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A Data Envelopment Analysis Application for Measuring Efficiency of University Departments

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Abstract

Data envelopment analysis (DEA), which has developed to measure the effectiveness of economic decision-making units (DMU) that referred to as decision making units and similar in terms of their products or services, is an efficiency measurement technique without parameters. This technique ensures to define how existing sources can be used effectively to create the outputs of DMU.

The interest in the measurement of the performance and efficiency in non-profit public organisations such as universities has increasing day by day. Recently, in many studies DEA method has been using to evaluate performance of universities.

The DEA methodology enables to get global technical efficiency scores, local pure technical efficiency scores and finally scale scores of units. And by using DEA it is possible to obtain an overall performance measure through the comparison of a group of decision units.

This paper involves Data Envelopment Analysis in order to determine the performance levels departments in Dokuz Eylul University (Turkey). We discuss about the technical scores and scale scores of departments and try to reveal main cause of inefficiency. And also in this study, input and output goals of departments will be fixed for a better efficiency.

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Keywords: Data Envelopment Analysis; education efficiency; departments' performances

JEL Classification Codes: C80, C67

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1. Introduction

The main purpose of this study is measuring the effectiveness of university units. The effectiveness of the organization is important to determine how well the organization's resources are used, how well the outputs are obtained and how processes are managed.

Sherman (1988), defines efficiency as "the ability to produce the outputs or services with a minimum resource level required". Similarly, productivity is defined as the efficiency of production. Farrell (1957), who is known with his studies about measurement of productive efficiency, recognized the importance of measuring the extent to which outputs can be increased through higher efficiency without using additional resources (inputs) (Avkiran, 2001).

The simplest definition of productivity is the ratio of the output to the input. In this context, the concept of efficiency is not a relative concept. It is the possible that measurement of efficiency of examined decision making units independently (Tarım, 2001).

DMU is to be rated as fully (100%) efficient on the basis of available evidence if and only if the performances of other DMUs does not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs (Cooper et al., 2011).

Non-parametric measuring efficiency methods try to measure the distance to efficiency border by using linear programming based techniques. Unlike parametric methods, these methods are relatively advantageous since they are not required to take behavioral assumptions into account about the structure of the production unit. In addition, these methods have superiority such as using more than one explanatory variable. The most common non-parametric method is data envelopment analysis (DEA) that was developed by Charnes, Cooper and Rhodes in 1978 (Seyrek & Ata, 2010). In this study, the units which have similar processes are compared by analyzing effectiveness of university units. The process has inherently non-parametric property.

DEA is a mathematical programming approach to provide a relative efficiency assessment (called DEA efficient) for a group of decision making units (DMU) with multiple numbers of inputs and outputs (Quanling, 2001). The process, runs in the non-profit organizations such as universities, has multiple inputs and outputs which cannot be modeled linearly due to its structure. In consequence, DEA has been chosen to measure efficiency in this study.

More specifically, we consider calculating efficiency scores of the university units, by using input variables (outdoor-indoor area of university, number of academic staff and number of administrative staff) and output variables (number of publications and number of graduate students).

2. Data Envelopment Analysis (DEA)

Data envelopment analysis (DEA) was suggested by Charnes, Cooper and Rhodes (CCR) (1978), ideas of Farrell which is concerned with the estimation of technical efficiency and efficient frontiers (Yun, Nakayama & Tanino, 2004).

DEA is a "data-oriented" approach for evaluating the performance of a set of peer entities called Decision-Making Units (DMUs), which convert multiple inputs into multiple outputs. The definition of a DMU is generic and flexible. Recent years have seen a great variety of applications of DEA for use in evaluating the performances of many different kinds of entities engaged in many different activities in many different contexts in many different countries. These DEA applications have used DMUs of various forms to evaluate the performance of entities, such as hospitals, US Air Force wings, universities, cities, courts, business firms, and others, including the performance of countries, regions, etc. Because it requires very few assumptions, DEA has also opened up possibilities for use in cases that have been resistant to other approaches because of the complex (often unknown) nature of the relations between the multiple inputs and multiple outputs involved in DMUs (Cooper et al., 2011).

DEA is used to measure efficiency when there are multiple inputs and outputs and there are no generally acceptable weights for aggregating inputs and aggregating outputs. In the case of one input and one output, the output-input ratio reveals efficiency (Mcmillan, & Datta, 1998).

Various theoretical extensions have been developed, based on the original CCR model: Banker et al. (1984) developed a variable returns-to-scale variation; the multiplicative model was developed by Charnes et al. (1978) in which the data are transformed using a logarithmic structure; Charnes et al. (1978) developed the additive variation, in which the objective function contains slack variables alone. Seiford and Thrall (1990) provide a useful discussion and comparison of all the basic models available to date in DEA (Adler, Friedman & Sinuany-Stern, 2002).

DEA is particularly appropriate when the researcher is interested in investigating the efficiency of converting multiple inputs into multiple outputs. For example, DEA can identify alternative configurations of inputs that can result in higher outputs without necessarily raising the overall use of resources. DEA is a linear programming technique that enables management to benchmark the best practice DMU, i.e. a university. Further, DEA provides estimates of potential improvements for inefficient DMUs (Avkiran, 2001).

Charnes et al. described DEA as a mathematical programming model applied to observational data [which] provides a new way of obtaining empirical estimates of extremal relations such as the production functions and/or efficient production possibility surfaces that are a cornerstone of modern economics (Adler at al., 2002).

As a technical analysis, DEA is relative. From the set of DMUs analyzed, it determines an efficient group. It still might be possible, however, to improve the technical efficiency of even those efficient units were the best production possibilities known. However, the actual production function is not known and none is assumed. The efficient units in DEA are the most efficient of those observed, not in comparison to some ideal. Thus, the DEA efficient group is that subset demonstrating the "best practices" among a group of operating units. Inefficient DMUs are compared to those units demonstrating superior performance (Mcmillan, & Datta, 1998).

As an efficient frontier technique, DEA identifies the inefficiency in a particular DMU by comparing it to similar DMUs regarded as efficient, rather than trying to associate a DMU's performance with statistical averages that may not be applicable to that DMU (Avkiran, 2001).

By mathematical programming, DEA finds a weighting system (in the absence of prices) that allows inputs and outputs each to be aggregated and efficiency scores to be calculated. No single set of weights is required. Rather, DEA, by repeated solutions, finds a set of weights for each DMU. The weights are those that are most favourable to the unit; that is, give it the highest efficiency score subject to no weights being negative and that the weights, when applied to any unit, do not result in any one having an efficiency score exceeding 1.0 (on a scale of zero to one with 1.0 indicating an efficient DMU) (Mcmillan, & Datta, 1998).

DEA has particular appeal in that it deals with multiple outputs and multiple inputs and does not require a priori or subjective tradeoffs between various types of outputs or the use of prices for aggregating the resources. Further, the method uses standard LP codes to identify peer groups for each unit being evaluated. Using as a reference these peer group members, DEA provides quantitative insights as to the aspects and sizes of adjustments needed to render an inefficient unit efficient (Banker & Morey, 1986). The research and applications of DEA attract a great amount of interest from both academic field and industrial practice (Quanling, 2001). Applications of this efficiency analysis technique to criminal superior courts, Armed Forces recruiting districts, school districts, pharmacies, hospitals, electric power generation plants, manufacturing productivity analysis, etc., also demonstrate the flexibility of DEA (Banker & Morey, 1986).

2.1 DEA Models

DEA is a nonparametric method of measuring the efficiency of a DMU such as a firm or a public sector agency, first introduced into the Operation Research literature by Charnes, Cooper and Rhodes (CCR). The original CCR model was applicable only to technologies characterized by constant returns to scale globally. In what turned out to be a major breakthrough, Banker, Charnes, and Cooper (BCC) (1984), extended the CCR model to accommodate technologies that exhibit variable returns to scale (Ray, 2004).

Different DEA models are extended and thoroughly discussed. This includes the additive model, Log-type DEA models, DEA models with a cone ratio of decision makers' preference, semi-infinite programming DEA models with infinitely many DMUs, stochastic DEA models, etc. The economic and management background of DEA models and methods are extensively investigated (Quanling, 2001).

Charnes, Cooper and Rhodes introduced the CCR model of DEA to evaluate the relative efficiency of DMUs. Banker, Charnes and Cooper (1984) subsequently introduced the BCC model which separates technical efficiency and scale efficiency (SE). Later, Banker (1984) showed how the CCR formulation can be employed to estimate most productive scale size (MPSS) and returns to scale (RTS). More recently, Banker and Thrall (1992) showed that the

BCC and CCR methods of returns to scale estimation in Banker (1984) and Banker, Charnes and Cooper (1984) are equivalent (Banker et al., 1996).

The most basic forms of DEA are CCR and BCC. These can be analyzed as input and output oriented. İf decision maker can control inputs; input oriented analysis should be done. Otherwise, output oriented analysis should be done.

Comparisons of the (input-oriented) CCR and BCC scores deserve consideration. The CCR model assumes the constant returns-to-scale production possibility set, i.e., it is postulated that the radial expansion and reduction of all observed DMUs and their nonnegative combinations are possible and hence the CCR score is called *globol technical* efficiency (GTE). On the other hand, the BCC model assumes that convex combinations of the observed DMUs form the production possibility set and the BCC score is called *local pure technical* efficiency (LPTE)(Cooper at al., 2007). Scale efficiency can be obtained with the proportion of these two scores.

2.1.1 Charnes, Cooper and Rhodes (CCR)

The CCR ratio form introduced by Charnes at al., (1978), as part of their Data Envelopment Analysis approach, comprehends both technical and scale inefficiencies via the optimal value of the ratio form, as obtained directly from the data without requiring a priori specification of weights and/or explicit delineation of assumed functional forms of relations between inputs and outputs (Banker at al., 1984). In the influential Charnes et al. it is stated: "CCR used the optimization method of mathematical programming to generalize the Farrell (1957) single-output/input technical efficiency measure to the multiple output/multiple-input cases…." (Forsund & Sarafoglou, 2000).

"To allow for applications to a wide variety of activities, we use the term DMU to refer to any entity that is to be evaluated in terms of its abilities to convert inputs into outputs. These evaluations can involve governmental agencies and nonprofits organizations as well as profit oriented organizations. The evaluation can also be directed to educational institutions and hospitals as well as police forces (or subdivision thereof) or army units for which comparative evaluations of their performance are to be made (Cooper at al., 2011).

Table 1 presents the CCR model in input- and output-oriented versions, each in the form of a pair of dual linear programs.

Table 1. CCR Models (Cooper, Seiford & Zhu, 2011)

Envelopment model		Multiplier model
Input-oriented		
$\min \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$		$\max z = \sum_{r=1}^{s} \mu_r y_{ro}$
subject to		subject to
$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{io}$	$i = 1, 2, \ldots, m;$	$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$
$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro}$	$r = 1, 2, \ldots, s;$	$\sum_{i=1}^{m} v_i x_{io} = 1$
$\lambda_j \geq 0$	$j = 1, 2, \ldots, n$	$\mu_r, v_i \geq \varepsilon > 0$
Output-oriented		
Envelopment model		**Multiplier model**
$\max \varphi + \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$		$\min q = \sum_{i=1}^{m} v_i x_{io}$
subject to		subject to
$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{io}$	$i = 1, 2, \ldots, m;$	$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} \geq 0$
$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \varphi y_{ro}$	$r = 1, 2, \ldots, s;$	$\sum_{r=1}^{s} \mu_r y_{ro} = 1$
$\lambda_j \geq 0$	$j = 1, 2, \ldots, n.$	$\mu_r, v_i \geq \varepsilon > 0$

These are known as CCR models. If the following constraint (1) is adjoined to dual models, they are known as BCC (Banker et al. 1984) models.

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad (1)$$

2.1.2 Banker, Charnes and Cooper (BCC)

Banker, Charnes and Cooper suggested a model for estimating technical efficiency and scale inefficiency in DEA. The BCC model relaxed the constant returns to scale assumption of the CCR model and made it possible to inverstigate whether the performance of each DMU was conducted in region of increasing, constant or decreasing returns to scale in multiple outputs and multiple inputs situations (Yun at al., 2004).

The BCC models are seen as following formulas. The BCC (Banker et al., 1984) model (2, 3) adds an additional constant variable in order to permit variable returns-to-scale:

$$\max z = \sum_{r=1}^{s} u_r y_{ro} - u_o$$

subject to

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_o \leq 0 \qquad j=1,2,\dots,n \qquad (2)$$

$$\sum_{i=1}^{m} v_i x_{io} = 1 \qquad v_i \geq \varepsilon \quad u_r \geq \varepsilon$$

$$E_o = \mathrm{Min} \sum_{j=1}^{m} v_i x_{io} - \rho_o$$

subject to

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + \rho_o \leq 0 \qquad j=1,2,\dots,n \qquad (3)$$

$$\sum_{r=1}^{s} u_r y_{ro} = 1 \qquad u_r \geq \varepsilon \quad v_i \geq \varepsilon$$

It should be noted that the results of the CCR input-minimized or output-maximized formulations are the same, which is not the case in the BCC model. Thus, in the output-oriented BCC model, the formulation maximizes the outputs given the inputs and vice versa (Adler et al., 2002).

The structure of DEA problem is in the form of LP as described above. Decision problems can be solved like solving of LP model by using DEA. DEA calculations can be also conducted using a number of different computer programs such as Excel, SAS, SHAZAM, IDEAS, Frontier Analyst, Warwick DEA, DEAP, EMS etc.

3. Application

3.1 Review of the Literature about Data Envelopment Analysis Applications in Universities

DEA was initially been used to investigate the relative efficiency of not-for-profit organizations, only to quickly spread to profit-making organizations. DEA has been successfully applied in such diverse settings as schools, hospitals, courts, the US Air Force, rate departments and banks (Avkiran, 2001).

The initial DEA model, as originally presented in Charnes, Cooper, and Rhodes (CCR), was built on the earlier work of Farrell. This work by Charnes, Cooper, and Rhodes originated in the early 1970s in response to the thesis efforts of Edwardo Rhodes at Carnegie Mellon University's School of Urban & Public Affairs – now the H.J. Heinz III School of Public Policy and Management. Under the supervision of W.W. Cooper, this thesis was to be directed to evaluating educational programs for disadvantaged students (mainly black or Hispanic) in a series of large scale studies undertaken in US public schools with support from the Federal government (Cooper at al., 2011)

Some studies appearing in Özden, (2008) about measuring the efficiency of the universities, are listed in Table 2, which includes also used input and output variables for each study.

Table 2. Some studies about measuring the efficiency of the universities (Özden, 2008)

Author	Used Input Variables	Used Output Variables
Tomkins and Green (1988)	Number of full-time employees Personnel Costs Operating Costs Other Costs	Number of University Students Number of PhD Students Total Income Number of Publications
Beasley (1995)	Research income Operating Costs Personnel Costs	Number of Undergraduate Students and Postgraduate Students Number of Publications that take part in indexes
Abbott & Doucouliagos (2003)	Number of Academic Staff Number of Non-Academic Staff Operating Costs Fixed Assets	Number of Students Number of graduate students from Associate degree, Undergraduate and Postgraduate degree Amount of research
Flegg et al. (2004)	Number of Faculty Members Number of Undergraduate Students Number of Postgraduate Students Total Expenses	Research and Consultancy Income Number of graduate students from Undergraduate degree Number of graduate students from Postgraduate degree
Warning (2004)	Personnel Costs Other Costs	Number of Publications that take part in indexes Number of Students
Kutlar and Kartal (2004)	Number of Academic Staff Number of Administrative Staff Personnel, Service Procurement and Consumption Expenses Acreage	Number of Students Student Fees Projects Number of Postgraduate Students
Baysal et al. (2005)	Personnel Costs Other Current Expenditures Investment Expenses Transfers Number of Faculty Members	Number of Undergraduate Students Number of Postgraduate Students Number of PhD Students Number of Publications
Babacan, Kartal et al. (2007)	General Budget Expenditures Expenditures out of budget Number of Professor Number of Associate Professor Number of Assistant Professor Number of Assistant Instructor Number of Administrative Staff	Number of Publications that take part in indexes University Income Number of Undergraduate Students Number of graduate students from Undergraduate degree Number of Postgraduate Students Number of graduate students from Postgraduate degree
Kutlar and Babacan (2008)	General Budget Expenditures Expenditures out of budget Number of Professor Number of Associate Professor Number of Assistant Professor Number of Assistant Instructor Number of Administrative Staff	Number of Publications that take part in indexes University Income Number of Undergraduate Students Number of graduate students from Undergraduate degree Number of Postgraduate Students Number of graduate students from Postgraduate degree

In addition to studies above, according to Avkıran (2001), other studies in the literature are shown with their used input and output variables in Table 3.

Table 3. Some studies about measuring the efficiency of the universities (Avkıran, 2001)

Author	Used Input Variables	Used Output Variables
Bessent et al. (1983)	Revenue from state government Number of students completing a program Employer satisfaction with training of students	Student contact hours Number of full-time equivalent instructors Square feet of facilities for each program Direct instructional expenditures.
Beasley (1990)	Research income Expenditure were treated	Undergraduate student numbers Postgraduate student numbers Research ratings.
Johnes and Johnes (1993)	Research income	Research output
Stern et al. (1994)	Operating costs Salaries	Research grants Publications Graduate students Contact hours

3.2 Application for Dokuz Eylül University

In this study, the relative efficiency analysis has been done for decision making units that include institutes, faculties, colleges and vocational schools of higher education in Dokuz Eylül University.

3.2.1 Choosing Input / Output Variables and Decision Making Units

In education, it is difficult to use market mechanisms such as profits to determine the performance of a DMU. A key advantage of DEA is that educational administrators or their nominated researchers can choose inputs and outputs to represent a particular perspective or approach. For example, key business drivers critical to success of the organization can be the outputs. Then, those variables that can be argued to manifest themselves as outputs become the inputs (Avkiran, 2001).

In this efficiency analysis, considering other studies in the literature, input variables have been chosen as outdoor-indoor area of university, Number of Academic Staff and Number of Administrative Staff, output variables have been chosen as Number of Publications and Number of Graduate Students. This analysis is a situation analysis for 2012, because data refer to 2012. Moreover, data in the study obtained from the IT department of the university. Academicians in some units may take charge in the other units for assignment. For this reason, the actual numbers in some units have not been obtained. These conditions can be rated among limitations of this study.

DMUs' performances may differ from each other but DMUs should be homogeneous in terms of features in order that they can be compared (Tütek, Gümüşoğlu, & Özdemir, 2012). In this study, there are 26 DMUs, process structures of which are the same. According to Cooper et al. (2011), number of DMUs should be $3(m+s)$ at least. Numbers of Inputs and outputs have been demonstrated respectively as m and s. Number of DMUs, inputs and outputs that have been incorporated into this analysis accord with this approach.

3.2.2 Model Summary

EMS (Efficiency Measurement System) Version 1.3 was used for the solution of DEA in the study.[†] In this decision problem, input oriented model was chosen because decision makers can control inputs. As above correspondence, model summary is shown in Table 4, DMUs, input and output data are shown in Table 5.

[†] For more information; http://www.holger-scheel.de/ems/ about EMS and http://www.microtheory.uni-jena.de/download/ems.pdf about user manual can be examined.

Table 3. Model Summary

Inputs	outdoor-indoor area of university, Number of Academic Staff and Number of Administrative Staff
Outputs	Number of Publications and Number of graduate students
Number of DMUs	26
Used Model	CCR: to determine GTE scores, target values of input-output factors and improvement ratio BCC: to determine LPTE scores and scale efficiency
Model Version	Input oriented
Used software	EMS V.1.3

Table 5. DMUs, Input and Output Data

		Inputs			Outputs	
DMU No.	**DMU**	**Outdoor-Indoor Area (m^2)**	**Number of Academic Staff**	**Number of Administrative Staff**	**Number of Publications**	**Number of graduate students**
1	Faculty of Law	16505	74	32	48	346
2	Vocational School of Health Services	9531	32	20	155	142
3	Faculty of Economics and Administrative Sciences	58483	181	94	121	1.453
4	The Institute of Fine Arts	632	3	10	5	41
5	The Ataturk Institute for Modern Turkish History	3986,5	19	8	18	36
6	Graduate School of Social Sciences	2530	13	31	24	285
7	Faculty of Sciences	32235	112	24	236	201
8	Faculty of Engineering	135646	366	175	503	790
9	Seferihisar Vocational School of Social Sciences	13497	6	18	1	45
10	Faculty of Fine Arts	41003	137	52	5	184
11	İzmir Vocational School	15599	97	49	98	1.326
12	Buca Faculty of Education	110544	207	97	257	1.826
13	Institute of Educational Sciences	416	5	18	6	126
14	Vocational School of Judicial Practices	2108	4	9	2	105
15	School of Physical Therapy and Rehabilitation	4712	30	27	48	71
16	Faculty of Letters	32236	90	25	109	179
17	Graduate School of Natural and Applied Sciences	3986,5	12	22	142	226
18	School of State Conservatory	16359	42	21	10	26
19	Faculty of Business	15624	91	25	90	215
20	Institute of Health Sciences	470	33	18	155	74
21	Torbalı Vocational School	82153	17	33	46	71
22	Faculty of Medicine	66823	963	149	1457	143
23	Faculty of Divinity	38408	74	47	45	110
24	Faculty of Architecture	33355	78	28	96	135
25	Faculty of Nursing	9531	30	20	104	84
26	Maritime Faculty	16342	44	28	46	135

3.2.3 Findings

The results of the empirical analysis are presented in Table 6.

Table 6. CCR, BCC and Scale Efficiency Scores

DMU No.	DMU	CCR (GTE)	BCC(LPTE)	SE(GTE/ LPTE)
1	Faculty of Law	0,4554	0,5722	0,795876
2	Vocational School of Health Services	0,9892	0,9936	0,995572
3	Faculty of Economics and Administrative Sciences	0,5867	0,6903	0,84992
4	The Institute of Fine Arts	0,5632	1	0,5632
5	The Ataturk Institute for Modern Turkish History	0,3417	1	0,3417
6	Graduate School of Social Sciences	1	1	1
7	Faculty of Sciences	1	1	1
8	Faculty of Engineering	0,4008	0,8577	0,467296
9	Seferihisar Vocational School of Social Sciences	0,2863	0,5417	0,528521
10	Faculty of Fine Arts	0,1308	0,2228	0,587074
11	İzmir Vocational School	1	1	1
12	Buca Faculty of Education	0,8051	1	0,8051
13	Institute of Educational Sciences	1	1	1
14	Vocational School of Judicial Practices	1	1	1
15	School of Physical Therapy and Rehabilitation	0,2638	0,4321	0,610507
16	Faculty of Letters	0,5643	0,6668	0,846281
17	Graduate School of Natural and Applied Sciences	1	1	1
18	School of State Conservatory	0,0815	0,3894	0,209296
19	Faculty of Business	0,5687	0,6805	0,835709
20	Institute of Health Sciences	1	1	1
21	Torbalı Vocational School	0,2287	0,395	0,578987
22	Faculty of Medicine	1	1	1
23	Faculty of Divinity	0,1637	0,2478	0,660613
24	Faculty of Architecture	0,4421	0,5365	0,824045
25	Faculty of Nursing	0,6568	0,7577	0,866834
26	Maritime Faculty	0,3059	0,4415	0,692865

Global technical efficiency score by input oriented CCR analysis, local pure technical efficiency score by input oriented BCC analysis and scale efficiency score for each DMUs by proportioning of these values were calculated. According to CCR analysis results, DMU_6, DMU_7, DMU_{11}, DMU_{13}, DMU_{14}, DMU_{17}, DMU_{20} and DMU_{22} are efficient. To find efficiency scores of relative efficient units and sort these units, analysis were done using the super efficiency module which allow that efficiency score is higher than 1. Accordingly, Institute of Health Sciences has been found as a unit that has a highest efficiency score. Graduate School of Natural and Applied Sciences, Institute of Educational Sciences, İzmir Vocational School, Vocational School of Judicial Practices, Faculty of Sciences, Faculty of Medicine, Graduate School of Social Sciences follow Institute of Health Sciences respectively. DMU_6, DMU_7, DMU_{11}, DMU_{13}, DMU_{14}, DMU_{17}, DMU_{20} and DMU_{22} have been found efficient according to CCR analysis as well as BCC analysis. (It should be noted that this is a local efficiency value and does not show a global efficiency. DMUs which have been found efficient in the local sense should look for improvement in their processes and scales with other benchmarks.) DMU_4, DMU_5 and DMU_{12} are not efficient in terms of CCR (Global technical efficiency). However, they are efficient in terms of BCC. It may be reached the conclusion that inefficiency in these units is due to inefficiency in scale size, i.e., due to disadvantageous conditions. DMU_1, DMU_2, DMU_3, DMU_8, DMU_9, DMU_{10}, DMU_{15}, DMU_{16}, DMU_{18}, DMU_{19}, DMU_{21}, DMU_{23}, DMU_{24}, DMU_{25} and DMU_{26} are efficient in terms of neither CCR nor BCC. These units are poor in terms of both scale efficiency and local pure technical efficiency. These units should make improvement input and output factors that are under the control of decision makers. In addition to calculating global technical efficiency, reference unit groups have been specified by CCR analysis for inefficient units that have been determined in the sense of global technical efficiency. Also, coefficients are presented to determine the target values for input variables. Reference groups and coefficients are shown in Table 7.

Table 7. Inefficient DMUs, Coefficients and Reference Groups

Inefficient DMU No	Obtained Coefficients and Reference Groups by Using CCR
1	7(0,09) 11(0,24) 17(0,02)
2	7(0,09) 17(0,38) 20(0,52)
3	7(0) 11(1,08) 17(0,10)
4	13(0,21) 14(0,08) 17(0,03)
5	7(0,03) 11(0,02) 17(0,03) 20(0,04)
8	7(1) 11(0,14) 17(1,79)
9	14(0,43) 17(0)
10	11(0,14)
12	7(0,36) 11(1,26) 17(0,35)
15	7(0,01) 11(0,01) 17(0,20) 20(0,11)
16	7(0,39) 11(0,06) 17(0,07)
18	7(0,02) 11(0,01) 17(0,03)
19	7(0,22) 11(0,12) 20(0,18)
21	17(0,32)
23	7(0,05) 11(0,04) 17(0,20)
24	7(0,26) 11(0,02) 17(0,22)
25	7(0,02) 17(0,21) 20(0,45)
26	7(0,05) 11(0,06) 17(0,21)

Target values can be found with the help of reference groups and coefficients for input and output factors of inefficient units.

For example, according to Table 6, target value of number of academic staff that is one of input factors of DMU_{18} which has the lowest CCR efficiency score (0,0815) can be calculated as below taking DMU_7, DMU_{11} and DMU_{17} into account;

Target value of academic staff for 18.DMU = AS_{18}

$$\begin{aligned} AS_{18} &= AS_7\,(0,05) + AS_{11}\,(0,04) + AS_{17}\,(0,20) \\ &= 112(0,05)+97(0,04)+12(0,20) \\ &= 11,88 \approx 12 \end{aligned} \tag{4}$$

DMU_{18} should reduce number of academic staff from 74 to 12. Improvement ratio for number of academic staff of DMU_{18} can be found as below;

$$\text{I.R.} = (74 - 12)/74 \approx 0,83 \tag{5}$$

From this point of view, it can be interpreted that decision makers of DMU_{18} should make improvement about %83 in number of academic staff. Target values and improvement ratios can be calculated similarly for other input and output factors.

4. Results and Conclusion

Data envelopment analysis (DEA), which has been developed to measure the effectiveness of economic decision-making units (DMU) that referred to as decision making units and similar in terms of their products or services, is an efficiency measurement technique without parameters. This technique ensures to define how existing sources can be used effectively to create the outputs of DMU.

DEA is a nonparametric method of measuring the efficiency of a DMU such as a firm or a public sector agency, first introduced into the Operation Research literature by Charnes, Cooper and Rhodes (CCR). The original CCR model was applicable only to technologies characterized by constant returns to scale globally. In what turned out to be a major breakthrough, Banker, Charnes, and Cooper (BCC) extended the CCR model to accommodate technologies that exhibit variable returns to scale (Ray, 2004).

Global technical efficiency score by input oriented CCR analysis, local pure technical efficiency score by input oriented BCC analysis and scale efficiency score for each DMUs by proportioning of these values were calculated. To find efficiency scores of relative efficient units and sort these units, analysis were done using the super efficiency module which allow that efficiency score is higher than 1. Some units are poor in terms of both scale efficiency and local pure technical efficiency.

In this study, input oriented method has been preferred because input factors could be controlled by decision makers in university. By means of obtained results, inefficient units can be attained more efficient structure by way of change that decision makers will have on inputs. It is clear that improvement which will be made in inputs will or affects positively the value of on the number of publications and number of graduate students which are important for all units of the university. Units can do a similar analysis with different input and output factors that are important for them. However, it should be noted that this study is a relative efficiency analysis. The university units should keep under control their processes and progress with improvement specifying target values on input-output factors by means of benchmark or other similar ways even if the result of the similar analysis show that they are efficient.

In this study, we analyzed the data of different units of Dokuz Eylül University. We used the data of the year 2012. However, improvements about processes, target values and target attainment rates can be determined better (truer, optimal) for each unit by using previous years' data. By doing so, the analysis include not only for one year but also longer period of time and can determine more realistic results.

In conclusion, relative efficiency analysis of units of Dokuz Eylül University which is a non-profit organization has been done by using data envelopment analysis in this study. This offered model to get efficiency scores of university units can be useful for universities. By using this model, decision makers of universities could take reliable decisions.

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