Grading Countries/Territories Using DEA Frontiers

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Abstract

Several approaches exist related to categorizing academic journals/institutions/countries into different levels. Most existing grading methods use either a weighted sum of quantitative indicators (including the case of one properly defined quantitative indicator) or quantified peer review results. An important issue of concern for science and technology management is the efficiency of resource utilization. In this paper we deal with this issue and use multi-level frontiers of data envelopment analysis (DEA) models to grade countries/territories. Research funding and numbers of researchers as used as inputs, while papers and citations are output variables. The research results show that using DEA frontiers we can grade countries/territories on six levels. These levels reflect the corresponding countries' level of efficiency in S&T resource utilization. Furthermore, we use papers and citations as single outputs (with research funding and researchers as inputs) to show changes in country/territory level.

Conference Topic

Science Policy and Research Assessment

Introduction

The efficiency of science and technology (S&T) resource utilization is one of the important issues for S&T management (Yang et al., 2013a; Yang et al., 2014a). Johnes and Johnes (1992) evaluated the efficiency of S&T organizations using data envelopment analysis (DEA) as a performance analysis tool. Rousseau and Rousseau (1997, 1998) assessed the efficiency of countries using gross domestic product, active population and research and development (R&D) expenditure as inputs, and publications and patents as outputs. They showed that DEA can be used in scientometrics as a tool to measure the efficiency of decision making units (DMUs, e.g., countries) by gauging closeness to the efficiency frontier. Similar techniques have been used by other researchers (Kao & Lin, 1999; Roy & Nagpaul, 2001; Shim & Kantor, 1998). Yang and Chang (2009) used DEA under constant and variable returns to scale (RTS) to measure firms' efficiency. Worthington (2001) conducted an empirical survey of frontier efficiency measurement techniques in education. Other researchers have analyzed the efficiency or productivity in the education sector, (e.g., Abbott & Doucouliagos, 2003, Avkiran, 2001, Carrington et al., 2005, Worthington & Lee, 2008, Flegg et al., 2004, Johnes & Johnes, 1995, Johnes, 2006a,b, Kempkes & Pohl, 2010, Wolszczak-Derlacz & Parteka, 2011, and Aristovnik, 2012). When studying the standard university model, Brandt and Schubert (2013) observed that universities are large agglomerations of many (often loosely affiliated) small research groups. They explained this observation by typical features of the scientific production process. In particular, they argued that there are decreasing RTS on the level of the individual research groups. RTS is a concept with strong relation to scale efficiency. Somewhat similar observations (decreasing RTS) were published earlier by Bonaccorsi and Daraio (2005). Schubert (2014) used non-parametric techniques of multidimensional efficiency measurement, such as DEA, to analyse the RTS in scientific production based on survey data for German research groups from three scientific fields. Based on DEA models, Yang et al. (2013a, 2014a) analyzed the directional RTS of a couple of biological institutes in the Chinese Academy of Sciences (CAS).

Some fairly recent studies have examined the efficiency of countries or regions in utilizing R&D expenditures or other resources. Lee and Park (2005) evaluated R&D efficiency across nations using patents, technology balance of receipts and journal articles as outputs. Wang and Huang (2007) analyzed R&D efficiency of nations by considering patents and papers as outputs. Lee et al. (2009) used DEA to measure and compare the performance of national R&D programs in South Korea. Sharma and Thomas (2008) investigated the R&D efficiency of developing countries in relation to developed countries, taking into account time lags. Other, and similar, studies include Chen et al. (2011), Sueyoshi and Goto (2013), and Zhong et al. (2011).

The literature referred to hitherto focuses on the quantitative measurement of efficiency of resource utilization. In this context, DEA is one of the most popular mathematical tools for estimating the relative efficiency of DMUs. However, Banker (1993) pointed out that DEA efficiency scores usually overestimate efficiency and are biased. Smith (1997) argued that the extent of the overestimation is highly dependent on sample size and the complexity of the production process (as indicated by the numbers of inputs and outputs). However, in many cases we only need to know the general level (grade) of DMUs in terms of efficiency instead of their exact scores or complete ranking.

Several efforts have been made regarding categorization of academic journals, institutions and countries into different levels of standing or quality. Since 2007, the Association of Business School (ABS) has issued the Academic Journal Quality Guide, which classifies journals in business and management into four categories (grade 1 to 4) recognizing the quality of those journals based on a survey of hundreds of experts in the field (Harvey et al., 2007a,b; 2008). From 2010, a new category, termed 4*, was added to the four existing categories to recognize the quality of the top journals (Harvey et al., 2010). Bandyopadhyay (2013) categorized business and management journals into four categories (Excellent, Very Good, Standard, Satisfactory) based on multiple inputs, including Thomson Reuters' Social Science Citation lists of ranked journals and WoS impact factor analyses. In 2005, CAS evaluated its dependent institutes and classified them into three grades (Excellent, Good, and Satisfactory) (CAS, 2006). Glänzel (2011) used characteristic scores and scales as parameter-free tools to identify top journals. Yang et al. (2013b) analyzed the overall development and the balance of the disciplinary structure of China's science based on papers covered by Science Citation Index and with the use of bibliometric methods. These authors further categorized selected countries to reflect their developmental status.

The grading methods in the research reported above use either a weighted sum of quantitative indicators (including the case of one properly defined quantitative indicator) or quantified peer review results. In general, the weighted sum approach normally needs indicator weights and corresponding threshold values as a priori information, while the peer review process usually costs a lot of time and expenditures (Smith, 1996). In the light of these downsides, this paper presents an alternative approach, involving multiple DEA frontiers, to divide various countries/territories into different levels with respect to the efficiency of their S&T resource utilization.

The rest of the paper is organized as follows. The next section introduces the input and output indicators, and the corresponding dataset used in the analysis. The used methods are described in the third section, in which we treat multi-level efficient frontiers and show how to divide the countries/territories into grades using these frontiers. In the fourth section, the results of the study are given, whereas conclusions appear in the final section.

Indicators and data

In this work, research funding and researchers are used as input indicators. Research funding here means Gross Domestic Expenditure on R&D (million current PPP$). The total number of researchers (full time equivalents, FTEs) in one country is used as indicator for researchers. For the output indicators, we used the number of papers covered by the Science Citation Index (SCI) and Social Science Citation Index (SSCI) from the Web of Science (WoS), and the number of citations to these papers in the year 2011. We use OECD statistics and Thomson Reuters' research evaluation tool InCites as sources for input and output data, respectively. All 34 OECD member countries and seven non-OECD member countries/territories were selected for the study. The other non-OECD member countries, covered by OECD statistics, were excluded due to lack of input data. This also holds for the two OECD members Australia and Switzerland (the Gross Domestic Expenditure in 2011 on R&D of these two countries is missing), and thereby the number of OECD member countries included in the study is 32. See Table 1 for details.

Methods

DEA models and their frontiers

DEA is an approach based on linear programming for analyzing performance of organizations and operational processes. This approach was first proposed by Charnes et al. (1978). All DEA models use input and output data to evaluate the relative efficiency of DMUs without prior knowledge of input/output functions and the weights for indicators. Nowadays, numerous theoretical and empirical works on this method have been published, extending the original approach in different ways, and applying them to many areas, including the private and the public sector (e.g., Cooper et al., 2007).

Let $X = (x_1, x_2, \dots, x_m)$ and $Y = (y_1, y_2, \dots, y_s)$ be input and output vectors of n DMUs, respectively of m and s dimensions. Then the Production Possibility Set (*PPS*) is defined by

$$PPS = \{(X, Y) \colon X\ can\ produce\ Y\} \quad (1)$$

There can be different forms of PPS based on different assumptions. Banker (1984) defined the PPS under the assumption of variable RTS to obtain the BCC-DEA model:

$$PPS(X, Y) = \left\{(X, Y) | X \geq \sum_{j=1}^{n} \lambda_j X_j , Y \leq \sum_{j=1}^{n} \lambda_j Y_j , \sum_{j=1}^{n} \lambda_j = 1 , \lambda_j \geq 0, j = 1, \dots, n\right\} \quad (2)$$

where λ_j is a coefficient.

The *PPS* implied in the CCR-DEA model, which was proposed by Charnes et al. (1978) under the assumption of constant RTS, is defined as follows:

$$PPS(X, Y) = \left\{(X, Y) | X \geq \sum_{j=1}^{n} \lambda_j X_j , Y \leq \sum_{j=1}^{n} \lambda_j Y_j , \lambda_j \geq 0, j = 1, \dots, n\right\} \quad (3)$$

The boundary of the *PPS* is referred to as the production technology or production frontier.

Table 1. Values of input and output indicators across 39 countries/territories.

No.	*Countries/Territories*	*Output*		*Input*	
		Papers	*Citations*	*Research Funding (PPP)*	*Researcher (FTE)*
1	Argentina	8136	40201	4592.313295	50340
2	Austria	12843	100412	9971.246479	37113.8
3	Belgium	18876	152731	9739.425206	42685.77
4	Canada	59025	427079	24756.76203	157360
5	Chile	5795	31737	1172.833167	6082.9
6	China	162794	846720	247808.3033	1318086
7	Czech Republic	9866	55662	4659.446488	30681.59
8	Denmark	13608	124330	6934.707773	37944.1
9	Estonia	1509	10731	733.5776566	4511
10	Finland	10761	82802	7897.729287	40002.61
11	France	67407	480151	53310.69922	249086.3
12	Germany	95935	738284	96971.46462	338608
13	Greece	10819	62818	2006.921474	24674.25
14	Hungary	5934	36137	2721.690282	23019
15	Iceland	815	9013	317.6389104	2258.3
16	Ireland	7438	57682	3169.659323	15172
17	Israel	12478	88753	9306.312467	49797
18	Italy	55338	385416	25780.80141	106151.3
19	Japan	77453	429710	148389.2294	656651
20	Luxembourg	678	4480	660.3865084	3031
21	Mexico	10490	46668	8058.470588	46124.96
22	Netherlands	33845	302477	14597.91748	58447.26
23	New Zealand	8181	50974	1766.588573	16300
24	Norway	10825	78889	5064.393225	27228
25	Poland	21057	91097	6409.165974	64132.8
26	Portugal	10789	66489	4152.692178	50061.2
27	Romania	6927	24373	1725.931612	16080
28	Russia	29072	85915	35192.07719	447579
29	Singapore	9950	82648	6922.39777	33718.5
30	Slovakia	3083	13861	921.2876157	15325.9
31	Slovenia	3776	17682	1429.743722	8774
32	South Africa	9477	48450	4652.174133	20115.06
33	South Korea	45588	222201	58379.65416	288901
34	Spain	50677	332172	20106.98571	130234.9
35	Sweden	21568	172220	13366.28061	48589
36	Taiwan	27283	129286	26184.28683	134047.7
37	Turkey	23920	72981	11301.84442	72108.6
38	UK	100895	784071	39217.4483	251357.6
39	USA	364548	2774572	429143	1252948

Data sources: Input: OECD Statistics. http://www.oecd-ilibrary.org/statistics; Output: InCites. http://incites.isiknowledge.com/Home.action.

Definition 1: The efficient frontier of *PPS* is defined as follows:

$$EF = \{(X,Y) \in PPS \,|\, there\ is\ no\ (\bar{X},\bar{Y}) \in PPS\ such\ that\ (-\bar{X},\bar{Y}) > (-X,Y)\} \quad (4)$$

Note: This unobservable production frontier is called the true efficient frontier hereinafter. When there is only a single output, the production frontier is known in the economic literature as the production function. DMUs, which are technically efficient, operate on the frontier, while technically inefficient DMUs operate at points in the interior of the *PPS*. Thus it is rational to rank DMUs according to their distance to the true frontier.

The core idea of classic DEA is to identify first the production frontier. DMUs on the frontier are regarded as efficient. DMUs not situated on the frontier are compared with their peers or projections on the frontier to measure their relative efficiency. All DMUs on the frontier are considered to represent the best practices and have the same level of performance.

Let $\{(x_j, y_j)|j = 1, \ldots, n\}$ be a group of observed input and output data. Based on such observations, DEA models construct a piecewise linear production frontier, a non-parametric estimate of the unobservable true frontier. Then DEA models measure the efficiency of a DMU via its distance to the estimated frontier. Using radial measurement and input orientation, we have the following input-based CCR-DEA model (Charnes et al., 1978):

$$\theta_c^* = \min \theta$$
$$s.t. \begin{cases} \sum_{j=1}^{n} x_{ij}\lambda_j \le \theta x_{i0}, i = 1, \ldots, m, \\ \sum_{j=1}^{n} y_{rj}\lambda_j \ge y_{r0}, r = 1, \ldots, s, \\ \lambda_j \ge 0, j = 1, \ldots, n. \end{cases} \quad (5)$$

where $\lambda_j \ge 0$ are the multipliers of inputs and outputs. Here θ_c^* measures the degree of efficiency by radial measurement under the assumption of constant RTS.

If we assume that the production technology satisfies the variable returns to scale assumption, we have the following input-based BCC-DEA model (Banker et al., 1984):

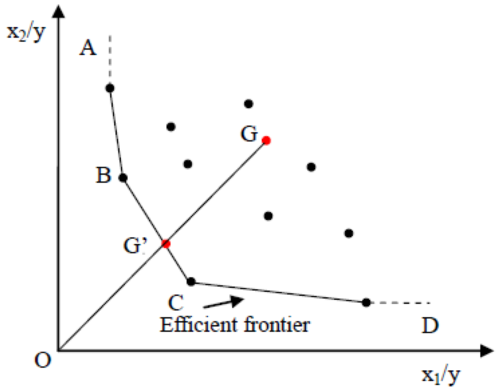
$$\theta_b^* = \min \theta$$
$$s.t. \begin{cases} \sum_{j=1}^{n} x_{ij}\lambda_j \le \theta x_{i0}, i = 1, \ldots, m, \\ \sum_{j=1}^{n} y_{rj}\lambda_j \ge y_{r0}, r = 1, \ldots, s, \\ \sum_{j=1}^{n} \lambda_j = 1, \\ \lambda_j \ge 0, j = 1, \ldots, n. \end{cases} \quad (6)$$

where θ_b^* measures the degree of efficiency by radial measurement under the assumption of variable returns to scale. It should be noted that Model (6) differs from Model (5) only regarding the constraint $\sum_{j=1}^{n} \lambda_j = 1$, which yields that the variable RTS assumption is satisfied.

Obviously, if $\theta_c^* = 1$ in model (5) or $\theta_b^* = 1$ in Model (6), then the DMU is situated on the efficient frontier in CCR-DEA or BCC-DEA, respectively.

We visualize the frontier of a DEA model in Figure 1, using two inputs (x_1 and x_2) and one output (y). The piecewise linear line ABCD defines the efficient frontier of the existing observations. For example, for point G, representing a DMU, its efficiency score can be calculated as the ratio of distance OG' to distance OG.

We now give an example to illustrate the detection of the efficient frontier and the evaluation of DMUs using a DEA model. We suppose there are six DMUs with two inputs and a single output. In Table 2, hypothetical data is given.



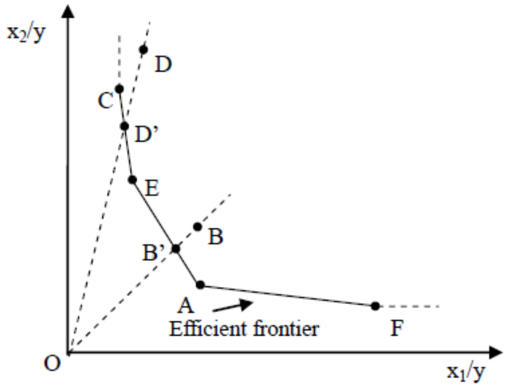


Figure 1. Efficient Frontier of a DEA model. Figure 2. Efficient Frontier and DMUs.

First, for comparison, we expand the inputs and output of each DMU proportionally and let the output of each DMU be 120 (Table 3).

Table 2. 6 DMUs with 2 inputs and a single output.

DMUs	*DMU_1*	*DMU_2*	*DMU_3*	*DMU_4*	*DMU_5*	*DMU_6*
Output (y)	120	8	24	40	120	24
Input 1 (x_1)	19	1	1	2	10	8
Input 2 (x_2)	10	1	6	15	17	1

We show these six DMUs in Figure 2 (which gives projections in input space) using points A-F to denote DMU_1-DMU_6.

Table 3. Expanded DMUs with 2 inputs and single output.

DMUs	*DMU_1*	*DMU_2*	*DMU_3*	*DMU_4*	*DMU_5*	*DMU_6*
Output(y)	120	120	120	120	120	120
Input 1(x_1)	19	15	5	6	10	40
Input 2(x_2)	10	15	30	45	17	5

We use a piecewise linear curve to link points C, E, A, F and merge it with the horizontal and vertical lines from point F and C, respectively, to obtain the piecewise linear convex hull, which is the efficient frontier produced from this DEA model. Points C, E, A, F are on the efficient frontier and their efficiencies are all unity. On the contrary, points B and D are inside the convex hull, so these two DMUs are inefficient compared with their peers or projections (points B' and D') on the efficient frontier. Taking point B as example, the DEA model uses the ratio of distance OB' to the distance OB to measure point Bs relative efficiency.

Decomposition of countries/territories based on multi-level frontiers in DEA

In the preceding section, we showed how the effective frontier can be detected. If we remove the efficient DMUs on the frontier, we can use the DEA model again to obtain a new frontier. We do this repeatedly in order to decompose DMUs into different levels. This process is illustrated in Figure 3. In this figure, the first tier of the efficient frontier is the piecewise line ABCD (Efficient frontier – tier1), on which the DMUs with the best level of efficiency are located. After we remove the DMUs on the Efficient frontier – tier1, we rerun the DEA model, obtaining the DMUs on the efficient frontier – tier2 as the second group, and so on.

This process is iterated until there is no DMU left, and the grading of the DMUs ends. The efficient frontier in Figure 1 is the same as the efficient frontier– tier1 in Figure 3.

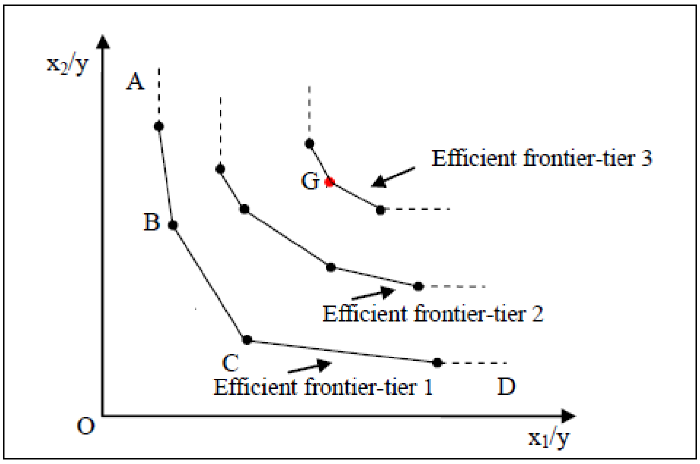


Figure 3. Multi-level efficient frontiers of a DEA model.

In earlier works, DEA frontiers have been used either to measure the relative efficiency of the DMUs (e.g., Charnes et al., 1978; Cook and Seiford, 2009) by comparing them with their peers or projections on the frontier, or to estimate the RTS by the frontier's shape (Banker et al., 2004). To the best of our knowledge, no research similar to the research reported in this paper has used multi-level frontiers in DEA models to decompose DMUs into different grades to reflect different levels of performance.

In the process of decomposing the DMUs into different grades, we need to ensure that a given DMU can only be assigned to one level to avoid conflicts. An efficient frontier is a convex hull. This implies that if a point belongs to F_k it cannot belong to any other F_{k+l} (if it exists, where l is a positive integer). Indeed a point on the frontier is a convex linear combination of efficient points on the frontier. If point P would belong to F_k and F_{k+l} this would mean that P is a convex linear combination of points that do not belong to F_k, which is not possible. Thus, one country/territory can only be assigned to one level.

Results

The BCC-DEA model was applied to produce multi-level efficient frontiers, and these were used to decompose the countries/territories of the study into different grades. Table 4 reports the levels of the countries/territories for the three experiments: two inputs & two outputs, two inputs & the first output (papers), and two inputs & the second output (citations).

We first consider the case of two inputs and two outputs. The results show that Chile, Greece, Iceland, Italy, Netherlands, UK and USA are the first level countries in the sense of efficiency of S&T resource utilization (Table 4). Mexico is the least efficient unit among the 39 countries/territories and belongs to the last level (Tier 6).

We reused the multi-level efficient frontiers in the BCC-DEA model on the 39 countries/territories with two inputs and the first output (papers) to decompose the countries/territories into different grades. We can see that now Chile, Greece, Iceland, Italy, Netherlands, UK and USA are the most efficient countries/territories (Table 4). Mexico, Finland, Israel and Singapore have with the lowest efficiencies.

We also used the multi-level efficient frontiers in the BCC-DEA model on the 39 countries/territories with two inputs and the second output (Citations), which is shown in table 4. Also in this case Chile, Greece, Iceland, Netherlands, UK and USA are first level countries, and Italy has moved into Tier 2. The latter means that Italy performs better for papers than for citations. Mexico and Turkey are in the last tier, Tier 7. It is interesting to see that Turkey is in Tier 3 in the case of two inputs and two outputs while in Tier 7 in the case of two inputs and the second output, which means that the citation performance of Turkey is considerably worse than its performance for papers.

Table 4. Levels of the countries/territories.

No.	*Countries /Territories*	*two inputs & two outputs*	*two inputs & first output(paper)*	*two inputs & second output(citation)*
1	Chile	1	1	1
2	Greece	1	1	1
3	Iceland	1	1	1
4	Netherlands	1	1	1
5	UK	1	1	1
6	USA	1	1	1
7	Italy	1	1	2
8	Canada	2	2	2
9	China	2	2	2
10	Estonia	2	2	2
11	Germany	2	2	2
12	Luxembourg	2	2	2
13	New Zealand	2	2	2
14	Spain	2	2	2
15	Belgium	2	2	3
16	Slovakia	2	2	3
17	Sweden	2	2	3
18	Poland	2	2	4
19	Ireland	2	3	2
20	Denmark	2	4	3
21	France	3	3	3
22	Slovenia	3	3	3
23	Japan	3	3	4
24	Romania	3	3	4
25	South Africa	3	3	4
26	Turkey	3	3	7
27	Norway	3	4	4
28	Portugal	3	4	4
29	Austria	3	5	4
30	South Korea	4	4	4
31	Hungary	4	4	5
32	Taiwan	4	4	5
33	Czech Republic	4	5	6
34	Israel	4	6	5
35	Singapore	4	6	5
36	Argentina	5	5	6
37	Russia	5	5	6
38	Finland	5	7	6
39	Mexico	6	8	7

Figure 4 corresponds to Table 4 and visualizes the levels of the countries/territories when using two inputs and two outputs, two inputs and the first output (paper), and two inputs and the second output (citation). From this figure, it is clear that some countries/territories (e.g., Argentina, Belgium, Czech Republic, Turkey) belong to a lower level in the case of two inputs & the second output (citations) compared to the case of two inputs & the first output (papers), which indicates that these countries perform more efficient for papers than for citations. Inversely, some countries (e.g., Austria, Denmark, Finland) perform more efficient for citations than for papers.

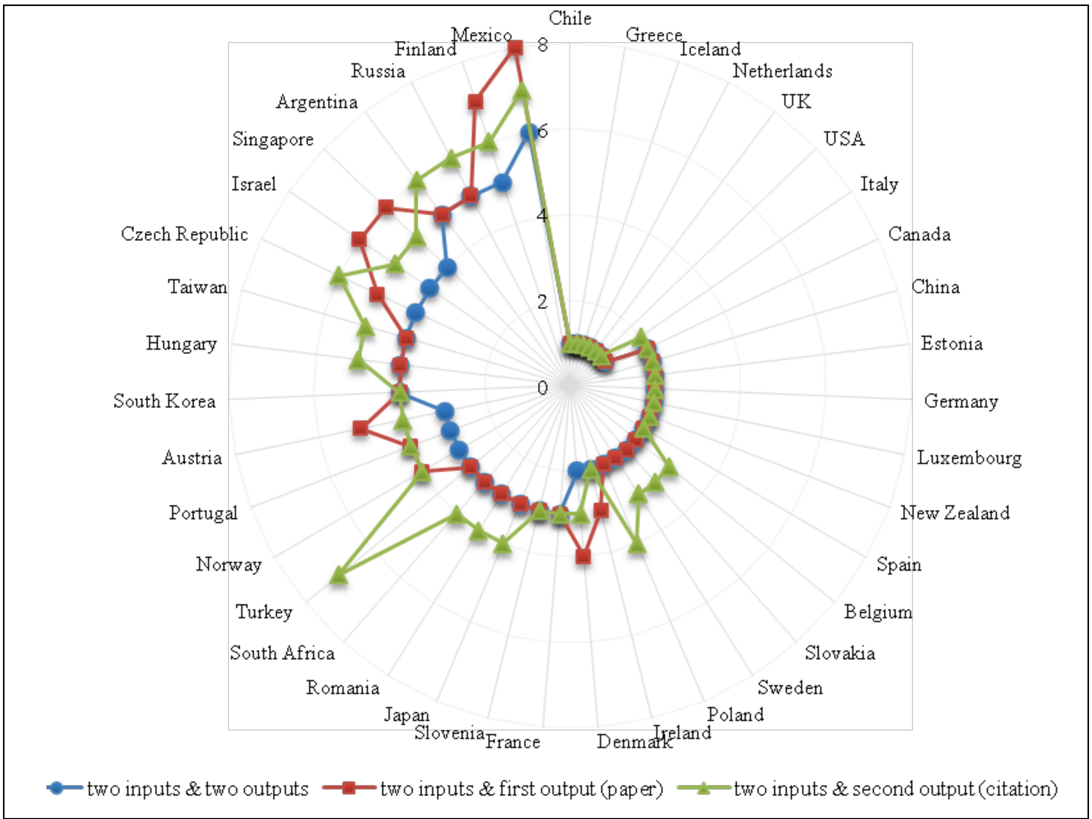


Figure 4. Visualisation of the levels of the countries/territories.

It is surprising that Greece and Chile are rated first level countries together with S&T-developed countries like USA and UK. For papers as output, we can verify this result using the ratios Papers to Researcher and Papers to Research Funding. From Table 5, we can see that Greece and Chile perform very well for these two ratios. On the contrary, we can see China, Japan and South Korea have low performance compared to other countries. We believe that a reason for this is that researchers from these countries publish relatively frequently in domestic journals that are not covered by WoS. We do not tabulate the values of the corresponding two ratios for citations, but it turned out that Chile and Greece perform well also with respect to these ratios.

Discussion and conclusions

In this paper we have shown that multi-level frontiers of DEA can be used to decompose countries/territories into different levels, reflecting the efficiency of S&T resource utilization of the countries/territories. The approach put forward is not restricted to the grading of countries/territories. It can also be used to grade, for instance, journals and research institutions based on properly selected indicators. In case of no explicit inputs, e.g., when journals should be graded, we can assume that there is single constant input, which is equal to unity for all observations (e.g., Yang et al. 2014b).

There are two main advantages of the grading approach proposed in this paper. First, it is a nonparametric and recursive approach, which needs no a priori information such as indicator weights and threshold values for different grading levels. Second, the observations within the same level are indifferent in the sense of efficiency of resource utilization. The main disadvantage of the approach is that in some cases there are too few indicators (single input and single output). Under such circumstances, it might be the case that each level includes exactly one observation (in our case, exactly one DMU). Thus, the approach is more suitable for grading observations with multiple input and output indicators.

For future research, we would like to investigate the multiple DEA frontiers regarding weight restrictions in DEA models. There are at least four types of restrictions on the weights of input and output variables (e.g., Allen et al., 1997), and the efficient frontiers will vary accordingly and show different properties. Furthermore, this grading approach can be easily extended to the classification of scientific journals, research institutions, etc.

Table 5. Ratios of Papers to Researcher and Research Funding.

No.	*Countries/Territories*	*Papers/Researcher*	*Papers/Research Funding*	*No.*	*Countries/Territories*	*Papers/Researcher*	*Papers/Research Funding*
1	Argentina	0.1616	1.7717	21	Mexico	0.2274	1.3017
2	Austria	0.3460	1.2880	22	Netherlands	0.5791	2.3185
3	Belgium	0.4422	1.9381	23	New Zealand	0.5019	4.6310
4	Canada	0.3751	2.3842	24	Norway	0.3976	2.1375
5	Chile	0.9527	4.9410	25	Poland	0.3283	3.2855
6	China	0.1235	0.6569	26	Portugal	0.2155	2.5981
7	Czech Republic	0.3216	2.1174	27	Romania	0.4308	4.0135
8	Denmark	0.3586	1.9623	28	Russia	0.0650	0.8261
9	Estonia	0.3345	2.0570	29	Singapore	0.2951	1.4374
10	Finland	0.2690	1.3625	30	Slovakia	0.2012	3.3464
11	France	0.2706	1.2644	31	Slovenia	0.4304	2.6410
12	Germany	0.2833	0.9893	32	South Africa	0.4711	2.0371
13	Greece	0.4385	5.3908	33	South Korea	0.1578	0.7809
14	Hungary	0.2578	2.1803	34	Spain	0.3891	2.5204
15	Iceland	0.3609	2.5658	35	Sweden	0.4439	1.6136
16	Ireland	0.4902	2.3466	36	Taiwan	0.2035	1.0420
17	Israel	0.2506	1.3408	37	Turkey	0.3317	2.1165
18	Italy	0.5213	2.1465	38	UK	0.4014	2.5727
19	Japan	0.1180	0.5220	39	USA	0.2910	0.8495
20	Luxembourg	0.2237	1.0267				

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