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MEASURING AND RANKING R&D PERFORMANCE AT THE COUNTRY LEVEL

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ABSTRACT. In the context of generally growing interest in R&D (Research and Development) efficiency, the main objective of this work is evaluation and ranking of the R&D performance on a set of selected countries with the highest worldwide level of engagement in R&D activities. To that aim, R&D efficiency of the sample countries is assessed with Data Envelopment Analysis, then the overall performance score is obtained with the cross-efficiency method and the considered countries are listed in the order according to their R&D performance. The findings of this study point at Switzerland, the United Kingdom and the Netherlands as the three leading countries as far as R&D performance is concerned, while the countries that make important investment efforts in terms of their GDP, such as Japan or Israel, do not seem to obtain the desired results and need to implement targeted policy actions to encourage R&D outputs.

Introduction

Economic growth has been the central issue for economists and policy-makers for a long time, and many research efforts have been devoted to understanding the most important factors behind growth. Neoclassical considerations about the effect of technological progress on economic growth were followed in the last decades of the past century by new theories of endogenous growth emphasizing the role of Research and Development (R&D) activities as important drivers of economic growth (Barro & Sala-i-Martín, 1995).

Subsequent theoretical as well as empirical research on this topic has been undertaken and a general agreement has been reached on the links between innovations, R&D and economic growth (Horvath, 2011; Inekwe, 2015; Pessoa, 2010). Technological developments are claimed to help increase productivity within a context of limited resources (Grossman & Helpman, 1994) and in that sense, innovation becomes crucial for sustainable growth, social welfare and quality of life (Akcali & Sismanoglu, 2015). It is also known that R&D investments represent a major source in fostering knowledge creation and innovation, therefore, policies based on raising R&D expenditures are expected to have a positive effect on productivity and competitiveness of nations on the global scale. This idea has encouraged governments of many countries to significantly increase the level of R&D expenditures in an effort to enhance their capacity for innovation (Sokolov-Mladenović et al., 2016).

R&D and innovation have also become the key policy components in the EU's agenda for growth in the current decade. The Europe 2020 strategy established a target of investing on average 3% of GDP in R&D, as it is understood that greater capacity for R&D in combination with increased resource efficiency will strengthen the whole economy by enhancing employment, tertiary educational attainment and innovation, which ultimately contributes to energy efficiency improvements and sustainability (European Commission, 2010).

However, a great dispersion in R&D activity is observed across nations. According to the data provided by the Main Science and Technology Indicators (MSTI) of the OECD (Organisation for Economic Co-operation and Development), in 2015 the top investors in R&D were the United States, accounting for 25% of the total R&D investment worldwide, closely followed by China, a country that has been steadily increasing its volume of R&D spending during the last decade, and was responsible in 2015 for 21% of global R&D expenditures. Another indicator that gives a more precise idea of the real efforts that countries devote to innovation activities is known as R&D intensity and refers to the R&D spending as percentage of GDP. R&D intensity figures for 2015 show that Israel and Republic of Korea are indisputable leaders with more than 4% of their GDP being invested in R&D, closely followed by Japan, Switzerland and Sweden with an R&D spending near 3.3% of their GDP. To further illustrate the differences across countries, Figure 1 shows R&D expenditures per capita in relation to GDP per capita for the selected countries that exhibit notable R&D intensity.
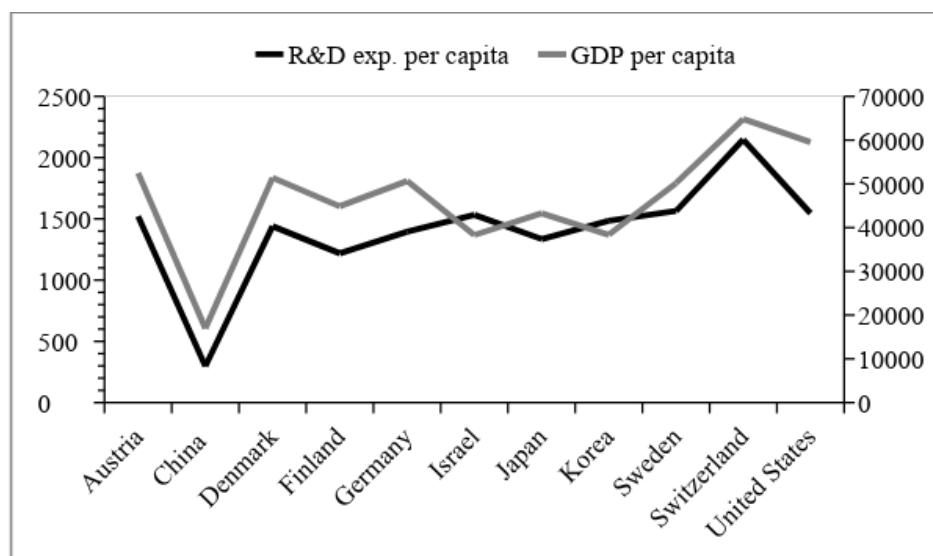

Figure 1. R&D expenditures per capita and GDP per capita for top R&D investors
Source: *OECD MSTI*

Regardless the amount of the investment effort made in R&D, its main objectives of stimulating technological progress and fostering economic growth might not be achieved if R&D resources are used inefficiently (Wang and Huang, 2007). Given the severe financial constraints that currently affect both public and private sectors, the evaluation of how efficiently R&D processes are performing becomes of key importance for the allocation of resources. For this reason, recent years have seen a growing number of studies that attempt to assess and compare R&D efficiency at different scales of analysis (Aristovnik, 2012; Cullman & Zloczysti, 2014; Han et al., 2017; Lee & Lee, 2015).

In the measurement of the efficiency of R&D activities, observation units (whether countries, regions, research institutes or firms) are regarded as entities operating a production process where a number of inputs, mainly capital and manpower, are transformed to produce a number of R&D outputs (Wang, 2007), and in this context Data Envelopment Analysis (DEA) is increasingly being used in the empirical literature (Lee & Shin, 2014).

Efficiency evaluation in DEA relies on a self-appraisal scheme, where units are allowed to exploit their strengths as to receive the most favorable assessment (Cooper et al., 2011). As a consequence, poor discrimination is often observed in empirical applications, meaning that several units are evaluated as efficient performers but being otherwise indistinguishable. This is particularly inconvenient when an unambiguous ordering of the observed units according to their performance is needed, a requirement that is becoming more and more common with the pervasiveness of ranking lists in our society..

Admittedly, rankings can sometimes be controversial, but they have important effects on decision making and policy making. Particularly when studying the performance of R&D programs or research institutes, a ranked list is needed for making funding-related decisions. At a country level, competitiveness demands comparative information for benchmarking performance against partners or competitors. Besides, given that industries support worldwide R&D to a great extent, a ranked list of countries according to their R&D performance would be valuable for managers and stakeholders in defining their strategic goals. However, while existent studies concerning the efficiency of R&D investments succeed in identifying whether the countries use their R&D resources efficiently or not, they are unable to produce country ranking outcomes. This work aims at filling this gap by approaching the evaluation of R&D efficiency at the country level with the additional objective of obtaining a ranked list of the countries considered. The sample of our study will be comprised of the countries with a significant involvement in R&D activities, showing R&D intensity figures above 1%. Using DEA the technically efficient performers will be identified and then, using cross-efficiency evaluation, an overall R&D performance score will be obtained that provides a country ranking.

The remainder of the paper is organized as follows. Next section presents a review of the existing literature on the evaluation of R&D performance with DEA that evidences a lack of ranking studies. Section 2 describes the methodology used in this study as well as the empirical data used. The results of our study are presented in Section 3 and some concluding remarks are provided in the final section.

1. Literature review

Throughout the past decades, many efforts have been devoted to study the impacts of R&D and innovation on raising productivity and competitiveness of nations, regions, industries and firms, and the role of R&D as a driver of economic growth is now sufficiently well established (Blanco et al. 2016; Goto and Suzuki, 1989; Guloglu and Tekin, 2012; Hovarth, 2011; Kaur and Singh, 2016) with little attention being generally paid to how efficiently R&D resources were being used. But whatever the scope of the analysis, the ability to operate efficiently and the identification of possible inefficiencies become essential for an optimal allocation of resources as well as for the formulation of strategies for improving R&D performance (Wang, 2007).

Efficiency analysis studies evaluate the performance of a certain number of production units in terms of their ability to operate close to or on the boundary of their production set. Production frontier approaches, which are based on comparing the actual performance of individual units against the best-practice frontier, are widely used for this purpose, and both parametric and nonparametric techniques have been adopted in the R&D-related empirical

literature. Parametric methods, such as Stochastic Frontier Analysis (SFA), apply econometric techniques that require the specification of a functional form for the production frontier, and inefficiency is modeled as a stochastic term. Nonparametric methods like Data Envelopment Analysis (DEA) are frequently the preferred option when no functional form is known for the production function. A major advantage of DEA is that it can successfully handle multiple inputs and multiple outputs, and it also can deal with situations where prior information on preferences about the variables involved does not exist, which fits particularly well the problem of R&D performance evaluation where no universal agreement on the importance of inputs and outputs exist (Lee, Park and Choi, 2009). Moreover, DEA has been claimed to have attractive features for the analysis of public sector activities (Zabala-Iturriagagoitia et al., 2007). Its usefulness in assessing efficiency in Science and Technology has also been highlighted (Bonaccorsi and Daraio, 2004) and in recent years it has been more and more adopted for measuring R&D performance (Lee and Shin, 2014). Therefore, although some interesting cross-country studies based on a parametric R&D efficiency analysis have been performed (see for example Cullman and Zloczysti, 2014; Fu and Yang, 2009; Wang, 2007) , the present research will be focused on DEA.

The original DEA model was developed by Charnes et al. (1978) under the assumption that production exhibits constant returns to scale (CRS) and it later was extended by Banker et al. (1984) for its application in a variable returns to scale (VRS) framework. DEA models are also distinguished by their objective, either minimize inputs given a fixed level of outputs (input-oriented) or maximize outputs at the current level of inputs (output-oriented).

One of the pioneering applications of DEA in R&D performance analysis can be found in Rousseau and Rousseau (1998), which elaborates on an earlier contribution by the same authors. In that work the efficiency of R&D investments in 18 developed countries is assessed using 1993 data with GDP, active population and R&D expenditures as inputs and publications and patents as outputs. Their results identified eight efficient countries under the CRS input-oriented framework, and when additional restrictions on the contribution of inputs and outputs to the efficiency index were imposed, Switzerland and Netherlands were found to be the most efficient countries. The authors hinted that using data from the European Patent Office could negatively affect the results for non-European countries like USA, Canada or Japan. They also suggested that a time lag between input data and output data should be taken into account, given that outputs result from inputs occurred some years earlier.

Using an output-oriented formulation, twenty seven nations, most of them OECD member countries, were analyzed in Lee and Park (2005) under the CRS assumption, although they suggested that there is no enough evidence on that case and the VRS framework should be taken into account. They found that six countries, namely Austria, Finland, Germany, Hungary, New Zealand and the United Kingdom, were performing efficiently, whereas China, Republic of Korea and Taiwan were lagging in R&D efficiency and required the implementation of policies to enhance R&D performance to a satisfactory level.

The analysis performed in Wang and Huang (2007) was based on an input-oriented VRS DEA formulation. The authors assessed R&D efficiency of 30 developed countries using R&D expenditures, researchers and technicians as inputs and patents and publications as output variables and found that about one third of the countries considered achieved maximum efficiency. They also investigated the effect of environmental factors on R&D efficiency and concluded that an increase in the national English proficiency indicator and the rate of higher education enrollment can help improve the R&D performance of the countries.

With a similar model in terms of structure and variables employed, Sharma and Thomas (2008) also studied the efficiency of the R&D process across 22 nations that included developed as well as developing economies. According to their results, six countries were

classified as efficient performers, including Japan, Republic of Korea, China, India, Slovenia and Hungary, while some critical inefficiencies in the use of R&D resources were highlighted in some developed countries.

Aristovnik (2012) evaluated the R&D performance of a group of 32 selected European and OECD countries. Efficiency scores computed with an output-oriented DEA formulation with two inputs and three outputs under the VRS assumption showed that six European countries were performing efficiently, including Switzerland, Netherlands, Iceland, Hungary, Cyprus and Turkey, while a relatively high inefficiency level was observed among non-efficient countries in their sample. In particular they concluded that countries that had recently been incorporated as EU member states and some of the less-developed OECD economies showed generally low R&D performance, and therefore the improvement of the sector's efficiency should be a key priority for those countries.

Further contributions of DEA to the evaluation of R&D efficiency differ in the scope and focus of the analysis implemented. Kocher et al. (2006) performed a cross-country analysis focused on the productivity of economic research, while selected European regions became the target of the analysis in Roman (2010) and Zabala-Iturriagagoitia et al. (2007). Han et al. (2017) evaluated R&D efficiency across China's high-tech industrial sectors, and universities or other research institutes were evaluated in Abramo et al. (2011), Lee and Lee (2015), Meng et al. (2008), Liu and Lu (2010), to name a few. Both CRS and VRS DEA formulations have been used in applications related to R&D performance, either with an input or an output orientation, but the output-oriented VRS model has recently become more and more common (Lee and Lee, 2015).

As can be seen from the above review, a typical feature of all DEA applications is that very often multiple production units are classified as efficient performers, achieving the most favorable efficiency score but not allowing further discrimination or ranking among them. This lack of discrimination in DEA is well documented, particularly when the number of inputs and outputs is too high in relation to the number of observed units, and some recommendations have been made to limit the number of variables included in the model and avoid too many efficient units. Several strategies have been proposed to increase the discriminative power of DEA (see for example Adler, Friedman and Sinuany-Stern, 2002). In the context of R&D performance analysis, some attempts have been made to overcome the discrimination issues of DEA, but either the procedures involved are too intricate for a practical use (Liu and Lu, 2010) or they fail to achieve complete discrimination (Meng et al., 2008).

In this work the lack of discrimination in DEA will be handled by means of a cross-efficiency analysis, which represents an interesting option for deriving a realistic ranking of the observed units according to their performance. Noteworthy, this kind of analysis has not been explored before in the R&D literature, to this author's knowledge.

2. Methodology and Data

2.1. DEA and Cross-Efficiency

DEA is a non-parametric technique for measuring the relative efficiency of a homogeneous set of decision making units (DMUs) that operate in a production system where multiple inputs are consumed to produce multiple outputs. After four decades of development, DEA has proved to be a valuable tool for performance evaluation in many different contexts, including R&D performance. Practical applications of DEA are countless in banking, healthcare, agriculture, energy, education or finance, among others (Lo Storto & Goncharuk, 2017; Liu, et al., 2013).

Various types of DEA models can be formulated according to the assumptions about returns to scale (CRS or VRS) and orientation (input or output oriented). Input-oriented formulations are focused on proportional reduction of inputs without changing the output levels, while output-oriented efficiency measures study how much outputs can be proportionally increased with the current level of inputs. In practice, which of these two measures is more appropriate depends on whether input reduction is more important than output augmentation (Daraio & Simar, 2007). Since the main objective of R&D can be said to be increasing outputs, rather than decreasing inputs, we will choose an output orientation. As for the R&D returns to scale, there is no evidence of CRS in the production of knowledge, and it has been found that R&D activity can exhibit increasing or decreasing returns to scale as well as constant returns to scale (Lee, Park & Choi, 2009). Therefore, the VRS DEA formulation will be used in this study.

DEA builds an efficient frontier using a self-evaluation scheme that allows DMUs to choose their own weights on inputs and outputs that yield the most favorable efficiency score. Specifically, assuming that there are n production units or DMUs, each of them being evaluated in terms of r inputs and s outputs, where x_{ij} and y_{kj} are nonnegative values denoting respectively the amount of input i consumed and the amount of output k produced by the j-th DMU ($i = 1,...r$, $k = 1,...s$, $j = 1,...n$), the output-oriented VRS model in multiplier form can be expressed as follows (Lim & Zhu, 2015)

$$
\begin{aligned}
min \quad & \sum_{i=1}^{r} v_{iq}x_{iq} + w_q \\
s.t. \quad & \sum_{k=1}^{s} u_{kq}y_{kq} = 1 \\
& \sum_{i=1}^{r} v_{iq}x_{ij} - \sum_{k=1}^{s} u_{kq}y_{kj} + w_q \geq 0 \quad j = 1,..n \\
& u_{kq}, v_{iq} \geq 0, \qquad \forall k, i
\end{aligned}
\tag{1}
$$

When the above model is solved, an output-oriented (self-evaluated) efficiency score of DMU q is obtained as the ratio

$$
E_{qq} = \frac{\sum_{i=1}^{r} v_{iq}^* x_{iq} + w_q^*}{\sum_{k=1}^{s} u_{kq}^* y_{kq}}
$$

where $u_{kq}^*, v_{iq}^*, w_q^*$ denote the optimal weight values chosen by DMU q in (1). By solving the above model n times, this process easily distinguishes between efficient units, which obtain a unitary efficiency value, and inefficient units, which lie away from the efficient frontier. However, this evaluation scheme may often lead to unreasonable weighting profiles that tend to overestimate the efficiency scores (Cooper et al., 2011), thus producing many efficient units that cannot be further discriminated by this means. To overcome this drawback, a cross-efficiency evaluation can be undertaken.

Cross-efficiency evaluation, originally proposed by Sexton et al. (1986) and further developed by Doyle and Green (1994), introduced the idea of peer-appraisal in combination with the traditional DEA self-appraisal mode, in such a way that DMUs are repeatedly assessed using the range of optimal weights selected by all the peer units instead of their own set of weights only, and therefore a more thorough evaluation of the performance of the units is attained. In this way, when the most favorable weights for DMU q are used to evaluate the other DMUs in a peer-evaluation mode, we obtain output-oriented cross-efficiency scores as:

$$
E_{jq} = \frac{\sum_{i=1}^{r} v_{iq}^* x_{ij} + w_q^*}{\sum_{k=1}^{s} u_{kq}^* y_{kj}}
$$

which measures the performance of DMU j when assessed under the perspective of DMU q. Note that the second constraint in (1) guarantees that $E_{jq} \geq 1$ for all j, q. Then, by averaging the self-rated and the peer-rated efficiency scores that each DMU receives, the Average Cross-Efficiency (ACE) score is obtained that represents an overall performance measure of the jth DMU and takes into account the preferences over the input and output variables expressed by all DMUs:

$$ACE_j = \frac{1}{n} \sum_{q=1}^{n} E_{jq}$$

This evaluation framework has proved to exhibit strong discrimination properties and therefore a ranking of the DMUs according to their performance can be obtained for decision purposes, with the smallest value representing the best performance. Besides, an appealing feature of the cross-evaluation approach relates to the democratic connotation it enjoys (Doyle & Green, 1994, p. 570), as all the DMUs play an evaluating role and all the assessments they make are considered when computing the average cross-efficiency score, which can thus be considered as a consensual performance index. These advantages have made cross-efficiency evaluation approaches being profusely used in a vast number of applications (see Ruiz & Sirvent, 2016 and references therein).

A major limitation in the cross-evaluation approach is the possible existence of multiple optimal solutions to problem (1), which can lead to non-uniqueness of cross-efficiency scores E_{jq} depending on the particular optimal weight pattern used by DMU q for the assessments. The use of a secondary goal that uniquely determines an optimal bundle of weights for each DMU was proposed to overcome this drawback (Doyle and Green 1994; Sexton et al., 1984). These secondary goals could be established either with a benevolent or aggressive motivation, depending on whether they are intended to (benevolently) improve or (aggressively) deteriorate the other DMUs' scores while maintaining self-efficiency. Each of these approaches add slightly different connotations to the cross-evaluation process, although benevolent formulations can be considered more consistent with the classical DEA principle based on being as favorable as possible to each DMU (Lim, 2012). Therefore, in the present work we will compute benevolent average cross-efficiency scores.

2.2. Empirical data

This study is focused on measuring R&D and innovation performance at the country level. In order to have a comparable group of countries for the analysis, only the countries with a moderate or high involvement in R&D activities have been included in our sample. Given the last available Gross Domestic Expenditure on R&D (GERD) figures corresponding to 2015, all countries exhibiting R&D expenditure above 1% of their Gross Domestic Product (GDP) in 2015 have been considered. A total of 36 countries met this requirement, although 3 of them (Lithuania, Malaysia and Taiwan) had to be disregarded due to incomplete or unavailable data. As a consequence, our final sample consists of 33 countries, 30 of them are members of the OECD and 20 of them are European Union (EU) member states.

Table 1 shows the complete list of the countries considered and the evolution of their R&D intensity (defined as the ratio of GERD to GDP) over the 2004-2015 time frame covered in this study. Except for a few countries, most economies show a growing commitment to R&D investment in the time frame considered. As seen, Israel and Republic of Korea are the countries devoting the greatest efforts to R&D activities, followed by Japan and some European countries such as Switzerland, Sweden, Austria and Denmark. Other countries, despite revealing lower levels of engagement in R&D, have been experiencing

important increments in their R&D intensity figures in the last decade, such as China, Slovak Republic, Poland or Estonia.

The process of innovation production is complex and multiple factors are involved. In order to appropriately approach innovation performance measurement, our selection of input and output variables for this study has been based on the previous literature, which shows a general agreement in relation to the relevant factors. The inputs to innovation activities considered in previous studies are mainly physical resources and human capital, which have been proxied here by GERD, expressed in purchasing power parity (PPP) million $, and Total Researchers, expressed in full-time equivalent units, respectively. The corresponding data were collected from the OCDE Main Scientific Technology Indicators (MSTI) database.

Table 1. R&D intensity for the sample considered

	R&D intensity	
Country	2004	2015
Australia	1,7	1,9
Austria	2,2	3,0
Belgium	1,8	2,5
Canada	2,0	1,6
China	1,2	2,1
Czech Republic	1,1	1,9
Denmark	2,4	3,0
Estonia	0,9	1,5
Finland	3,3	2,9
France	2,1	2,3
Germany	2,4	2,9
Hungary	0,9	1,4
Iceland	2,7	2,2
Ireland	1,2	1,2
Israel	3,9	4,3
Italy	1,1	1,3
Japan	3,0	3,3
Republic of Korea	2,5	4,2
Luxembourg	1,6	1,3
Netherlands	1,8	2,0
New Zealand	1,1	1,3
Norway	1,5	1,9
Poland	0,6	1,0
Portugal	0,7	1,2
Russia	1,1	1,1
Singapore	2,1	2,2
Slovak Republic	0,5	1,2
Slovenia	1,4	2,2
Spain	1,0	1,2
Sweden	3,4	3,3
Switzerland	2,7	3,4
United Kingdom	1,5	1,7
United States	2,5	2,7

Source: *OECD MSTI*

As far as the outputs is concerned, patent number is the most widely adopted measure of innovative output, and academic publications are also frequently used to evaluate

performance of researchers and as an indicator of scientific knowledge (Lee et al., 2009). Moreover, as high-tech products are defined as products involving a high intensity of R&D, the volume of high-tech exports can be also considered as an output of the R&D process that captures the economic benefits of the results of innovation (Matei & Aldea, 2012). Therefore, the outputs used in this study comprise the number of patents granted to residents, the number of scientific publications and level of high-tech exports (including pharmaceutical, aerospace, computer, electronic and optical industries), expressed in PPP million $, which have been collected from the World Intellectual Property Organization (WIPO), SCImago and MSTI, respectively.

Lastly, it is known that a certain length of time is required for the inputs of the R&D process to be transformed into outputs, and the importance of taking this factor into account when measuring R&D efficiency has been previously acknowledged (Sharma and Thomas, 2008). Preliminary tests have shown that a 3-year lag is appropriate in the study of relative efficiency of R&D processes at the country level based on aggregate data (Wang and Huang, 2007). According to this, the input variables in our study will be lagged by 3 years as compared to the outputs. Our analysis will be then carried out for the periods 2004-2007 and 2012-2015 to gain a perspective of where the countries stand on the overall R&D picture and how the situation has changed during the last decade.

3. Results

Using the methodology described above, the R&D efficiency of our selected sample of 33 countries has been evaluated in both time periods considered. Columns 2 and 3 in Table 2 report the efficiency scores obtained with an output-oriented VRS DEA model based on the input and output variables selected in the preceding section. Figures in parentheses indicate the rank order of each country according to the computed efficiency score, where all efficient countries tie for first ranking position. As seen, 16 out of the 33 countries studied are found to perform efficiently in 2015 and up to 18 countries are considered efficient performers in 2007, a result that confirms the low discrimination power of this method.

Among the countries that are evaluated as efficient throughout the whole time frame we find ten European countries (Germany, Iceland, Ireland, Italy, Luxembourg, Netherlands, Poland, Slovakia, Switzerland and United Kingdom) and four Asian countries (China, Japan, Republic of Korea, and Singapore) with New Zealand and United States ending the list. Within that group, the United States, China, Japan, Germany and Republic of Korea are the top 5 world investors in R&D, which together are responsible for 65% of the global R&D expenditure.

Australia, Czech Republic and Portugal can be said to perform near efficiency in the 2012-2015 period, while the remaining 14 countries still have some room for improvement and a higher level of outputs can still be obtained with the quantities of inputs being currently employed, suggesting the need to implement specific policies for encouraging R&D outcomes. Special attention deserves the score obtained for Israel, which shows the worst efficiency score in the table despite being the country with the world's largest share of GDP devoted to R&D, implying that there is much more to R&D performance than spending levels. In this case, DEA results suggest that Israel should be able to increase its outputs by 83% with the actual input levels.

With nearly half the countries in the sample being classified as efficient, it is difficult to further compare their performance. In order to obtain a complete ranked list of countries, we compute the Average Cross-Efficiency (*ACE*) scores as described in the preceding section, which are reported in columns 4 and 5 of Table 2 with the corresponding ranking position in parenthesis. According to these results, United Kingdom, Switzerland and Netherlands are the

3-top performers in the time period 2012-2015, with similar ranking positions being earned in the earlier period 2004-2007. On the contrary, Luxembourg, Estonia and Iceland are the three worst countries as regards R&D performance in both time periods considered, a result that should call the attention of policy-makers.

Table 2. VRS DEA scores and *ACE* scores, with rankings in parenthesis

Country	VRS DEA scores		*ACE* scores	
	2004-2007	**2012-2015**	**2004-2007**	**2012-2015**
Australia	1,10 (21)	1,04 (18)	1,44 (7)	1,34 (5)
Austria	1,60 (29)	1,72 (31)	2,16 (20)	2,04 (22)
Belgium	1,19 (23)	1,23 (22)	1,57 (10)	1,52 (11)
Canada	1,29 (26)	1,24 (23)	1,51 (8)	1,36 (7)
China	1,00 (1)	1,00 (1)	1,74 (14)	1,81 (17)
Czech Republic	1,02 (19)	1,09 (19)	1,81 (15)	1,66 (14)
Denmark	1,48 (28)	1,33 (29)	2,21 (21)	1,72 (16)
Estonia	1,00 (1)	1,26 (24)	10,9 (31)	6,96 (32)
Finland	1,76 (31)	1,45 (30)	2,54 (25)	2,11 (24)
France	1,27 (25)	1,22 (21)	1,72 (13)	1,64 (12)
Germany	1,00 (1)	1,00 (1)	1,61 (11)	1,67 (15)
Hungary	1,02 (20)	1,32 (28)	2,08 (19)	2,45 (26)
Iceland	1,00 (1)	1,00 (1)	20,7 (32)	13,31 (33)
Ireland	1,00 (1)	1,00 (1)	1,92 (17)	1,65 (13)
Italy	1,00 (1)	1,00 (1)	1,15 (3)	1,13 (4)
Israel	1,85 (33)	1,83 (33)	2,38 (22)	2,38 (25)
Japan	1,00 (1)	1,00 (1)	2,63 (27)	2,51 (27)
Republic of Korea	1,00 (1)	1,00 (1)	1,52 (9)	1,93 (18)
Luxembourg	1,00 (1)	1,00 (1)	21,75 (33)	5,58 (31)
Netherlands	1,00 (1)	1,00 (1)	1,14 (1)	1,11 (3)
New Zealand	1,00 (1)	1,00 (1)	2,38 (23)	2,09 (23)
Norway	1,41 (27)	1,28 (25)	2,46 (24)	1,97 (20)
Poland	1,00 (1)	1,00 (1)	1,70 (12)	1,39 (8)
Portugal	1,22 (24)	1,03 (17)	2,56 (26)	2,02 (21)
Russia	1,77 (32)	1,79 (32)	5,24 (30)	3,25 (29)
Singapore	1,00 (1)	1,00 (1)	1,30 (5)	1,43 (9)
Slovak Republic	1,00 (1)	1,00 (1)	3,77 (28)	2,79 (28)
Slovenia	1,00 (1)	1,29 (26)	4,43 (29)	3,74 (30)
Spain	1,11 (22)	1,11 (20)	1,44 (6)	1,34 (6)
Sweden	1,60 (30)	1,30 (27)	1,91 (16)	1,49 (10)
Switzerland	1,00 (1)	1,00 (1)	1,16 (4)	1,06 (2)
United Kingdom	1,00 (1)	1,00 (1)	1,14 (2)	1,05 (1)
United States	1,00 (1)	1,00 (1)	2,04 (18)	1,96 (19)

Source: *own computation*

Also, the fact that Iceland and Luxembourg rank at the very last positions of the ordered list despite being classified as efficient with the VRS DEA model draws particular

attention. Other DEA-efficient countries such as Japan, Slovak Republic or New Zealand also appear in the last quartile of the ranked list obtained in terms of *ACE* score, while the inverse situation is observed for Israel, a country that improved its position from 33rd place when using DEA score up to the 25th spot in the ordering derived from *ACE* score. These are not uncommon phenomena when shifting from a self-assessment framework, where DMUs may appear efficient in ways that are difficult to justify (Cooper et al., 2011), to a peer-assessment framework where multiple evaluations are averaged into an agreed summary performance score.

Certainly, it is well-established that since DEA scores are based on an endogenous and quite flexible weighting system, some DMUs can achieve efficiency by selecting highly specialized input and output weights that enhance their strengths and ignore their weaknesses, and the existence of many efficient DMUs is not necessarily a result of uniformly outstanding performance but of some units using an unusual mix of inputs and outputs (Wang & Huang, 2007; Ruiz & Sirvent, 2016). Cross-efficiency evaluation suitably overcomes this issue by relying on a peer-evaluation scheme, and since all the DMUs are assessed with a range of weight profiles, units that achieved efficiency with highly specialized set of weights will generally obtain poor rates from their peers. In that sense, cross-efficiency scores can be said to approximate actual performance of countries more realistically (Martić & Savić, 2001)

A comparative analysis of the ranking positions attained by the countries in the time periods considered can provide useful insights for benchmarking developments against best-performer economies and defining future courses of action. In this sense, it can be seen that Sweden underwent the most notable improvement in the 2004-2015 time frame, moving up six positions in the ranking list to the 10th place and outperforming some world R&D leaders such as Germany, which lost two ranking positions in this period, or Republic of Korea, which shows the most notable backward shift losing 7 positions from the 9th down to 18th place. This suggests that some countries are more successful than others in the strategic management of their R&D resources. Other EU countries also improved their position in the list, such as Denmark and Portugal, which moved up 5 ranking places, or Poland and Ireland, who climbed up 4 spots. Although except Poland, they still rank out of the top 10 positions, their advancement shows their efforts in raising the efficiency of their R&D processes. The same tendency is not observed, however, in all EU countries, and we can find that Hungary and Germany have dropped seven and four places, respectively, revealing the need to revise their R&D policies.

Other economies have not experienced significant shifts in their ranking positions along the studied period. Besides the top-3 performers, countries such as Australia, Canada, Italy, Singapore and Spain have been able to remain roughly stable in the top ten, suggesting that a certain degree of stability has been reached in their R&D processes. On the other hand, Japan, Slovak Republic, Slovenia, Russia, Estonia, Iceland and Luxembourg systematically take the last seven ranking places and therefore policy initiatives for an efficient management of R&D processes are key for these countries. In the middle of the table, the picture has remained practically unaltered during the time span studied for Czech Republic, Finland, France, New Zealand and United States.

Another remarkable observation is that the most important contributors to global R&D expenditure are not necessarily ranked as world-top performers, with some lower R&D-intensive economies, such as Poland, Spain or Italy ranking higher than some of the largest world's investors such as the United States, China or Republic of Korea. This might be explained by the increased degree of coordination and bureaucratic control that larger-scale R&D processes require, making management activities monopolize a great deal of resources (Zabala-Iturriagagoitia et al., 2017).

Conclusion

Given the importance of R&D activities as a driver for growth and competitiveness, and with acute financial constraints affecting both the public and private sectors, there is an increasing interest in measuring how efficiently R&D resources are being used. Following the path undertaken in previous studies, this work evaluates and compares the R&D performance of 33 countries over the period 2004-2015.

Using an output-oriented Data Envelopment Analysis model, we find that 16 out of the 33 countries considered were operating in the production frontier. Since DEA does not allow further discrimination among the efficient units, a cross-efficiency evaluation approach is carried out to obtain an overall score that enables comparison and ranking of the countries with regard to their R&D performance. Cross-efficiency scores can be said to represent a quite realistic performance measure due to its peer-assessment foundation, as opposed to the self-assessment scheme used to define DEA scores that produces biased, overestimated values.

As to this author's knowledge, the application of a cross-efficiency approach for the evaluation of country R&D performance is unknown in the literature, with prior studies focused on the classification of countries (or firms) into efficient and non-efficient performers. However, a ranked list of countries provides useful managerial insights for the different agents involved in R&D processes. On one side, governments constantly demand information about how their own country performs in different areas, including R&D, and how their performance compares to that of their partners or competitors. Rankings are thus a useful tool in this setting to monitor performance over time and to benchmark developments against outstanding economies. On the other side, funding organizations also make use of this kind of ordered lists to estimate the risk of their investments and make informed decisions. Therefore, the study proposed here deals with a relevant issue for R&D management.

In summary, the results obtained with the cross-efficiency approach indicate that Switzerland, United Kingdom and Netherlands are the three leading countries in the considered period as far as R&D performance is concerned, and therefore they are not expected to be able to significantly expand their R&D outputs with their current level of inputs. Some EU countries such as Sweden, Denmark and Poland have experienced important improvements in their performance relative to the other countries, suggesting that they are successfully implementing strategies for raising their R&D efficiency. On the contrary, a notable shift to the lower-half positions of the list is experienced by Republic of Korea, in spite of being the country with the second highest R&D intensity in 2015. This indicates that the increasing efforts of Republic of Korea in R&D are not having the expected results and there is still room for improving the effectiveness of R&D policies in that country.

Another remarkable observation is that countries that lead the worldwide contribution to GERD like United States, China or Republic of Korea do not always earn as high a ranking position as expected with the *ACE* performance score, a fact that could be explained by the increasing resources that must be devoted to managing such large-scale R&D activities.

Therefore, the key implication of this analysis is that strategic management of R&D resources is critical for achieving the desired results. By monitoring country performance over time, policy makers should identify strengths and weaknesses in their R&D processes, formulate specific strategies for fostering innovation and implement targeted policies when required.

A limitation of this study relates to data availability. On the one hand, an important R&D investor such as Taiwan has been excluded from our analysis due to a lack of information regarded the variables considered. On the other hand, although the quantitative side of R&D outputs has been covered, qualitative issues have not been taken into account,

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despite the fact that the quality of patents and publications are acknowledged as essential for technological progress and knowledge creation. Since it is known that the inputs and outputs included in a DEA model may have significant effects on the results, this aspect will have to be considered in future research.

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