 and 34 years.

$I_2$: Population with tertiary education per 100 population aged 25-64. This is a percent of the persons in age class with some form of postsecondary education in total population between 25 and 64 years.

$I_3$: Participation in life long learning per 100 population aged 25-64. It is calculated as a ratio between number of persons involved in life-long learning (defined as participation in any type of education or training course during the four weeks prior the survey) and the population between 25 and 64 years.

$I_4$: Public R&D expenditures (% of GDP), represents the ratio between all R&D expenditures in the government sector and the higher education sector and Gross Domestic Product.

$I_5$: Private credit (relative to GDP). The nominator of this indicator is given by the claims on the private sector by commercial banks and other financial institutions that accept transferable deposits such as demand deposits and the denominator is the Gross Domestic Product.

$I_6$: Business R&D expenditures (% of GDP) shows all the R&D expenditures in the business sector as a percent of GDP.

$I_7$: Public-private co-publications per million population. The nominator of this indicator is the number of public-private co-authored research publications in Web of Science Database and the denominator is Total population.

The indicators we choose to describe the outputs of the innovation process are:

$O_1$: Employment in medium-high and high-tech manufacturing (% of total workforce)

$O_2$: Medium and high-tech manufacturing exports (% of total exports).

Because it takes time before inputs transfer into outputs, we must include time lags between them. This is the reason why the inputs data are drawn from EIS 2005 and the outputs from EIS 2009.

We must reduce the dimensionality because in the DEA model, which is nonparametric is present the course of dimensionality. Given that we only have a sample of 31 countries, we reduced the dimensionality from 7+2 to 1+1 using an aggregation procedure described by Daraio (Daraio, 2007). The indicator reflecting the innovation inputs is computed as a linear combination of $I_1, I_2, I_3, I_4, I_5, I_6, I_7$.

First we correct the scale of the inputs by dividing each input by its mean. So if the original matrix has the columns $I_1, I_2, I_3, I_4, I_5, I_6, I_7$ we use the notation $X$ for the new matrix of the scaled inputs. The purpose is to find a factor, $I$ calculated as a linear combination of all inputs: $I = Xv = v_1 I_1 + v_2 I_2 + v_3 I_3 + v_4 I_4 + v_5 I_5 + v_6 I_6 + v_7 I_7$

We will use the idea suggested by Daraio (2007). The vector $v$ is determined by computing an eigenvector of the matrix $XX$ corresponding to its largest eigenvalue.
The eigenvalues of the matrix $X^T X$ are: $a_1 = 296.805$, $a_2 = 18.466$, $a_3 = 12.070$, $a_4 = 4.813$, $a_5 = 2.513$, $a_6 = 2.174$, $a_7 = 1.283$.

<table>
<thead>
<tr>
<th>Correlation</th>
<th>I2</th>
<th>I3</th>
<th>I4</th>
<th>I6</th>
<th>I7</th>
<th>I8</th>
<th>I9</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>0.657</td>
<td>0.667</td>
<td>0.938</td>
<td>0.836</td>
<td>0.628</td>
<td>0.922</td>
<td>0.958</td>
</tr>
</tbody>
</table>

*Table 1 Correlations between new input and the original variables*

These eigenvalues do not represent the factors variance because the data is not centered. An eigenvector corresponding to $a_1 = 296.805$ is $v = (0.353, 0.312, 0.409, 0.341, 0.333, 0.399, 0.474)^T$ and we used it to obtain the factor $I$. Correlations between the new factor and the original input variables show that this factor represents well the original indicators. Also the ratio $a_1/(a_1 + a_2 + a_3 + a_4 + a_5 + a_6 + a_7)$ is close to 1 (0.87) indicating that the inertia explained by $I$ is high.

In the output space, using the same method, we aggregate $O_1$ and $O_2$. Thus is calculated the output factor $O = Y u = u_1 O_1 + u_2 O_2$, where $Y$ is a matrix with the columns $O_1$ and $O_2$ (scaled), $u = (0.728, 0.685)^T$ and represents the eigenvector corresponding to the first eigenvalue of the matrix $Y^T Y$, $a_1 = 75.248$.

<table>
<thead>
<tr>
<th>Correlation</th>
<th>O1</th>
<th>O3</th>
</tr>
</thead>
<tbody>
<tr>
<td>O</td>
<td>0.959</td>
<td>0.888</td>
</tr>
</tbody>
</table>

*Table 2 Correlations between new output and the original variables*

Correlations between $O$, $O_1$ and $O_2$ are 0.959 respectively 0.888 and the ratio between first eigenvalue and the sum of the $Y^T Y$ eigenvalues is 0.977 indicating that the factor $O$ represents the original variables very well, without loosing too much information.

The cloud of points representing the countries in our sample is illustrated in Figure 1.

*Fig. 1 Decision making units*
As we can see in the figure above, Romania, Bulgaria, Turkey are the countries with the lowest level of input. There are countries with low levels of inputs but with a high level of output: Slovakia, Hungary, Czech Republic.

4. Technical efficiency estimation for NIS

4.1 Testing return to scale

Using the new variables to describe the efforts and the results of the 31 DMU’s we compute the efficiency scores for every DMU using a DEA output oriented model considering both a variable return to scale and a constant return to scale. Next we have compared the CRS and the VRS scores for each country by computing the ratio of efficiency score obtained with a CRS DEA model to the efficiency score obtained with a VRS DEA model. The average of these 31 values represents the observed value of the statistic defined in a previous section, $T_{obs} = 0.591$.

In order to decide if we should use a CRS or a VRS model when estimating the efficiency scores in the innovation process, we must compute a p-value for the test which has a null hypothesis that the frontier of the production set is CRS. We obtained this p-value by using the homogeneous bootstrap algorithm of Simar and Wilson (Simar et al., 1999) as follows:

1. **Step 1:** $B=1000$ bootstrap samples of size 31 were generated from a smooth estimate of the density $f(x,y)$. This estimate was constructed by a kernel method. We had to simulate the $B$ samples under the null, thus we used CRS estimate of the frontier for generating them.

2. **Step 2:** For every sample $b$, $b=1, 2… B$, were estimated the 31 efficiency scores using first a CRS DEA model and then a VRS DEA model.

3. **Step 3:** Performing the calculations described for the original sample we get 1000 average values of the ratios between CRS and VRS scores, denoted by $T^*$ which will be compared with $T_{obs}$.

4. **Step 4:** p-value was approximated by:

$$p-value = \frac{\sum_{b=1}^{1000} 1(T^* \leq 0.591)}{1000} = 0.005$$

Finally we obtain for this test with $B=1000$ a $p$-value of 0.005<0.05, hence we reject the null hypothesis of constant returns to scale. When the production process is the innovation process, the frontier of the production set is characterized by variable returns to scale. Hence a $n$ per cent increase in the innovation input produce a bigger or a smaller than $n$ per cent increase in innovation output.

4.2 Efficiency scores estimation

The results presented below are returned from a command in the FEAR library (Frontier Efficiency Analysis with R) that implements the homogenous bootstrap
algorithm described by Simar and Wilson. The bootstrap estimates were produced using \( B=2000 \) bootstrap replications. Table 3 displays results of the homogenous bootstrap algorithm, giving the original efficiency estimates as well as the bias corrected estimates and the 95% confidence intervals for DEA estimators.

The efficiency scores are estimated using a variable returns to scale, output oriented DEA with one input and one output. These are greater than or equal to 1 given that the FEAR command returned Farrell output efficiency estimates. The decisions making units with efficiency score equal to 1 are efficient. The DMU’s with scores greater than 1 are inefficient. The higher the efficiency score the more inefficient the DMU is.

<table>
<thead>
<tr>
<th>Country</th>
<th>Scores</th>
<th>Bias corrected scores</th>
<th>Lower bound</th>
<th>Upper bound</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>BE</td>
<td>1,590</td>
<td>1,692</td>
<td>1,595</td>
<td>1,852</td>
<td>0.005</td>
</tr>
<tr>
<td>BG</td>
<td>1,754</td>
<td>2,067</td>
<td>1,801</td>
<td>2,411</td>
<td>0.024</td>
</tr>
<tr>
<td>CZ</td>
<td>1,000</td>
<td>1,104</td>
<td>1,024</td>
<td>1,232</td>
<td>0.003</td>
</tr>
<tr>
<td>DK</td>
<td>1,764</td>
<td>1,853</td>
<td>1,767</td>
<td>2,023</td>
<td>0.005</td>
</tr>
<tr>
<td>DE</td>
<td>1,033</td>
<td>1,093</td>
<td>1,036</td>
<td>1,195</td>
<td>0.002</td>
</tr>
<tr>
<td>EE</td>
<td>2,059</td>
<td>2,262</td>
<td>2,086</td>
<td>2,518</td>
<td>0.012</td>
</tr>
<tr>
<td>IE</td>
<td>1,691</td>
<td>1,814</td>
<td>1,699</td>
<td>1,996</td>
<td>0.006</td>
</tr>
<tr>
<td>EL</td>
<td>3,167</td>
<td>3,528</td>
<td>3,207</td>
<td>4,021</td>
<td>0.047</td>
</tr>
<tr>
<td>ES</td>
<td>1,748</td>
<td>1,884</td>
<td>1,758</td>
<td>2,076</td>
<td>0.007</td>
</tr>
<tr>
<td>FR</td>
<td>1,483</td>
<td>1,580</td>
<td>1,488</td>
<td>1,732</td>
<td>0.004</td>
</tr>
<tr>
<td>IT</td>
<td>1,423</td>
<td>1,559</td>
<td>1,438</td>
<td>1,731</td>
<td>0.006</td>
</tr>
<tr>
<td>CY</td>
<td>3,545</td>
<td>3,907</td>
<td>3,596</td>
<td>4,408</td>
<td>0.047</td>
</tr>
<tr>
<td>LV</td>
<td>3,097</td>
<td>3,500</td>
<td>3,158</td>
<td>3,992</td>
<td>0.049</td>
</tr>
<tr>
<td>LT</td>
<td>2,582</td>
<td>2,854</td>
<td>2,618</td>
<td>3,232</td>
<td>0.028</td>
</tr>
<tr>
<td>HU</td>
<td>1,067</td>
<td>1,178</td>
<td>1,081</td>
<td>1,333</td>
<td>0.005</td>
</tr>
<tr>
<td>MT</td>
<td>1,178</td>
<td>1,363</td>
<td>1,199</td>
<td>1,558</td>
<td>0.009</td>
</tr>
<tr>
<td>NL</td>
<td>2,376</td>
<td>2,506</td>
<td>2,381</td>
<td>2,735</td>
<td>0.009</td>
</tr>
<tr>
<td>AT</td>
<td>1,581</td>
<td>1,668</td>
<td>1,584</td>
<td>1,820</td>
<td>0.004</td>
</tr>
<tr>
<td>PL</td>
<td>1,511</td>
<td>1,751</td>
<td>1,536</td>
<td>1,995</td>
<td>0.014</td>
</tr>
<tr>
<td>PT</td>
<td>2,462</td>
<td>2,664</td>
<td>2,480</td>
<td>2,942</td>
<td>0.014</td>
</tr>
<tr>
<td>RO</td>
<td>1,000</td>
<td>1,398</td>
<td>1,039</td>
<td>1,779</td>
<td>0.044</td>
</tr>
<tr>
<td>SI</td>
<td>1,201</td>
<td>1,284</td>
<td>1,206</td>
<td>1,411</td>
<td>0.003</td>
</tr>
<tr>
<td>SK</td>
<td>1,000</td>
<td>1,161</td>
<td>1,022</td>
<td>1,317</td>
<td>0.006</td>
</tr>
<tr>
<td>FI</td>
<td>1,429</td>
<td>1,500</td>
<td>1,431</td>
<td>1,638</td>
<td>0.003</td>
</tr>
<tr>
<td>SE</td>
<td>1,541</td>
<td>1,618</td>
<td>1,544</td>
<td>1,766</td>
<td>0.003</td>
</tr>
<tr>
<td>UK</td>
<td>1,761</td>
<td>1,857</td>
<td>1,765</td>
<td>2,027</td>
<td>0.005</td>
</tr>
<tr>
<td>HR</td>
<td>1,811</td>
<td>2,029</td>
<td>1,839</td>
<td>2,315</td>
<td>0.016</td>
</tr>
<tr>
<td>TR</td>
<td>1,295</td>
<td>1,648</td>
<td>1,318</td>
<td>2,119</td>
<td>0.045</td>
</tr>
<tr>
<td>IS</td>
<td>4,769</td>
<td>5,010</td>
<td>4,778</td>
<td>5,470</td>
<td>0.033</td>
</tr>
<tr>
<td>NO</td>
<td>3,209</td>
<td>3,391</td>
<td>3,218</td>
<td>3,705</td>
<td>0.016</td>
</tr>
<tr>
<td>CH</td>
<td>1,300</td>
<td>1,364</td>
<td>1,302</td>
<td>1,488</td>
<td>0.002</td>
</tr>
</tbody>
</table>

*Table 3 Efficiency scores (FEAR results)*
Given that the variance and also the standard error estimates are small relative to the bias estimates we will trust the bias corrected efficiency estimates. This is the reason why our ranking will be made according to the corrected scores. The most efficient NIS is the one in Germany, even if its initial efficiency score was not 1. Czech Republic and Slovakia come in at second position. The case of Romania is more interesting because even if the original score was equal to 1 it comes in at the 8th position. Thence it is evident that if a country receives a point estimate equal to 1 this is not a strong reason to consider that the country is 100% efficient.

It is interesting to compare the hierarchy determined using the results from the bootstrap algorithm (Table 3) with the comparative analysis from the report European Innovation Scoreboard 2009. Actually we want to see if countries with innovation performance well above that of EU average and all other countries (where the innovation performance is reflected by the composite index known as Summary Innovation Index-SII), known as innovation leaders are also technically efficient.

According to the report European Innovation Scoreboard 2009, Germany is one of the innovation leaders and as mentioned before its NIS is also technically efficient. But we can not say the same thing about the other innovation leaders like Denmark, UK, Finland and Switzerland which are not efficient, given their efficiency scores are over 1.3. Of these 4 countries, Switzerland is the most efficient (ranked the 7th) in our ranking based on DEA results.

According to EIS 2009, Slovakia and Czech Republic are among the countries with innovation performance below the EU27. But their efficiency scores are close to 1, showing they are technically efficient when transforming innovation inputs into innovation outputs.

The results in Table 3 show that the most inefficient national innovation systems are those of Latvia, Greece, Cyprus, and Iceland. Cyprus and Iceland have technically inefficient innovation systems although they are considered innovation followers in EIS report. This means their innovation performance reflected by Summary Innovation Index is below that of the innovation leaders but close to or above that of the EU27. However, we find a concordance between innovation performances measured by SII and technical efficiency estimated using DEA models in the Latvia case which belongs to the caching up countries group.

Conclusions

We think that it is important for policy makers to see how their countries position themselves, in terms of achieved efficiency in relation to other countries. Thus we propose a ranking based on bias corrected estimates of the efficiency scores which will show which are the most efficient countries. Then the inefficient countries could study the strategies and the policies of the most efficient countries in order to improve their ability to transform innovation inputs into innovation outputs.

The efficiency scores obtained from a DEA model show that the countries considered innovation leaders, because their innovation performance reflected by Summary Innovation Index is well above that of EU average, are not also technically efficient when transforming innovation inputs into innovation outputs. We think that
these results should motivate the building of a database with comparable and standardized indicators for a larger number of countries.

References


European Innovation Scoreboard 2009; Comparative analysis of Innovation Performance, *Pro INNO Europe Paper 10, 2010*