EVALUATION OF HEALTH EFFICIENCY OF OECD COUNTRIES WITH DATA ENVELOPMENT AND INVERSE DATA ENVELOPMENT ANALYSES

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Abstract

In the present study, the purpose was to evaluate the health effectiveness of the Organization for Economic Development and Co-operation (OECD) countries, including Turkey, with input-oriented DEA and inverse DEA models. The input and output variables were determined by examining the studies in the literature. In this respect, the input variables were identified as the number of physicians per thousand people, the number of hospital beds per thousand people, health expenditure per capita; and output variables were expected life expectancy at birth, and rate of surviving infants. According to the DEA results, only Turkey, Mexico and Colombia were found to be efficient. In addition, the input variable which affects at most the health efficiency scores of countries was determined as the number of physicians. According to the findings of the inverse DEA obtained in the study, it was determined that the current number of physicians in Turkey was sufficient, and that the healthcare expenditure per person and the number of hospital beds should be increased.

Keywords: *OECD Countries, Data Envelopment Analysis, Inverse Data Envelopment Analysis, Resource Allocation.*
JEL Classification: *C61, I115,O57*

OECD ÜLKELERİNİN SAĞLIK ETKİNLİKLERİNİN VERİ ZARFLAMA VE TERS VERİ ZARFLAMA ANALİZLERİ İLE DEĞERLENDİRİLMESİ

Öz

Bu çalışmada 2018 yılı için Türkiye'nin de içinde bulunduğu Ekonomik Kalkınma ve İşbirliği Örgütü (OECD) ülkelerinin sağlık alanındaki etkinliklerinin girdi yönlü DEA ve ters DEA modelleri ile değerlendirilmesi amaçlanmıştır. Girdi ve çıktı değişkenleri literatürdeki çalışmalar incelenerek belirlenmiştir. Buna göre girdi değişkenleri bin kişi başına düşen hekim sayısı, bin kişi başına düşen hastane yatağı sayısı, kişi başına düşen sağlık harcaması, çıktı değişkenleri ise doğumda beklenen yaşam süresi ve hayatta kalan bebek oranıdır. DEA sonuçlarına göre sadece Türkiye, Meksika ve Kolombiya etkin bulunmuştur. Ayrıca ülkelerin sağlık etkinlik puanlarını en fazla etkileyen girdi değişkeni doktor sayısı olarak belirlenmiştir. Elde edilen ters DEA bulgularına göre ise doğumda yaşam beklentisi ve bebek hayatta kalma oranı değerlerinin örneklemdeki en iyi değerlere yükseltilmesi için Türkiye'nin mevcut doktor sayısının yeterli olduğu, kişi başı sağlık harcamasının ve hastane yatak sayısının ise arttırılması gerektiği ortaya koyulmuştur.

Anahtar Kelimeler: *OECD Ülkeleri, Veri Zarflama Analizi, Ters Veri Zarflama Analizi, Kaynak Tahsisi.*
JEL Sınıflandırması: *C61, I115,O57*

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1. Introduction

One of the sub-dimensions of human capital, which is one of the indicators of development, is health. For this reason, health effectiveness is one of the main factors in achieving sustainable development, as one of the most important research issues for researchers and policymakers. The effectiveness of a healthcare system can be defined based on how well physical and financial resources are used to produce health-related outcomes.

The resources allocated for healthcare are constantly increasing in most countries; however, the improvement in health outcomes is at a slower level (OECD, 2014). In other words, there are criticisms that resources are not used effectively at adequate levels. In addition to obtaining maximum outputs with available resources in effectiveness measurement, obtaining targeted output with minimum resources can also be used as a measurement method. For this purpose, Data Envelopment Analysis (DEA) is a widely used analysis method.

DEA, which is based on linear programming, was developed by Charnes, Cooper and Rhodes (CCR) (1978). CCR was developed under the assumption of constant return according to the scale (CRS), aimed at measuring the relative efficiency of systems producing similar goods or services, which are called Decision Making Unit (DMU). The CCR method measures the relatively total factor effectiveness of DMU when there are too many input-output variables with different measurement units. In the literature, CCR is widely used in evaluating the performance of various DMU's like schools, hospitals, banks, companies, etc.

Unlike CCR, systems that have VRS in real life are also very common. Banker, Charnes and Cooper (1984) developed a model that revised the CCR model by considering the VRS status. This model is simply called BCC.

DEA is highly sensitive to the changes in input and output variables since the efficient frontier of production possibility set will changes. An important problem that arises here is how to maintain the efficiency score of DMU when changes occur in the input-output set in the short term. These problems, which are also known as the reallocation of resources in the literature, are treated as inverse optimization problems, and system parameters are recalculated based on a given optimal solution.

The inverse DEA model, which was developed by Wei et al. (2000), is a classic Multiple Objective Linear Programming (MOLP) problem. This problem seeks answers to the question of "how much should be output (input) when input (output) levels change" for any DMU. While the main problem in the DEA is to rank DMU's according to efficiency scores, inverse DEA is an approach to predict the expected input-output change levels under the assumption that no DMU efficiency scores are changed.

In this study, the purpose was to evaluate the health efficiency of OECD countries, including Turkey, with DEA and Inverse DEA Models. There are very few studies in the literature with allocated resources with inverse DEA model. For this reason, it is considered that this study will contribute to the literature.

In the present study, literature studies on DEA and inverse DEA were included firstly. Then, DEAs were applied separately under the assumption of constant and variable return according to scale to determine the health effectiveness of OECD countries. After the findings obtained in this way were interpreted, inverse DEA was applied for Turkey. Useful inferences were made by calculating how much Turkey should increase its input to achieve the best health output available and also how much health output it should obtain with its existing inputs.

2. Literature

In the literature, the first study on the effectiveness of health systems with DEA is known to be a thesis study of Sherman (1981) (Cooper et al., 2004). Over time, researchers conducted numerous health studies measuring health effectiveness with DEA. When studies were examined, it was determined that many of these studies covered OECD countries in particular. One of the studies that investigated the health effectiveness of OECD countries was conducted by Spinks and Hollingsworth (2005), who applied DEA to compare the technical effectiveness of OECD health systems. They used the level of education, the unemployment rate, gross domestic product per capita (GDP), total health expenditure per capita as input variables, and the expected life expectancy at birth as output variable. According to the analysis results, the average technical effectiveness score for OECD countries was 0.961, and the total factor efficiency was 0.956 on average. Afonso and Aubyn (2006) analyzed the effectiveness of the healthcare production process with DEA and Tobit regression. They used the number of general practitioners, nurses and MRI devices per thousand people as input, and the infant mortality rate, expected life expectancy at birth, and average life expectancy variables as output. Also, education level, smoking habits, and obesity data were included as environmental factors in the analyses. As a result, all of the independent variables were found to have effects on healthcare efficiency. A negative relation was detected between obesity and smoking habits and healthcare effectiveness, and a positive relation was found between GDP per person and education level and efficiency scores. In another study conducted by Afonso and Aubyn (2007), factor analysis and DEA were used to analyze health effectiveness of countries. They used the number of physicians, number of nurses, number of hospital beds and the number of MRI as input, and average life expectancy, infant mortality rate, and healthy life expectancy as output. According to the VRS model, a total of 33.3% of health systems were efficient in the analyses, which included 21 OECD countries. The countries that were found efficient were Canada, Finland, Japan, South Korea, Spain, Sweden, and the United States (USA). Mirmirani (2008) conducted detailed efficiency analyses with Albania, Armenia, Belarus, Estonia, Lithuania, Romania, Russia and Latvia in addition to OECD countries, and measured the efficiency of health systems with DEA and the data from 1997-2001. In their study, the number of physicians, number of hospital beds, health expenditure and immunizations were used as input, and average life expectancy and infant mortality rate were used as output. Albania was found to be efficient in five years, according to CRS model results. OECD countries were not found to be effective as group only in 1999, and Lithuania, Latvia, Romania and Russia were not effective for any year. Hadad et al. (2013) conducted a study to determine factors determining the efficiency of the health systems of OECD countries, and used physician density, inpatient density, health expenditure per capita, gross domestic product per capita, vegetable and fruit consumption variables per capita. As output data, they used life expectancy at birth and infant mortality rate. As a result, they found Czech Republic, Estonia, Iceland, Japan, South Korea, Poland, Portugal and Slovenia as effective. Sonğur et al. (2017) used DEA and multiple compliance analysis in their study on the efficiency of OECD countries, and found 14 countries to be effective in all effectiveness measurement methods. When the ranking of efficient countries with super efficiency scores were evaluated, Chile was the most effective country according to the CCR method in the input-oriented approach, and Finland, Japan and Italy were according to the BCC method. Şenol et al. (2019) evaluated the OECD and Turkish health systems with the help of certain indicators with DEA. In their study, the number of physicians per thousand people, the number of beds per thousand people, health expenditure per person, the GDP share were used as the input variables, and the expected life expectancy at birth and the infant mortality rate per thousand people were used as output variables. As a result of their analyses, the overall efficiency rate was found to be 85% according to CCR input-oriented technique, and 92% according to BCC input-oriented technique. A total of countries among the 32 OECD countries were found to be efficient according to the CCR output-oriented analysis technique, and 16 countries were efficient according to the BCC output-oriented analysis technique. According to the CCR method, Canada, Czech Republic, Estonia, Japan, Korea, Mexico, Slovenia and Turkey were found to be at efficiency frontier. Tokatoğlu and Ertong (2020) tried to determine OECD member states which are efficient in the field of health by means of DEA. In the study, the share of total health expenditure in GDP, total health expenditure per capita and number of beds (menstrual) were used input variables, and infant mortality rate and maternal mortality rate were used as output variables. Among the 35 OECD countries, the health care systems of Estonia, Iceland, Israel, Luxembourg and Poland were fully efficient. Turkey, on the other hand, ranked 34th in the health system effectiveness score, outpacing the United States.

Many studies have also been conducted on the health activities of non-OECD countries. In one of this studies, NgChu (2011) aimed to measure by means of DEA the regional efficiency of the hospitals after the health reform in China. In the study, number of physicians, nurses, pharmacists, other medical personnel and beds as input variables were included, the number of inpatient and outpatients variables were taken as output variables. According to the results of the analysis, it was determined that economic development did not directly affect hospitals in terms of effectiveness on a regional basis. Asandului et al. (2014) conducted a study on the health system of 30 European countries, and analyzed three inputs and three output variables. The input variables were number of physicians, number of hospital beds and the share allocated to health from GDP. Output variables were life expectancy, healthy life expectancy, and infant mortality rates at birth. According to VRS, only 6 out of the 30 countries were found to be efficient. These countries were Bulgaria, Cyprus, Malta, Romania, the UK and Sweden. However, Malta was inefficient in the CRS model. Countries with below-the-average scores were Germany, France, Lithuania, Czech Republic and Hungary. In their study, Medeiros and Schwierz (2015) defined the effectiveness prediction of health systems of all European countries with DEA and clustering analysis. As a result of the analysis, the country group with the lowest efficiency score was Czech Republic, Lithuania and Slovakia. Hungary, Latvia, Poland and Estonia had low efficiency scores, although they were good compared to the previous group. Belgium, Cyprus, Spain, France, Italy, Sweden and the Netherlands constituted the country group with high efficiency performance.

When studies conducted with inverse DEA were examined, it was determined that there were usually theoretical studies, and that there were not may studies on the basis of application. In one of the limited studies on this subject, Wei (2000) et all developed an inverse DEA model. Yan, We and Hao (2002) expanded the model of Wei et al. (2000) to a new model with additional restrictions so that decision makers could include their specific preferences and policies. Jahanshahloo et al. (2004) developed an approach to identify extra inputs (maximum reduction amounts in inputs) for inverse DEA models recommended by Yan et al. (2002). Jahanshahloo et al. (2005) developed a revised inverse DEA model for sensitivity analysis of the efficiency classifications of DMU's. Unlike other inverse DEA models, Hadi-Vencheh and Foroughi (2006) proposed a generalized inverse DEA model allowing simultaneous calculation of increases and decreases in other output (input) variables due to increases and decreases in DMU variables. Alinezhad et al. (2007) used the inverse DEA model for Iran banks, and proposed an interactive method using Multiple Objective Linear Programming to solve it. Hadi-Vencheh et al. (2008) claimed that the model using the current weak effectiveness solution failed in estimating the required input amounts in case output was increased. They also suggested sufficiency conditions. Lertworasirikul et al. (2011) proposed an inversed DEA model based on the variable return scale assumption. Since the existing DEA models in the literature were based on precise number and real-life problems contain uncertainty and fuzziness, Rad et al. (2012) showed that the inverse DEA could be used with fuzzy data. Hadi-Vencheh et al. (2014) developed a range DEA model based on range numbers. Jahanshahloo et al. (2014) discussed inverse DEA by using the non-radial Russell Model, and proposed various conditions based on Pareto solutions to determine input-output. Ghobadi and Jahangiri (2014) adressed an application of inverse DEA for assessing educational departments in a university. Ghiyasi (2015) claimed that solution method of the inverse DEA model proposed previously by Lertworasirikul et al. (2011) was flawed, and revised the method. Amin and Al-Muharrani (2016) introduced new inverse DEA models for target setting of a merger between two or more decision making units, in the presence of negative data. Zhang and Cui (2016) developed individual inverse DEA models for each by considering all possible relation changes between the inputs and outputs of DMU. Hassanzadeh et al. (2018) proposed a solution method to apply the inverse DEA method with negative data, which is also a major problem in classical DEA. In Solaimani et al (2019) inverse DEA was applied to preservate their cost efficiency for European and American banks. Hu et al. (2020) proposed a revised inverse DEA model which considers slack variables while solving the multipurpose linear programming problem for inverse DEA model. Amin and Boamah (2020) introduced a new inverse DEA based on a cost efficiency model for estimating potential gains from mergers. Çakır (2020) applied inverse DEA in order to re-allocate resources to airline companies included in Global 2000.

3. Methodology

In the present study, after the health efficiency scores of OECD countries were calculated with DEA method, sensitivity analysis was carried out for Turkey with inverse DEA method. The 2018 data were compiled from the OECD and the World Bank. The descriptive statistics and variable correlation coefficients are given in Table 1.

As it is seen, the correlation coefficients between the inputs were very low, which indicates that there are no duplicated variables as inputs. Also, since the correlations between inputs and outputs were significant, it can said input-output selection was appropriate.

The analysis method DEA used in the study was a linear programming-based method allowing the efficiency of DMUs to be measured relatively by using multiple inputs and outputs. DEA evaluates each DMU based on its location on efficient frontier. The main difference of the DEA method from other efficiency analysis methods is its availability for systems that have numerous inputs and outputs. By this method, the efficiency score of each DMU can be predicted, and reference DMU's for inefficient DMU's can be defined.

Table 1: Descriptive statics and correlations

	BN	**HE**	**DN**	**LE**	**ISR**
Max	12,98	10637,14	6,353	84,2	998,4
Min	0,98	1144,895	1,873	74,9	987,1
Average	4,529	3984,285	3,600	80,735	996,051
SD	2,591	1925,19	1,012	2,572	2,515
CORRELATION					
	BN	HE	DN	LE	ISR
HBN	1	0,033	0,141	0,029	0,255*
HE		1	0,135	,367**	,158
DN			1	0,135	0,358**
*Significant at .0.05 level. ** Significant at .0.01 level.					

One of the models related to DEA is the (CCR) model that was developed by Charnes et al. The efficiency calculations in CCR are made under the CRS assumption (1978). Another model is the BCC model that was developed by Banker et al., and was based on VRS assumption (Banker et al., 1984: 1078-1092). It also gives technical efficiency score by discriminating between technical and scale efficiency under the VRS assumption. This discrimination can be made by dividing the CCR efficiency score by BCC efficiency score. Here, technical efficiency refers to the appropriateness of input-output combination, and the scale efficiency refers to the success in production in proper scale.

Both the CCR and BCC model can be expressed in two different ways as *input* and *output-orientated*. While output-oriented models try to obtain the maximum outputs at a certain input level, input-oriented models try to use minimum input to a certain output. Since the health outputs employed in this study were not variables that could be easily affected and improved in the short term, it does not seem realistic to try to maximize them. However, if the inputs that were used to obtain the present outputs are minimized, surplus sources can be directed to other areas to achieve more efficient use of them. Based on this viewpoint, input-oriented models were preferred in the study. It was also considered that the VRS approach was more realistic to measure the efficiency of health systems of different countries, and would better reflect the changes of the real world. For this reason, efficiency calculations were made with BCC model in addition to CCR to calculate scale efficiency.

The input-oriented DEA model which is under the CRS assumption is shown in model (1).

$$
\begin{aligned}
& min\theta_k \\
& \textstyle\sum_{i=1}^{n} \lambda_i X_{ji} \leq \theta_k X_{jk} && j = 1, \dots, m \\
& \textstyle\sum_{i=1}^{n} \lambda_i Y_{ji} \geq Y_{jk} && j = 1, \dots, s \qquad (1) \\
& \lambda_j \geq 0 && j = 1, \dots, n
\end{aligned}
$$

Here θ_k refers to the efficiency score of the DMU_k, m refers to the number of inputs, n refers to the number of DMUs, and s refers to the number of outputs. In the case of the VRS assumption, the $\sum_{j=1}^{n} \lambda_j = 1$ must added to model (1).

It is very important to properly determine the inputs and outputs for the accuracy and reliability of the analyses in DEA. For this reason, based on the wide literature review conducted in this study, inputs and outputs given in Table 2 were determined among the numerous variables (Afonso and Aubyn, 2006; Spinks and Hollingsworth, 2005; Asandului, 2014; Ibrahim and Daneshvar, 2018; Ahmed et al., 2019).

Table 2: Variables

Input	Definition	Source
DN	Doctor count (Per thousand people)	World Bank Data Bank
HBN	Hospital bed count (Per thousand people)	OECD Data Bank
HE	Health expenditure (Per capita, current $)	OECD Data Bank
Output		
LE	Life expectancy at birth (Year)	OECD Data Bank
ISR	Infant Survive Rate (Per thousand infants)	OECD Data Bank

One of the main requirements of DEA is a positive relation between output and efficiency score. In other words, when input is fixed, the efficiency score is desired to increase when output increases. For this reason, the infant mortality data obtained from the OECD website were inversed and the infant survival rate output data were created.

Inverse DEA calculates necessary output quantity for any DMU when all or part of its input quantities are changed, without changing the its efficiency score which is calculated with classic DEA. Similarly, inverse DEA can be expressed as a model determining how much input amounts should be to access the targeted output quantities without changing DMU efficiency score. (Wei et al., 2000).

The input-oriented inverse DEA model under assumption of constant return scale is as follows. In the case of variable return scale assumption, the $\sum_{j=1}^{n} \lambda_j = 1$ constraint should be added to model (2).

min $(\alpha_{1k}, \alpha_{2k}, \dots, \alpha_{mk})$

$s.t. \sum_{j=1}^{n} \alpha_{ij}\lambda_j \leq \theta_0 \alpha i_0$ $\quad i = 1, \ldots, m \quad j = 1, \ldots, n$

$\sum_{j=1}^{n} \beta_{rj}\lambda_j \geq \beta_{rk}\, r = 1, \ldots, s$ (2)

$\alpha_{ik} \geq \alpha_{i0}$ $\quad i = 1, \ldots, m$

$\lambda_j \geq 0$ $\quad j = 1, \ldots, n$

Here, *0* index refers to the current values of the considered DMU, and *k* index refers to the its new values that should be. Also, m refers to the number of inputs, *n* refers to the number of DMUs, and *s* refers to the number of outputs; and θ_0 refers to the efficiency score of the DMU.

Model (2) is a MOLP problem. There are various methods for solving such problems. In the present study, the Weighted Sum Method, which was recommended by Steuer (1986), and which can be explained as minimizing the weighted sum of inputs, was used.

4. Findings

DEA efficiency scores and correlations between variables are given below, and then, the inverse DEA results for Turkey are given and interpreted.

Under the CRS assumption, only Turkey, Mexico and Colombia were found to be efficient. The fact that the CCR total efficiency scores of these countries was found to be 1 shows that they have both appropriate scale size and can use resources effectively. Under the VRS assumption, 8 countries were found to be technically efficient, which were Canada, Chili, Colombia, Japan, Korea, Mexico, Sweden and Turkey. Among these, Turkey, Mexico and Colombia had scale efficiency. In other words, these three countries constituted the efficient frontier. Among these technically efficient countries, although Canada, Chile, Japan, Korea and Sweden used resources efficiently, they did not have the appropriate scale sizes. All 34 countries aside from Turkey, Colombia and Mexico showed decreasing returns to scale, which means that the rate of increase in output was lower compared to the rate of increase in input.

Table 3: DEA Results

DMU	CCR	BCC	SCALE	RETURN
Australia	0,5926	0,8874	0,667794	Decreasing
Austria	0,3868	0,5986	0,646174	Decreasing
Belgium	0,6351	0,8451	0,751509	Decreasing
Canada	0,8801	1	0,8801	Decreasing
Chile	0,8766	1	0,8766	Decreasing
Colombia	1	1	1	Constant
Czech Republic	0,4592	0,7826	0,586762	Decreasing
Denmark	0,5931	0,8692	0,682352	Decreasing
Estonia	0,4983	0,9994	0,498599	Decreasing
Finland	0,5255	0,8826	0,5954	Decreasing
France	0,6062	0,8749	0,692879	Decreasing
Germany	0,4498	0,629	0,715103	Decreasing
Greece	0,544	0,9999	0,544054	Decreasing
Hungary	0,5681	0,9189	0,618239	Decreasing
Iceland	0,5896	0,9994	0,589954	Decreasing
Ireland	0,6846	0,9763	0,701219	Decreasing
Israel	0,5293	0,9999	0,529353	Decreasing
Italy	0,5932	0,9988	0,593913	Decreasing
Japan	0,8109	1	0,8109	Decreasing
Korea	0,818	1	0,818	Decreasing
Latvia	0,6452	0,9994	0,645587	Decreasing
Lithuania	0,4849	0,7946	0,610244	Decreasing
Luxembourg	0,6608	0,9034	0,731459	Decreasing
Mexico	1	1	1	Constant

Netherlands	0,6207	0,8344	0,743888	Decreasing
New Zealand	0,6558	0,9337	0,702367	Decreasing
Norway	0,7269	0,9998	0,727045	Decreasing
Poland	0,7722	0,9995	0,772586	Decreasing
Portugal	0,451	0,8722	0,517083	Decreasing
Slovak Republic	0,5675	0,8423	0,67375	Decreasing
Slovenia	0,6247	0,9996	0,62495	Decreasing
Spain	0,589	0,9999	0,589059	Decreasing
Sweden	0,613	1	0,613	Decreasing
Switzerland	0,5101	0,9996	0,510304	Decreasing
Turkey	1	1	1	Constant
United Kingdom	0,7981	0,9995	0,798499	Decreasing
United States	0,7878	0,9034	0,872039	Decreasing

When the correlation values in Table 4 are evaluated, health expenditure was correlated with the technical efficiency score under the VRS assumption, and the number of hospital beds was highly correlated with total and technical efficiency scores under both CRS and VRS assumptions. But the input that was mostly correlated with all three efficiency scores was the number of physicians. As for the correlation between the efficiency scores and outputs, the infant survival rate was correlated CCR and scale efficiency scores, and life expectancy at birth was found not correlated with the efficiency scores.

Table 4: Correlations Between Input-Output Values and Efficiency Scores

	CRS	VRS	SCALE	HBN	HE	DN	LE	ISR
CRS	1,000	,491**	,713**	-,339**	-,110	-,775**	-,085	-,370**
VRS		1,000	,197	-,345**	-,270*	-,372**	,140	-,045
SCALE			1,000	-,149	-,005	-,694**	-,191	-,470**
*Significant at .0.05 level.								
** Significant at .0.01 level.								

Inverse DEA shows what the amount of input must be to achieve an amount of output, provided that it maintains the DEA efficiency score, and vice versa. Based on this definition, it was accepted in this study that the efficiency score, which should be protected, was 1, and only Turkey was examined. If deemed necessary, other countries that are efficient or not can be analyzed in the same way.

In the inverse DEA analysis and under the CRS assumption, the amount of inputs required for the Turkey to reach maximum life expectancy value (Japan's) and maximum infant survival rate (Estonia's) which are in the sample without changing it's efficiency score were calculated. Results are follow Table 5.

Table 5: CRS Inverse DEA Result for Turkey

Output	Target Value	Input	Value Needed
LE	84,2	**DN**	2,85
IRS	998,4	**HBN**	2,3860
		HE	1267,353

According to the findings, the number of current physicians in Turkey is adequate to achieve the targeted outputs, health expenditure should be increased by $43.785 per capita, and the number of patient beds per thousand people should be increased by 0.513.

Under the VRS assumption, without the efficiency score of Turkey is changed, it is not possible for Turkey to reach, the Japan's life expectancy at birth value and Estonian's infant survival rate. In other words, no matter how much Turkey increases its resources, it will not reach these targets at the same time unless the input-output combination of Japan and Estonia changes. According to the findings, if Turkey reaches the level of Japan's life expectancy, infant survival rate in Turkey can be a maximum of 998.1 thousand. In addition, if Turkey reaches the level of Estonia's infant survival rate, life expectancy in Turkey can be a maximum of 78,4 year. These results are given in Table 6 below.

Table 6: VRS Inverse DEA Results for Turkey

	Target output	Input needed	Target output	Input needed
LE	84,2		78,4	
IRS	998,1		998,4	
DN		2,4838		4,4833
ISR		12,98		4,57
HE		4504,43		2368,13

5. Conclusion

Health is one of the most basic indicators of a developed society. Every reform in health and every new investment will positively affect many socio-economic variables of countries, increasing their development levels. Especially in the past 5 decades, intensive efforts were made to improve and disseminate healthcare in most countries, and new policies were adopted in this respect. In this context, one of the problems that was focused on was producing maximum health outcomes with existing inputs or determining the amount of resources needed to achieve targets. This problem, which can be defined as “effective use of existing resources”, was the main motivation of the study. For this reason, the efficiency of health systems in 37 OECD countries were analyzed with input-oriented DEA and inverse DEA.

Since the health outputs employed in the present study were not variables that could be affected and improved easily in the short term, it does not seem realistic to try to maximize these. However, if the inputs used to achieve the same outcomes are minimized, surplus resources can be reallocated to other fields to achieve using them more effectively, which can produce useful and meaningful information for policymakers. Based on this fact, input-oriented models were preferred in the study.

As a result of the analyses, the average efficiency score of OECD countries was 0.6526 under CRS assumption and only Turkey, Mexico and Colombia were efficient. However, this finding doesn’t suggest that these three countries are perfect in terms of health systems. It just means that they can achieve their available output with less input compared to other countries.

Under VRS assumption, on the other hand, the average technical efficiency score was 0.9282, and the average scale efficiency score was 0.7008. In addition, approximately 20% of 37 OECD countries were technically efficient, and only 8% were scale-efficient which can be interpreted that countries are in a better condition compared to scale efficiency in terms of using their existing resources effectively. In the present study, 34 out of 37 countries had decreasing returns to scale.

Also, the findings showed that input variable that most influenced the health efficiency scores of countries was the number of physicians. The fact that the number of physicians and efficiency scores is negatively correlated with each other can be interpreted as that OECD countries have adequate physicians in general to provide available outputs, and even more in some countries. This finding can be used as useful information for country executives and policymakers. However, the number of physicians must be re-evaluated if the need increases for health outcomes in the long term.

The fact that the efficiency score of Turkey was 1 does not mean it is perfect. Because there are countries among OECD countries whose outputs are better than Turkey. For this reason, increasing Turkey’s output quantities even more can be determined as a target. To achieve such targets, what Turkey’s inputs should be was investigated with inverse DEA method. According to the findings, it was determined that the current number of physicians in Turkey is sufficient to reach optimum values of the sample its life expectancy and infant survival rate values. On the contrary, the number of healthcare expenditure per person and the number of hospital beds should be increased. Of course, Turkey's targets should not be limited to OECD countries. Higher targets can be defined based on other countries in the world.

According to the results obtained here, it can be said that in order to use the resources efficiently, it is necessary to determine the health system policies based on resources and to re-allocate resources to the necessary areas. In this way, the reallocation of rare health resources can provide significant improvements and acquisitions not only in the field of health, but also in many other areas.

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