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MEASURING THE RELATIVE EFFICIENCIES OF STATISTICS DEPARTMENTS IN TURKEY USING DATA ENVELOPMENT ANALYSIS

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Abstract

Determinants of success of an education system can be the facilities offered during an educational process and the qualifications obtained afterwards. However, conversion of the offered facilities into outputs efficiently in the performance evaluation plays an important role for an educational system. On the contrary, comparison of Turkish university performances can be generally performed according to only output based performance indicators like academician performances and nationwide exam results of their graduates publicly. Aim of this study is to calculate the relative efficiencies of 18 statistics departments in Turkey, which are considered as decision making units, using data envelopment analysis. Reasons for inefficiencies of departments arise from pure technical efficiency component. Furthermore, a second stage analysis is implemented to observe the effects of external factors called non-discretionary inputs on efficiency results. Finally, efficiency differences between two types of departments are tested according to their education programs with a Mann - Whiney U Test.

Keywords: Data Envelopment Analysis, Relative Efficiency, Second Stage Analysis, Higher Education

Jel Code: C44, I21, I23

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TÜRKİYE'DEKİ İSTATİSTİK BÖLÜMLERİNİN GÖRELİ ETKİNLİKLERİNİN VERİ ZARFLAMA ANALİZİ ILE ÖLÇÜLMESİ

Özet

Bir eğitim sisteminin başarısındaki belirleyici faktörler: eğitim süreci içinde sunulan olanaklar ve eğitim süreci sonrası elde edilen yeterlilikler olabilmektedir. Bununla birlikte, eğitim sistemlerinin performanslarının değerlendirilmesinde sunulan olanakların çıktılara etkin bir şekilde dönüştürülmesi önemli bir rol oynamaktadır. Buna karşılık olarak Türkiye'deki üniversite performanslarının karşılaştırılmaları genellikle akademisyen performansları ve ülke genelinde yapılan ortak sınav sonuçları gibi performans belirleyicileri üzerinden sadece çıktı yönlü olarak yapıldığı gözlemlenmektedir. Bu çalışmanın amacı karar verme birimi olarak ele alınan Türkiye'deki üniversitelerde eğitim veren 18 adet istatistik bölümünün göreli etkinliklerinin veri zarflama analizi yardımı ile hesaplanmasıdır. Bölümlerin toplam etkin olamamaları teknik etkinsizliklerinden kaynaklandığı sonucuna ulaşılmıştır. Ayrıca, kontrol edilemeyen girdiler olarak adlandırılan dış etkenlerin etkinlik skorları üzerindeki etkileri bir ikinci aşama analizi kullanılarak araştırılmıştır. Son olarak ise iki farklı tipte eğitim veren istatistik bölümlerinin etkinlik skorları arasındaki farkın istatistiksel anlamlılığı Mann-Whitney U testi ile sınanmıştır.

Anahtar Kelimeler : Veri Zarflama Analizi, Göreli Etkinlik, İkinci Aşama Analizleri, Yüksek Eğitim
Jel Kodu : C44, I21, I23

1. INTRODUCTION

Importance of implementing performance measurement techniques in organizations has risen due to today's competitive market conditions, restricted human and physical resources. Therefore, conversion of the limited resources into services and products efficiently is highly significant for organizations. In addition, implementation of efficiency measurement enables comparison with the other organizational performances and the past performances of an organization. With the findings gathered from these techniques, organizations will be able to upgrade their own best performances and the performance among the other organizations.

Data Envelopment Analysis (DEA) is one of the most frequently used performance measurement techniques in literature that can be applicable for both profit and non-profit organizations. DEA can be defined as an application of linear programming that enables measurement of the relative efficiencies for homogeneous organizational units called DMUs (Decision Making Units). These DMUs can be educational institutions like universities and high schools, financial organizations like banks and insurance companies and even individuals like sportsmen and etc (Ramanathan 2003).

Prominent advantages of DEA over parametric approaches for efficiency measurement are the suitability for the usage of multiple input-outputs and the setting of the efficiency frontier according to the best practice(s). Furthermore, DEA provides potential targets for inefficient DMUs by identifying benchmarks on the efficiency border to be compared for inefficient units (Barros and Leach 2006).

To get a place in a higher education programme in Turkey, sufficient points are required in LYS and YGS exams which are organized by Turkish Student Selection and Placement Centre. YGS exam is a selection exam applied before LYS exam. Those applicants who get a score of 180 from this exam is given a chance to take LYS exam afterwards. Statistics departments accept students with a specific LYS exam score. The graduates of the statistics departments can find jobs in both private sector and public sector. However, there is another exam called KPSS for those interested in working in public sector.

In this paper, we aim to evaluate the performances of 18 statistics and statistics and statistics and computer sciences departments in Turkey by using DEA. KPSS exam results in three sectors are taken as output measures while the ratios of bachelors and graduate students to number of professors are taken as input measures. In addition, some departments have only daytime classes whereas the others have both daytime and evening programmes. Furthermore, quotas for statistics departments determined by the Turkish High Education Board and LYS exam results are selected as non-discretionary inputs. We also will answer the questions if the non-discretionary inputs have an effect on efficiency results and if there are meaningful differences in efficiency results between two groups of statistics departments.

After the foundation of the analysis, DEA literature has been growing rapidly with a huge diversity in both theoretical and applied studies. Popular research areas of efficiency measurement with DEA are education, finance, sports, energy sector and etc. A brief literature review in all areas especially in education will be given in the second part of the study.

The organization of the paper is as follows: in the second section we give a brief literature review of DEA history and related applications with the paper; section three includes the methodology and the DEA model chosen; we give description of the data and the results of the application in section four; finally we conclude the study in section five.

2. Literature Review

DEA history dates back to the work of Farrell (Farrell 1957). After 20 years time, Charnes et. al. introduced the term DEA and contributed the ideas of Farrell's. For the history and the detail theoretical background of the different DEA models, see (Cook and Seiford 2009; Cooper et al. 2000).

Application simplicity and the other advantages of DEA make it a popular tool for efficiency measurement. There are various theoretical and applied studies in operations research, management science and several other journals. Applications of DEA are mostly seen on fields such as in tourism (Wöber 2007), sports (Barros and Leach 2006), health (Gök and Sezen 2011) and finance (Kumar and Gulati 2008).

Inputs and outputs used in higher education institutions (HEIs) do not have real costs because of the non-profit making objective. Furthermore, HEIs convert several inputs like research funds, general funds and student to academics ratios to outputs like several exam scores, publications and so on. Therefore, efficiency measurement in a multiple input-output situation is required for HEIs. Another advantage of DEA is the assigning of virtual costs (weights) to input and output variables with the solution of the DEA model. This is a great asset for HEIs and all non-profit organizations. In short, mentioned properties make DEA a suitable analysis for efficiency measurement of HEIs (Johnes 2006).

We take departments as DMUs in this study as it is rarely seen in literature. Usually, selection of universities as DMUs in applied studies is widespread only with the different nation cases. Johnes stated the advantages and disadvantages of efficiency measurement techniques in higher education context and applied DEA to a data of 2000/2001 with more than 100 HEIs in England (Johnes 2006). Kempkes and Pohl analysed the efficiency of public universities in Germany between years 1998-2003 both with the use of stochastic frontier analysis and DEA (Kempkes and Pohl 2010). Australian case of relative efficiency measurement of universities was presented in the study of Abbott and Doucouliagos's with the aim of decomposing the overall technical efficiency (Abbott and Doucouliagos 2003). Selim and Bursalıoğlu proposed a two-stage efficiency analysis to determine both the efficiencies of Turkish universities at first stage and the effects of external factors on the efficiencies in 2006-2010 (Selim and Bursalıoğlu 2013) .Kağnıcıoğlu and İcan calculated the relative efficiencies of Turkish Universities in 2007 by taking academic stuff numbers as inputs, types of academic publishing and graduate student numbers as outputs (Kağnıcıoğlu and İcan 2011) . After efficiency analysis, also called second stage analysis, have been used to determine external factors effect on efficiency scores. McDonald mentioned these analyses detailed in his study and made a comparison of them (McDonald 2009). We also proposed a Two Limited

Tobit Regression as a second stage analysis in our case to find the factors that may affect the efficiency scores of departments.

3. Methodology

DEA models vary according to both efficient border assumptions called returns to scale assumptions and the selection of input or output orientation. The first DEA model (CCR model) is named after the founders of the model Charnes, Cooper and Rhodes (Charnes et al.1978). CCR model is based on the constant returns to scale assumption (CRS). The second DEA model called BCC model invented by Banker, Charnes and Cooper (Banker, et al. 1984) is based on variable returns to scale (VRS) assumption. Only difference is a convexity constraint added into the CCR model.

In input oriented models, proportional reduction in inputs investigated when outputs remain fixed. In output oriented models, the proportional expansion in outputs is investigated under the fixed inputs. Efficiency scores differ according to input or output orientation in BCC model only (Johnes 2006).

It is common in literature to decompose the overall technical efficiency into two mutually exclusive and non-additive components. These components are pure technical efficiency and scale efficiency. Overall technical efficiency results can be calculated through the solution of CCR-DEA model. Pure technical efficiency results can be calculated through the solution of BCC-DEA model.

Pure technical efficiency is an efficiency type without including scale efficiency and purely reflects the managerial performance. Scale efficiency expresses if an organization performs in the most productive scale or not. It is the ratio of overall technical efficiency to pure technical efficiency. The term returns to scale arises is related to efficiency border setting. It explains the behaviour of the rate of change in the output to the subsequent change in the inputs in the long run. If an output increases as the same proportion in the increase in inputs, there are constant returns to scale (CRS). If not variable returns to scale (VRS) prevails (Bogetoft and Otto 2011; Kumar and Gulati 2008). Efficiency borders can be demonstrated in Figure 1 under different returns to scale assumptions.

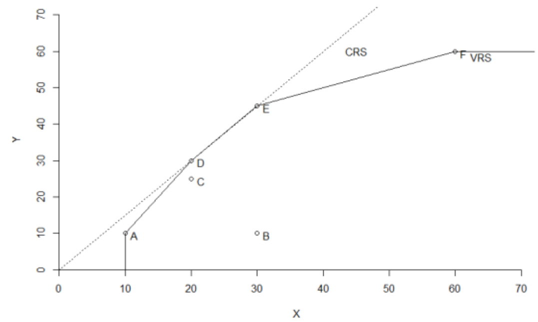

Figure 1. Different Return to Scales of Hypothetical Data

3.1. Data Envelopment Analysis

DEA models use the data (inputs-outputs) itself to calculate the relative efficiencies of DMUs. They can be simply shown as fractional programming models however they are convertible to linear programming models for practicality in calculations. Consider a production possibility set consist of n ($j=1,2,...,n$) DMUs which produces s ($r=1,2,...,s$) outputs using m ($i=1,2,...,m$) inputs. Then the productivity ratio for the j.th DMU e_J can be described as follows:

$$e_J = \frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \tag{1}$$

The numerator of the equation (3.1) is called the sum of virtual outputs whereas the denominator is called the sum of virtual inputs. This ratio is also known as benefit/cost ratio. Charnes et. al. proposed the calculation of weights from the solution of fractional programming model in the situation of unknown weights (prices) for inputs (v_i) and outputs (u_r) in equation (1) (Cook and Seiford 2009).

The input oriented fractional CCR model is as follows:

$$e_o = \max \frac{\sum_r u_r y_{ro}}{\sum_i v_i x_{io}} \tag{2}$$

s.t.

$$\sum_r u_r y_{rj} - \sum_i v_i x_{ij} \le 0 \text{, for } \forall j$$

$$u_r, v_i \ge \varepsilon \text{ for } \forall j$$

In model (2), y_{ro} is the r.th output of the DMU_o and x_{io} is the i.th input of the DMU_o. Model (2) should be solved "n" times for each DMU. Solution of model (2) gives us the overall technical efficiency scores. However, it can be decomposed into pure technical efficiency and scale efficiency with the help of BCC input oriented model results. With the change of variables, model (2) can be converted in a linear programming model. Finally, by duality the equivalent model of linear programming model (2) can be formed as in model (3).

$$e_o = \min \theta_o - \varepsilon \left(\sum_r s_r^{+} + \sum_i s_i^{-} \right) \tag{3}$$

s.t.

$$\sum_j \lambda_j x_{ij} + s_i^{-} = \theta_o x_{io} \quad i = 1,2,...,m$$

$$\sum_j \lambda_j y_{rj} + s_r^{+} = y_{ro} \quad r = 1,2,...,s$$

$$\lambda_j, s_r^{+}, s_i^{-} \ge 0, \theta_o \text{ unconstrained } \quad \forall r, i, j$$

Model (3) is called the envelopment model in literature. Solution of model (3) enables us to determine reference sets and also weights (λ_j's) assigned to the peers for inefficient DMUs. Therefore, improvements for inefficient DMUs to be efficient can be calculated. Here, θ_o is the shrinkage coefficient that shows the amount of reduction can be done radially in DMU_o's inputs. Model is efficient for only if the $\theta_o = 0$ and all the slack variables are equal to zero.

Input oriented BCC envelopment model is as follows:

$$e_o = \min \theta_o - \varepsilon \left(\sum_r s_r^{+} + \sum_i s_i^{-} \right) \tag{4}$$

s.t.

$$\sum_j \lambda_j x_{ij} + s_i^{-} = \theta_o x_{io} \quad i = 1,2,...,m$$

$$\sum_j \lambda_j y_{rj} + s_r^{+} = y_{ro} \quad r = 1,2,...,s$$

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

$$\lambda_j, s_r^{+}, s_i^{-} \ge 0, \theta_o \text{ unrestricted } \quad \forall r, i, j$$

The 3rd constraint of the model (4) is the convexity constraint. Addition of this constraint makes a change in the efficiency border from a straight line to a piecewise combination of several straight lines. We choose to solve both BCC and CCR input models to decompose the overall technical efficiency and to show the sources of inefficiencies.

3.2. Tobit Regression

After the calculation of efficiency scores with the help of DEA at first stage, researchers may have an interest on external factors affecting these scores. For this purpose, Ordinary Least Squares (OLS) Regression and Tobit Regression are used as a second stage analysis. A regression model will be fit to set the relationships between efficiency results and non-discretionary values.

Efficiency values must be between 0 and 1 closed interval. Values on the lower boundary of 1 are mostly seen whereas the values in the upper boundary 0 are rare. Classical OLS regression does not take into account this setting. It is not known that the fitted values of the regression model will be in the efficiency interval. Two Limited Tobit Regression can be used to eliminate this problem (Bogetoft and Otto 2011).

The underlying regression is:

$$E = \left\{ \begin{array}{ll} 0, & If \ \alpha z + \varepsilon \le 0 \\ \alpha z + \varepsilon, & If \ 0 < \alpha z + \varepsilon < 1 \\ 1, & If \ \alpha z + \varepsilon \ge 1 \end{array} \right\} \tag{5}$$

The aim of this model is to estimate "α"coefficients taking efficiency values as a stochastic dependent variable explained by non-discretionary independent variables. The fitted values above one will be assigned to one and the fitted values below zero will be assigned to zero. In the end, the fitted values will be censored according to the efficiency setting.

4. Application

Input and output data for year 2012 were collected from different sources because the departmental selection is a specific one. Input variables (non-discretionary inputs also included) are taken from the study of Çelikoğlu and Süner about Turkish Statistics Departments (Çelikoğlu and Süner 2013). Output variables including KPSS exam results on different subjects are taken from the site of Turkish Student Selection and Placement Centre's web site.

4.1. Data

Selection of inputs and outputs has a tremendous effect in an efficiency measurement study because they can affect directly on the efficiency results. Generally, the same kind of inputs and outputs are selected in the efficiency measurement studies of higher educational and educational systems. These are the number of academic staff (both teaching and research) or teachers, student/academic staff (student/teacher) ratios or the expenditures for inputs. Furthermore, several exam scores, honors degrees given to graduates and number of graduates can be taken as output measures (Abbott and Doucouliagos 2003; Johnes 2006; Kağnıcıoğlu and İcan 2011; Kempkes and Pohl 2010, Kıranoğlu 2005)

Explanations related to input and output data are given in the Table 1.

Table 1.Variable explanation chart for DEA

	Variables	Definition
Inputs:	X_1	Ratio of undergraduate students to professors in the departments.
	X_2	Ratio of graduate students to professors in the departments.
	Z_1	Minimum LYS exam score to be enrolled in a statistics department.
	Z_2	Maximum number of student for each department to be enrolled.
Outputs:	Y_1	KPSS exam quantitative section mean scores.
	Y_2	KPSS exam verbal section mean scores.
	Y_3	KPSS exam statistics section mean scores.

Z1 and Z2 are the external factors which cannot be controlled by the departments therefore they will be used in the second stage analysis. These variables can be determined by Turkish Council of Higher Education and Turkish Student Selection and Placement Centre. Departments have only a considerable control on input variables. In addition, for the inefficient DMUs source of inefficiency must be addressed. For these reasons, we chose input oriented DEA models in our study to evaluate the efficiencies of departments.

In this study, 18 statistics departments of public Turkish universities were taken as DMUs of the chosen DEA model. DMU number is 3 times greater than the sum of the number of inputs and outputs. In literature, the number of DMUs should be at least two or three times greater than the sum of number of inputs and outputs. It is needed to properly discriminate the efficient DMUs from inefficient DMUs as a rule of thumb.

Characteristics for inputs and outputs are given in the Table 2.

High standard deviations in non-discretionary variables and undergraduate/professors ratio are observed. Top universities accepts student with higher LYS exam results and also this will affect the KPSS exam results after university graduation. Furthermore, we believe the range of input variables will play an important role in efficiency calculations.

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Table 2. Descriptive statistics for inputs and outputs

Variables	Minimum	Maximum	Mean	Standard Deviation
X_1	23.65	95.75	53.86	24.16
X_2	0.60	8.75	4.43	2.21
Y_1	31.77	46.03	38.27	3.47
Y_2	16.26	25.52	22.02	2.38
Y_3	5.80	16.61	9.53	3.16
Z_1	192.96	401.29	261.42	53.58
Z_2	52	196	126.90	43.59

4.2. *Efficiency Results*

All the calculations are made in R programming language Benchmarking package (Bogetoft and Otto 2011). The relative efficiencies of the departments are presented in the Table 3 below.

Table 3: Efficiency results of departments

Statistics Departments	CCR-input (ote)	BCC-input (pte)	Scale Efficiency (se)
Afyon Kocatepe University	0.2557	0.2600	0.9836
Anadolu University	1.0000	1.0000	1.0000
Ankara University	0.7389	0.7400	0.9986
Çukurova University	0.3323	0.7633	0.4354
Dokuz Eylül University	0.5220	0.5361	0.9736
Ege University	0.2864	0.5359	0.5344
Eskişehir Osmangazi University	0.5124	0.5617	0.9123
Fırat University	0.3455	0.5712	0.6048
Gazi University	0.7651	0.7656	0.9993
Hacettepe University	1.0000	1.0000	1.0000
Karadeniz Technical University	0.6035	0.9294	0.6493
Mimar Sinan Fine Arts University	0.9785	0.9856	0.9928
Muğla Sıtkı Koçman University	0.5639	0.5677	0.9933
Ondokuz Mayıs University	0.4925	0.4996	0.9856
Middle East Technical University	1.0000	1.0000	1.0000
Selçuk University	0.3196	0.3209	0.9960
SinopUniversity	1.0000	1.0000	1.0000
Yıldız Technical University	0.5387	0.6313	0.8533

According to the relative efficiency results; statistics departments of Anadolu, Hacettepe, Sinop and Middle East Technical Universities (METU) are technically efficient. A DMU is CCR efficient only if it is both pure technically and scale efficient. Scale efficiency values are calculated as the ratio of overall technical efficiency (ote) values to the pure technical efficiency (pte) values. Despite being pure technically inefficient, some statistics departments like Afyon Kocatepe, Selçuk, Ondokuz Mayıs, Mimar Sinan Fine Arts, MuğlaSıtkı Koçman, Gazi and Ankara are approximately scale efficient. We can infer that these DMUs perform on the optimum scale with other technically efficient DMUs. Mean overall technical efficiency of the departments is 62.53%. Scale efficiency and pure technical efficiency means are 88.4% and 70.4% respectively. It is clearly seen that the source for the inefficiency is pure technical efficiency results. An important issue is the assigning of peers to inefficient DMUs with lambda values (weights). Inefficient DMUs can take DMUs in the efficiency border as a role model to improve themselves. With the help of assigned weights and peers inefficient DMUs hypothetical input-output levels can be calculated.

4.3. Second Stage Analysis

One of the inquiries stated in the beginning of the study is to find out whether external factors affect the efficiency values or not. We adopted a Two Limited Tobit Regression Analysis because of its suitability to the special situation of efficiency values. Regression coefficients of the model and their standard deviations are given in parenthesis in Table 4.

Table 4. Tobit Regression Results

	Coefficients
Z_1	0.003* (0.001)
Z_2	-0.003** (0.002)
Test Results	
Log likelihood	-3.496
Wald Test	11.776*** (df =2)
*Note: *p<0.1 ; **p<0.05 ;*p<0.01*	

Regression coefficients are both simultaneously (wald test) and individually significant according to the Tobit Regression results in given significance levels in Table 5. We can say that higher LYS exam scores lead to higher efficiency results. Furthermore, efficiency results tend to decrease if the department quotas will increase. A unit increase in LYS exam results will bring 0.003 unit increase in efficiency results if department quotas remain constant. Likewise, a unit increase in quotas will bring 0.003 unit decrease in efficiency results.

4.4. Efficiency Analysis for Different Type of Programs

In Figure 2, efficiency scores of two types of statistics departments in Turkey are presented as a bar graph below. As stated before, some of the statistics departments only have day time education while others have both day and night time education together. Statistical significance of efficiency differences for two types of statistics departments was tested with a Mann- Whitney U non-parametric statistical test. Our initial expectation is that we expected a significant statistical difference because of higher student numbers in departments which have both day and night time education. According to the Mann-Whitney U test, the significance value concerned to the test statistic is found 0.054. Therefore, we accept the null hypothesis of there is no statistical significant between efficiency values

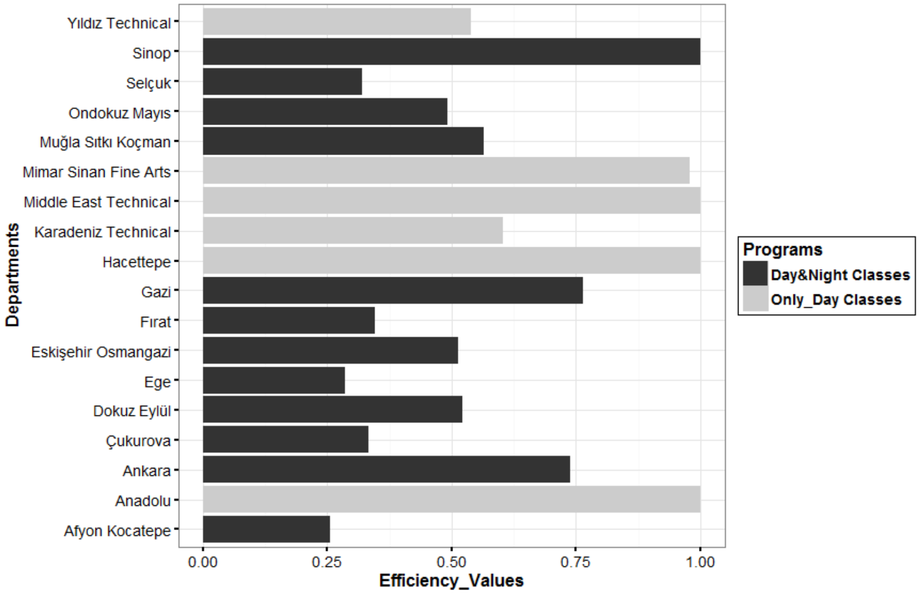

Figure 2. Efficiency Results of Different Type of Programs

among different statistics departments. Our first expectation is wrong and it is inferred that there is no significant difference in efficiency values. When registered student number to night time education for 2012 year is examined, it is seen that unfilled quotas still remain for many students in departments of Fırat, Ondokuz Mayıs, Selçuk, Sinop, Afyon, Çukurova and Muğla Sıtkı Koçman universities. This might be the reason why there is no difference between the two types of statistics departments.

5. Conclusion

In this study, we have provided a two stage efficiency analysis of Turkish statistical departments for the year 2012. We have chosen DEA as the suitable analysis to determine the relative efficiencies of statistics departments and to classify each department as efficient or inefficient .In many studies related to efficiency measurement in education, universities or faculties were selected as DMUs. For this study, 18 statistics departments are selected as DMUs of the analysis. These departments consist of two different groups according to their education programmes. Only 4 departments can be regarded as efficient according to the results after CCR input oriented model applied in “R Benchmarking” package. Related external factors which may affect the efficiency results of departments have been set and investigated. Both mentioned factors have affected the efficiency values according to the Tobit regression model. Finally, we implemented a Mann- Whitney U non- parametric statistical test to examine if there is a difference in efficiency values between the two types of departments. However, there is no significant difference between two groups of statistical departments contrary to the expected result. The reason of this may be the unfilled quotas in some departments' night education programmes.

The limitation of the study is the difficulty in the gathering of data. The case is very special so we take advantage of another study as a data source. Moreover, there are also disadvantages of DEA technique. DEA results can be easily affected by outliers in the data and random errors cannot be allowed in DEA. We could only deal with the educational efficiencies of departments in this study. Academic inputs and outputs can also be added to the present study or can be a subject for another study.

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References

Doucouliagos C, Abbott M, (2003) The efficiency of Australian universities: a data envelopment analysis. Economics of Education Review. 22:89-97.

Charnes A, Banker RD, Cooper WW (1984) Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. Management Science. 30(9):1078-1092.

Barros CP, Leach S (2006) Performance Evaluation of the English Premier Football League with Data Envelopment Analysis .Applied Economics. 38:1449-1458.

Otto L, Bogetoft P (2011) Benchmarking with DEA, SFA and R. Springer.

Charnes A, Rhodes E, Cooper WW (1978). Measuring the efficiency of decision making units. European Journal of Operational Researc, 2(6): 429-444.

Seiford LM, Cook WD, Cooper WW (2009). Data Envelopment Analysis (DEA) - Thirty Years on . European Journal of Operation Research. 192:1-17.

Seiford LM, Tone K (2000). Data Envelopment Analysis: A Comprehensive text with Models, Applications, References and DEA- Solver Software . Kluwer Academic Publishers.

Suner A, Çelikoğlu CC (2013). Türkiye'deki İstatistik Bölümlerine İlişkin İstatistikler. n'den N'ye Gezinti İstatistik Dergisi, 38-45.

Farrell M (1957). The Measurement of Productive Efficiency. Journal of the Royal Statistician Society. 120(3): 253-290.

Sezen B, Gök MŞ (2011). Analyzing the Efficiencies of Hospitals in Turkey: An Application of DEA. Journal of Global Strategic Management. 5(2): 137-146.

Johnes J (2006). Data envelopment analysis and its application to the measurement of efficiency in higher education. Economics of Education Review, 25, 273-288.

Kağnıcığıoğlu HC, İcan Ö. (2011). Measuring Relative Efficiencies of Turkish Universities in 2007: A DEA Case Study in R. Anadolu University Journal of Social Sciences. 11(1): 13-26.

Kempkes, G., & Pohl, C. (2010). The efficiency of German universities- some evidence from non-parametric and parametric methods. Applied Economics, 42, 2063-2079.

Kıranoğlu ME (2005). Measuring Secondary School Education Efficiencies of Turkish Provinces: An Application of Data Envelopment Analysis. T.C.Marmara University Institute For Graduate Studies In Pure And Applied Siıences : Thesis For The Degree Of Master Of Science In Industrial Engineering Programme.

Gulati R, Kumar S (2008). An Examination of Technical, Pure Technical, and Scale Efficiencies in Indian Public Sector Banks using Data Envelopment Analysis. Eurasian Journal of Business and Economics, 1(2): 33-69.

McDonald J (2009). Using least squares and tobit in second stage DEA effciency analyses. European Journal of Operational Research. 197: 792-798.

Ramanathan R (2003). An Introduction to Data Envelopment Analysis. Sage Publications.

Selim S, Bursalioğlu SA (2013). Analysis of the Determinants of Universities Efficiency in Turkey:Application of the Data Envelopment Analysis and Panel Tobit Model. Procedia - Social and Behavioral Sciences 895-900.

Wöber KW (2007). Data Envelopment Analysis. Journal of Travel & Tourism Marketing. 21(4): 91-108.