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Health Efficiency Measurement In Turkey By Using Data Envelopment Analysis

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Özet: A performance indicator of the relative activity measurements are classified into two groups, parametric and nonparametric methods. Nonparametric methods measure the distance between the value of the efficiency obtained from the calculation and the distance from the efficiency limit by using techniques of linear programming. Data Envelopment Analysis (DEA) which is frequently used in nonparametric measurement methods. Data Envelopment Analysis is a method used to measure the relative effectiveness of economic or non-profit organizations that convert the input called the decision-making unit into output. In this study, health performances of provinces were examined by using statistical yearbook published by Ministry of Health. CCR and BCC models, which are the basic models of data envelopment analysis, were examined according to the cases of constant returns to scale and variable returns to scale.

Keywords: Data Envelopment Analysis, Health performance, Efficiency, Turkey

1 Introduction

The main problem of many countries is the limited resources to meet the needs of the growing population. Therefore, it is very important to use the resources in the most appropriate way and to obtain the maximum output. The ability to use resources effectively determines the level of productivity. Being productive has become important for the health sector like other sectors. As it is known, hospitals have high input costs. There is intense competition in the health services market. In this competitive environment, hospitals need to reduce their costs and get more output in order to survive. In such a case, the efficiency levels of the hospitals should be determined and the input variables that should be reduced and the output variables that should be increased should be determined if they are below the effective limit. The desire to be productive and efficient production is not only the problem of the undeveloped and developing countries. Especially in health systems and health institutions, most of the efforts to increase efficiency are carried out by developed countries. Evaluating health institutions in terms of efficiency has a very recent history. The number of studies in this field is rapidly increasing in order to examine the health performances of countries and formulate the necessary health policies. Due to the unique characteristics of health services, the number of inputs and outputs is quite high. In addition, these input and output factors do not have the same unit of measurement. Data Envelopment Analysis (DEA), which is a parameterless method, was used to analyze all these variables together, to make comparisons, to determine the most effective, and to determine what should be done for those who fall below the effective limit. DEA is a technique that determines the efficiency levels of decision-making units with similar characteristics according to the input and output amounts. DEA is applied in healthcare institutions, military areas, schools, banks and similar institutions. DEA limits the most effective decision-making unit and evaluates other decision-making units according to this limit. With DEA program, it is possible to calculate which variable to change in order to become effective. In this context, efficiency levels of public hospital associations, factors causing inefficiency and the steps to be effective for those who are below the effective limit have been determined. Therefore, in this study, it is aimed to calculate the most appropriate input composition to be used in DEA using health indicators of our provinces. As a model; Data-Envelopment Analysis's input-oriented model is used under the assumption of variable returns to scale. The aim of the study is to determine which variables should be used more effectively in the health variables of the provinces and the necessary health performance policy.

2 Data envelopment analysis

If there are more than one decision points for a decision maker, it is important to estimate the efficiencies of these decision points and to shape the decision based on these efficiencies. Indeed the efficiency ranking of the decision points are important for the decision maker and the decision maker wants to know how scenarios that will increase the efficiency of decision points of those with less efficiency than the others will affect the overall efficiency of the decision. Here, the Data Envelopment Analysis can be defined as a linear programming-based method that utilizes similar inputs to obtain an output or outputs to evaluate the relative efficiency of responsible decision points. The primary characteristic that sets the Data Envelopment Analysis apart from other similar purpose methods is that it enables evaluation in cases where there are many inputs and outputs. As a result of the analysis, information regarding the efficiency value of each decision point, how to increase the efficiency of decision points that are not efficient using which input/output ratios (scenarios), and decision points that can be used as a reference are obtained.

The Data Envelopment Analysis first took form in 1957 by Farrell with the Boundary Production Function suggestion that was put forward in reply to the Mean Performance scale [1]. Based on Farrell's piecewise linear convex envelopment approach to effective boundary predictions, Charnes, Cooper and Rhodes introduced the Data Envelopment Analysis (DEA) technique to the literature with their study in 1978 [2]. Linear programming is a mathematical technique that aims to determine the most optimal out of the different alternatives for the efficient use of limited resources for a certain objective. This technique is used more often in the solution of optimal resource distribution problems.

DEA, which is a mathematical programming based approach, is a method based on linear programming principles that is used to transform the input also known as a decision making unit (DMU) to an output and to measure the relative efficiency of establishments or financial institutions [3]. DEA is a linear programming process that can be defined as the boundary analysis of multiple inputs and multiple outputs. The process requires no prior determination of weighting for the inputs and outputs, and aims to determine the efficient and inefficient decision making units. In the method, which is based on the distribution of weights to the inputs and outputs of each individual DMU, after the weights have been determined the calculated efficiency scores of the DMU's cannot exceed 1.

DEA is a non-parametric linear programming based technique. In DEA, an assumption regarding the production function is not required as in parametric methods. Another feature is that it considers the boundaries rather than the central tendency; meaning that DMU's are compared not with units with mean efficiency values but rather units with full efficiency.

Data Envelopment Analysis is a very effective tool when used correctly. The advantages of Data Envelopment Analysis can be listed as follows:

- Data Envelopment Analysis is capable of processing multiple inputs and multiple outputs.
- Data Envelopment Analysis does not require a functional form that associates inputs and outputs, except for the linear form.
- With Data Envelopment Analysis, decision-making units whose activities are calculated are compared to those with relatively full effectiveness.
- Inputs and outputs may have very different units. In this case, it is not necessary to use various assumptions and make transformations in order to measure them in the same way.

Disadvantages of Data Envelopment Analysis can be listed as follows:

- Data Envelopment Analysis is very sensitive to measurement error.
- Data Envelopment Analysis is sufficient to measure the performance of decision points, but does not provide clues about the interpretation of this assessment on the basis of absolute effectiveness.
- Since Data Envelopment Analysis is a non-parametric technique, it is difficult to apply statistical hypothesis tests to the results.
- Since a separate linear programming model is required for each decision point, the solution of large-scale problems with Data Envelopment Analysis can be time consuming in terms of calculation.

2.1 *Application phases of the data envelopment analysis*

The main phases in the implementation of the Data Envelopment Analysis is as given below:

2.1.1 Selection of decision making units: A decision making unit is defined as a unit that analyzes the efficiency of homogenous elements such as businesses, institutions, companies and establishments that, in the DEA, produce similar outputs by use of similar inputs. Two factors affect the selection of DMU's. The first of these are that DMU's must be homogenous units that have similar aims and undertake the same task. The other is the number of DMU's. According to Ramanathan [4], the number of DMU's must be at least 2 or 3 times the total number of input and outputs. Another view states that there must be at least $m + s + 1$ DMU's, where m is number of inputs, s is the number of outputs. The number of DMU's is dependent on the aim of the DEA study. If the number of DMU's increases, the number of DMU's that determine the effective boundary also increases.

2.1.2 Selection of inputs and outputs: Input can be stated as the necessary personnel, consumable resources, capital and cash necessary for any economic or institutional system to perform its services or to enable production. Output is the products and services that result from the projects and activities of the system in question.

One of the most frequently encountered problems in the implementation of the DEA is the selection of the inputs and outputs. The selection of input and outputs are related to the personal perspective of the decision maker, there are no special rules defined for the selection of input and outputs. However, there are certain suggested rules. First of all, the input and outputs relevant to the study must be extensively listed. Subsequently, input and outputs of appropriate levels must be selected and integrated to the variable solution system. The decomposition ability of the DEA increases as a result of this process. Another problem that is encountered in the selection of input and outputs is the classification of which variable is to be an input and which variable is to be an output. Additionally, a variable can be both an input and an output. In this case, one way of variable classification is related to whether the variable in question increases the DMU's performance or not. If the variable in question increases the performance of the DMU it is used as an output, otherwise it is used as an input.

2.1.3 Selection of the data envelopment analysis model: After the selection of DMU's, inputs and outputs, the decision maker must select the DEA model most suited according the data structure and production planning. If there are uncontrollable input factors, it is more appropriate to prefer the output oriented models in which the amount of input is constant. On the other hand, if the outputs are not selected to show the best performance but rather determined according to the objectives of the decision maker, it is more appropriate to select input oriented models in which the amount of output is constant. If the inputs and outputs are desired to be specifically determined in the analysis, then the multiplicative models must be used; if the relationship between DMU's are desired to be determined, the envelopment models must be used. Another model selection criterion is whether the performance of the DMU's are dependent on the economy of scale. If the performance of the DMU's are not dependent on the economy of scale, the assumption of constant return to scale is appropriate. In other situations, variable return to scale is more appropriate.

2.1.4 Measurement of efficiency with the data envelopment analysis model: After the most appropriate DEA model for the observation set is determined, the selected model is solved for each DMU and the results regarding the efficiency values, idle variable values and the reference DMU's consisting of the efficient DMU's are obtained. The efficiency value for each DMU is between 0 and 1. The DMU's whose efficiency score is equal to 1 form the best group of the implementation.

2.1.5 Determination of the reference set: In DEA, the DMU's are compared with each other and the efficient and inefficient DMU's are determined. The set that consists of the efficient units is called the reference set. The main assumption in DEA, is that inefficient DMU's try to regularly regulate resource consumption and become efficient by taking reference to efficient DMU's. The strength of the efficient DMU's that are in the reference set is dependent on how much these units are taken reference by inefficient units.

2.1.6 Determining an objective for inefficient decision making units: Determining an objective for inefficient DMU's in order to make them efficient is one of DEA's important features. These objectives are defined as the weighted mean of the inefficient DMU's and the efficient DMU's that make up the reference set.

2.1.7 Evaluating the results of the model: As a result, a general evaluation is done considering the entire input and outputs for each DMU.

2.2 Data envelopment analysis models

DEA is a combination of ideas, thoughts and methods that are intertwined with several models. Charnes Cooper Rhodes (CCR) and Banker Charnes Cooper (BCC) models are the main two models of this method. These models can be studied in two groups as "input oriented" and "output oriented". Input and output oriented DEA models are very similar in principle. Input oriented DEA models investigate the most optimal combination of inputs in order to produce a determined output combination in the most efficient way. Output oriented DEA models investigate the highest obtainable output combination from a determined input combination.

2.2.1 Charnes, Cooper, Rhodes (CCR) models: It is the model developed by Charnes, Cooper and Rhodes in 1978 [2]. It forms the basis of the DEA. The analysis is conducted under the assumption of constant return to scale. This model makes a general evaluation of total efficiency. The total efficiency value; consists of technical efficiency and scale efficiency.

The objective function and constraints of the input oriented CCR model is as follows:

$$E_k = \max \sum_{r=1}^{s} u_r y_{rk}$$

s.t.

$$\begin{aligned}
&\sum_{i=1}^{m} v_i x_{ik} = 1 \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \quad (j = 1, \ldots, n) \\
&u_1, u_2, \ldots, u_s \geq 0 \\
&v_1, v_2, \ldots, u_m \geq 0
\end{aligned}$$

The scores obtained from the solving of the model are the relative efficiency scales. This score being 1 means that the DMU whose efficiency is being analyzed is efficient, and the score being less than 1 means that the DMU is not efficient.

The inefficient DMU is rendered efficient in order to match the DMU's that make up the reference set. As forming reference sets in this model is difficult, the enveloping model, meaning a dual model is developed. The use of which and what amount of input and/or output for the DMU studied is observed in the enveloping model. Additionally in this method, the determination of the reference set is easier in comparison to the weighted method.

The objective function and constraints of the input oriented envelopment CCR model is provided below:

$$E_k = \min \alpha - \varepsilon \sum_{i=1}^{m} s_i^- - \varepsilon \sum_{i=1}^{s} s_r^+$$

s.t.

$$\begin{aligned}
&\sum_{j=1}^{n} X_{ij}\lambda_j + s_i^- - \alpha X_{ik} = 0, \quad i = 1, 2, \ldots, m \\
&\sum_{j=1}^{n} Y_{rj}\lambda_j - s_r^+ - Y_{rk} = 0, \quad r = 1, 2, \ldots, s \\
&\lambda_j \geq 0, j = 1, 2, \ldots, n \\
&s_i^- \geq 0, i = 1, 2, \ldots, m \\
&s_r^+ \geq 0, I = 1, 2, \ldots, s
\end{aligned}$$

Here;
α: contraction coefficient that determines how much the inputs of can be reduced for DMU k whose relative efficiency is being measured
λ_j: density value for DMU j
s_i^-: residual value for input i of DMU k
s_r^+: residual value for output r of DMU k

If the evaluated DMU is efficient, the relative efficiency level $E_k = 1$, no changes are made in the input and output vectors $\left(\alpha = 1, s^- = 0, s^+ = 0\right)$. Additionally it is found in its own reference set and $\lambda_k = 1$. If the evaluated DMU is inefficient, the contraction coefficient α that determines the level of efficiency is less than 1. This means that the input vectors can be reduced radially.

Output oriented CCR model

It investigates the highest amount of output attainable from a determined input combination. Ek being equal to 1 means that DMU k is efficient, whereas being greater than 1 means that it is inefficient.

The objective function and constraints of the output oriented CCR model is provided below:

$$E_k = \min \sum_{i=1}^{m} v_i x_{ik}$$

s.t.

$$\begin{aligned}
&\sum_{r=1}^{S} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \quad (j = 1, \ldots, n) \\
&\sum_{r=1}^{s} u_r y_{rk} = 1 \\
&u_1, u_2, \ldots, u_s \geq 0 \\
&v_1, v_2, \ldots, v_m \geq 0
\end{aligned}$$

As the identification of the reference sets for inefficient DMU's in this model is time-consuming, the envelopment model has been developed. The output oriented CCR envelopment model is obtained by taking the duality of the output oriented DEA model. With the help of this model, it is easy to determine which inefficient DMU's leave residuals in their inputs and outputs and define the DMU's that the inefficient DMU must refer to in order to become efficient.

$$E_k = \max \beta + \varepsilon \sum_{i=1}^{m} s_i^- + \varepsilon \sum_{r=1}^{s} s_r^+$$

s.t.

$$\begin{aligned}
&\sum_{j=1}^{n} x_{ij} \lambda_j + s_i^- - x_{ik} = 0, \quad i = 1, 2, \ldots, m \\
&\sum_{i=1}^{n} y_{rj} \lambda_j - s_r^+ - \beta y_{rk} = 0, \quad r = 1, 2, \ldots, s \\
&\lambda_j \geq 0, \quad j = 1, 2, \ldots, n \\
&s_i^-, s_r^+ \geq 0
\end{aligned}$$

Here;
β: expansion coefficient that determines how much the outputs of can be increased for DMU k whose relative efficiency is being measured
λ: density value for DMU j
s_i^-: residual value for input i. of DMU k
s_r^+: residual value for output r. of DMU k

If the evaluated DMU is efficient, the relative efficiency level E_k is equal to 1. The efficiency level of inefficient DMU's are greater than 1. If the measured DMU is inefficient, the expansion coefficient β that determines the level of efficiency is greater than 1. This means that the output vectors can ben increased radially.

2.2.2 Banker, Charnes, Cooper (BCC) models: This model, which was put forward by R.D. Banker, A. Charnes and W.W. Cooper in 1984 and is depicted with the first letters of the surnames of these people, is based on the assumption of variable return to scale [5]. A return to scale type can also be identified for all DMU's using the BCC model. The BCC boundary is always below the CCR boundary. Therefore the CCR efficiency value is equal to or less than the BCC efficiency value.

The only difference of the BCC model from the CCR model is that under the variable return to scale assumption, the total sum of the λ_j values (the value that provides the necessary information to establish the possible efficient input output combination for an inefficient decision point) obtained from the solution of the linear program for each DMU is equal to 1 [5]. The BCC model is formed by placing the u0 variable in the input oriented model and v0 variable in the output oriented model of the CCR model. Due to the u0 and v0 variables, the BCC model is based on the assumption of variable return to scale.

Input oriented BCC model

$$E_k = \max \sum_{r=1}^{s} u_r y_{rk} - u_0$$

s.t.

$$\sum_{i=1}^{m} v_i x_{ik} = 1$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_0 \leq 0, \quad j = 1, \dots, n$$
$$u_1, u_2, \dots, u_s \geq 0$$
$$v_1, v_2, \dots, v_m \geq 0$$
$$u_0, \text{ free}$$

The input oriented BCC envelopment model is obtained with the mathematical formulation given below by taking the duality of the input oriented weighted model. Additionally as u_0 is in the objective function of the input oriented weighted BCC model, the input oriented envelopment BCC model has a $\sum_{j=1}^{n} \lambda_j = 1$ convexity constraint.

$$E_k = \min \alpha - \varepsilon \sum_{i=1}^{m} s_i^- - \varepsilon \sum_{r=1}^{s} s_r^+$$

s.t.

$$\sum_{i=1}^{n} x_{ij} \lambda_j + s_i^- - \alpha x_{ik} = 0$$
$$\sum_{j=1}^{n} y_{rj} \lambda_j - s_r^+ - y_{rk} = 0$$
$$\sum_{j=1}^{n} \lambda_j = 1$$
$$\lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0$$

As a result of solving this model, if the DMU in question is efficient, the relative efficiency measure E_k is equal to 1, and no change is made to the input and output vectors $\left(\alpha = 1, s^- = 0, s^+ = 0\right)$. Additionally it is found in its own reference set and $\lambda_k = 1$. If the evaluated DMU is inefficient, the contraction coefficient α that determines the level of efficiency is less than 1. This means that the input vectors can be reduced radially.

Output oriented BCC model

$$E_k = \min \sum_{i=1}^{m} v_i x_{ik} - v_0$$

s.t.

$$\sum_{r=1}^{s} u_r y_{rk} = 1$$
$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{i=1}^{s} u_r y_{rj} - v_0 \geq 0, \quad j = 1, \dots, n$$
$$u_1, u_2, \dots, u_s \geq 0$$
$$v_1, v_2, \dots, v_m \geq 0$$
$$v_0, \text{ free}$$

The output oriented envelopment BCC model is obtained with the mathematical formulation given below by taking the duality of the output oriented weighted model.

Additionally as v_0 is in the objective function of the output oriented weighted BCC model, the input oriented envelopment BCC model has a $\sum_{j=1}^{n} \lambda_j = 1$ convexity constraint.

The output oriented envelopment BCC model is given below:

$$E_k = \max \beta + \varepsilon \sum_{i=1}^{m} s_i^- + \varepsilon \sum_{r=1}^{s} s_r^+$$

Inputs	Total number of doctors	Number of nurses	The number of other health staff
Outputs	Number of operations	Bed occupancy rate	Crude death rate

Tablo 1 Input and Output Variables

Provinces	CCR Score	BCC Score	Provinces	CCR Score	BCC Score
Adana	0,9025	0,9423	Konya	0,7953	0,8094
Adıyaman	0,5188	0,5202	Kütahya	0,7668	0,8256
Afyonkarahisar	0,8071	0,8083	Malatya	0,7779	0,7785
Ağrı	0,5758	0,6242	Manisa	0,6839	0,807
Amasya	0,769	0,8055	Kahramanmaraş	0,746	0,747
Ankara	0,7658	0,9363	Mardin	0,7393	0,7415
Antalya	0,8821	0,9281	Muğla	0,5704	0,5795
Artvin	0,8279	0,961	Muş	0,6378	0,6968
Aydın	0,7124	0,7135	Nevşehir	0,8652	0,879
Balıkesir	0,7941	**1**	Niğde	0,5884	0,5886
Bilecik	0,8811	**1**	Ordu	0,9515	0,9544
Bingöl	0,5299	0,5795	Rize	0,8468	0,8481
Bitlis	0,8643	0,8755	Sakarya	0,8252	0,8262
Bolu	0,7576	0,7605	**Samsun**	0,7808	**1**
Burdur	0,8542	0,8638	Siirt	0,7006	0,7451
Bursa	0,7805	**1**	Sinop	0,8983	0,9662
Çanakkale	0,7023	0,7027	Sivas	0,595	0,5951
Çankırı	0,8736	**1**	Tekirdağ	0,8351	0,8428
Çorum	0,5532	0,6014	Tokat	0,7016	0,7022
Denizli	0,911	0,9142	Trabzon	0,7382	0,7451
Diyarbakır	0,6618	0,664	Tunceli	0,7244	0,9394
Edirne	0,7022	0,7042	Şanlıurfa	0,8879	0,8948
Elazığ	0,6308	0,6396	Uşak	0,9293	0,9495
Erzincan	0,6824	0,6838	Van	0,7028	0,7224
Erzurum	0,9384	0,94	Yozgat	0,4472	0,4545
Eskişehir	0,8442	0,8512	Zonguldak	0,7892	0,7908
Gaziantep	**1**	**1**	Aksaray	0,8955	0,9049
Giresun	0,6793	0,6904	**Bayburt**	**1**	**1**
Gümüşhane	0,8644	**1**	Karaman	0,9255	0,9377
Hakkari	0,6728	0,7536	Kırıkkale	0,7648	0,783
Hatay	0,833	0,8402	Batman	0,9849	0,9865
Isparta	0,8846	0,8992	Şırnak	0,7549	0,791
Mersin	0,7709	0,7754	**Bartın**	0,9629	**1**
İstanbul	**1**	**1**	**Ardahan**	**1**	**1**
İzmir	0,7695	0,9687	Iğdır	0,777	0,8799
Kars	0,6599	0,6942	**Yalova**	**1**	**1**
Kastamonu	0,6709	0,761	Karabük	0,8075	0,8591
Kayseri	0,7186	0,7194	Kilis	1	1
Kırklareli	0,6395	0,6489	Osmaniye	0,9743	0,9777
Kırşehir	0,5448	0,5572	Düzce	0,9263	0,9365
Kocaeli	0,762	0,8276			

Tablo 2 Efficiency Scores

s.t.

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- - x_{ik} = 0$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ - \beta y_{rk} = 0$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0$$

If the evaluated DMU is efficient, the relative efficiency level E_k is equal to 1. The efficiency level of inefficient DMU's are greater than 1. If the measured DMU is inefficient, the expansion coefficient β that determines the level of efficiency is greater than 1. This means that the output vectors can ben increased radially.

The efficiency values in the BCC model are equal or greater than the CCR model. The reason for this is that the BCC model obtains a local technical efficiency value, whereas the CCR model obtains a general technical efficiency value.

Provinces	Input Reduction Rate	Reference Province and Reference Rate	Provinces	Input Reduction Rate	Reference Province and Reference Rate
1	0.05	27 (0,94) 34 (0,03) 77 (0,03)	42	0.19	27 (0,99) 34 (0,01)
2	0.47	27 (0,07) 79 (0,93)	43	0.17	27 (0,09) 77 (0,76) 79 (0,15)
3	0.19	27 (0,23) 79 (0,77)	44	0.22	27 (0,40) 79 (0,60)
4	0.38	27 (0,01) 79 (0,99)	45	0.19	10 (0,24) 27 (0,22) 34 (0,01) 55 (0,13) 77 (0,40)
5	0.19	27 (0,03) 77 (0,29) 79 (0,68)	46	0.25	27 (0,36) 79 (0,64)
6	0.06	27 (0,39) 34 (0,42) 77 (0,19)	47	0.25	27 (0,16) 79 (0,84)
7	0.07	27 (0,91) 34 (0,04) 77 (0,05)	48	0.42	27 (0,27) 69 (0,66) 77 (0,07)
8	0.03	11 (0,46) 69 (0,20) 74 (0,01) 77 (0,33)	49	0.30	27 (0,01) 79 (0,99)
9	0.29	27 (0,39) 69 (0,18) 77 (0,43)	50	0.12	27 (0,02) 79 (0,98)
12	0.42	69 (0,45) 79 (0,55)	51	0.41	27 (0,02) 69 (0,53) 77 (0,05) 79 (0,40)
13	0.13	27 (0,05) 79 (0,95)	52	0.04	27 (0,30) 77 (0,06) 79 (0,65)
14	0.24	27 (0,05) 77 (0,46) 79 (0,49)	53	0.16	27 (0,04) 77 (0,76) 79 (0,20)
15	0.13	27 (0,02) 79 (0,98)	54	0.17	27 (0,28) 69 (0,05) 77 (0,67)
17	0.29	27 (0,11) 77 (0,81) 79 (0,08)	56	0.26	27 (0,02) 79 (0,98)
19	0.40	27 (0,04) 77 (0,63) 79 (0,33)	57	0.03	69 (0,49) 77 (0,35) 79 (0,15)
20	0.09	27 (0,53) 69 (0,23) 77 (0,24)	58	0.40	27 (0,17) 69 (0,05) 77 (0,51) 79 (0,28)
21	0.34	27 (0,53) 79 (0,47)	59	0.15	27 (0,31) 69 (0,38) 77 (0,31)
22	0.30	27 (0,11) 77 (0,30) 79 (0,59)	60	0.29	27 (0,15) 79 (0,85)
23	0.36	27 (0,20) 79 (0,80)	61	0.25	27 (0,40) 77 (0,22) 79 (0,38)
24	0.31	27 (0,04) 69 (0,91) 77 (0,04)	62	0.06	69 (1,00)
25	0.06	27 (0,47) 79 (0,53)	63	0.10	27 (0,53) 79 (0,47)
26	0.15	27 (0,46) 77 (0,22) 79 (0,32)	64	0.05	27 (0,08) 77 (0,28) 79 (0,64)
28	0.31	27 (0,07) 77 (0,13) 79 (0,80)	65	0.28	27 (0,25) 79 (0,75)
30	0.25	69 (0,60) 79 (0,40)	66	0.55	27 (0,03) 79 (0,97)
31	0.16	27 (0,59) 77 (0,29) 79 (0,12)	67	0.21	27 (0,21) 77 (0,24) 79 (0,55)
32	0.10	27 (0,26) 77 (0,29) 79 (0,45)	68	0.09	27 (0,05) 79 (0,95)
33	0.23	27 (0,65) 77 (0,21) 79 (0,14)	70	0.06	27 (0,02) 79 (0,98)
35	0.03	10 (0,02) 34 (0,31) 77 (0,67)	71	0.21	27 (0,08) 69 (0,52) 77 (0,40)
36	0.31	27 (0,05) 69 (0,95)	72	0.01	27 (0,17) 79 (0,83)
37	0.24	69 (0,06) 77 (0,94)	73	0.21	27 (0,04) 69 (0,18) 79 (0,79)
38	0.28	27 (0,58) 79 (0,42)	76	0.12	69 (0,90) 79 (0,10)
39	0.35	27 (0,06) 69 (0,65) 79 (0,29)	78	0.14	27 (0,02) 77 (0,41) 79 (0,58)
40	0.44	27 (0,01) 69 (0,80) 77 (0,20)	80	0.02	27 (0,14) 79 (0,86)
41	0.17	10 (0,15) 16 (0,09) 27 (0,56) 55 (0,09) 77 (0,11)	81	0.06	27 (0,11) 69 (0,71) 77 (0,18)

Tablo 3 Inefficient Provinces, Their Input Variable Reduction Rates and the Provinces They Must Take as Reference

3 Application

This study consists of the annual health statistics of 2017 whose data sets are published by the Ministry of Health [6]. The aim of the study is to measure health performance using health statistics of Turkey. The data set is comprised of 81 provinces. The data envelopment analysis of the provincial health performance was done with the EMS program. The input oriented BCC model of the Data Envelopment Analysis was used.

The input and output variables used in the study are provided in Table 1.

Table 2 gives the total (CCR) and technical (BCC) efficiency scores of the provinces. Provinces that are efficient in CCR are also efficient in BCC. According to the CCR model, 6 provinces (Gaziantep, İstanbul, Bayburt, Ardahan, Yalova and Kilis); and according to the BCC model 13 provinces (Balıkesir, Bilecik, Bursa, Çankırı, Samsun, Bartın In addition, Table 2 shows how much inactive provinces should reduce each input. For example; Ankara needs to reduce its inputs by 7% in order to become active (given the BCC score). The mean efficiency score of the provinces was 0.82. The province with the lowest activity score and the farthest from the activity limit was Adıyaman. In order for Adıyaman to be active, its inputs must be reduced by 48%. Because the outputs obtained in response to the inputs used do not meet each other. Gümüşhane, Gaziantep, İstanbul, Bayburt, Ardahan, Yalova and Kilis) were found to be efficient.

It is possible to increase the efficiency levels of provinces that were not found to be efficient by saving on the inputs or by increasing the output levels. Information regarding the over-consumed input ratios of provinces and the level an inefficient province should take reference from which efficient province is provided in Table 3. Additionally, the last column of Table 3 gives the provinces that the inefficient provinces should take reference from.

4 Result

In this study was applied by selecting data envelopment analysis method which is one of the most widely used performance measurement methods, which can measure multiple input and output variables and carry the analysis results of decision making units to numerical values. DEA enables health managers to view production and service processes and make more effective decisions by using existing input and output variables. As a result of the analysis with DEA, the amount of input variables that are required to decrease the input variables were determined in order to become effective in the provinces below the efficiency limit. It has been determined which active provinces should take reference as well as the actions that inefficient provinces need to do in order to become effective.This study aims to evaluate the health performance of our provinces and the Data Envelopment Analysis method which is one of the non-parametric measurement methods is used. It was concluded that many of our provinces are not at a good level in terms of health performance. In terms of technical efficiency, 13 provinces were efficient whereas 68 provinces were below the efficiency limit and the mean was determined to be 0.82. As the input oriented model was preferred to evaluate performance, the conclusion was that the input variables used in the model must be reduced by an average of 0.17. Although the low amount of resources allocated to the Turkish health sector is known and accepted, this study has revealed the importance of resource consumption in hospitals and the necessity that they must be examined. Proper employment policies, managers placing emphasis on optimal use of resources and an effective auditing mechanism will prevent the wasting of resources. Finally, our recommendation; the efficiency levels of health care providers should be continuously examined by the Ministry of Health and related persons and organizations. The reasons for ineffectiveness should be identified and preventive actions should be initiated. It depends on the correct acquisition of activity and financial data in order to make accurate performance measurements in health institutions. Although the data is collected and analyzed regularly, these data must be properly analyzed and have the human resources to take the necessary steps.

5 Kaynaklar

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