Performance Measurement in Greek Hospital Sector: A Two-Stage Double-Bootstrap DEA Approach

Mitropoulos, P., Rafailidis, A., Mitropoulos, I.
Technological Educational Institute of Patras, Greece

pmitro@upatras ; grarafail@teipat.gr ; mitro@teipat.gr

Abstract: *This study presents evaluation of efficiency in public Hospitals in Greece, and identifies factors impeding the achievement of efficiency, with the aim of determining how the efficiency of hospitals could be improved. The efficiency of hospitals is assessed with two alternative conceptual models that incorporate different sets of factors: one model focusing on production efficiency and the other on economic efficiency. Then a second stage analysis is performed to account for the impact of explanatory variables on efficiency. Determining how these variables influence on efficiency is essential for determining performance improvement strategies. The results indicated the scope for substantial efficiency improvements.*
Keywords: *Hospital, Efficiency, Bootstrap, DEA, Truncated regression*

Introduction

This paper evaluates the efficiency of public hospitals with two alternative conceptual models. One model is targeting directly at resources usage to assess the production efficiency, while the other model incorporates financial results to assess the cost efficiency. The performance analysis of these models is conducting in two stages. We use at first data envelopment analysis to obtain the efficiency score of each hospital (stage one), and then we take into account the influence of operational environment on efficiency by regressing those scores on explanatory variables that concern the performance of hospitals services (stage two). Under the production approach, hospitals are making use of various labor and capital resources in order to provide different services to their users. Hence the production model doesn't use information from any financial activity. On the contrary, in cost containment approach, hospitals efficiency is defined as the minimum level of economic resources which must be consumed to produce a desired level of output. This model has a financial form and thus all resources consumed were converted in monetary terms. Given these differences, the scores obtained in each case have different interpretations, and are not comparable per se. However, one can gain some insight into a given hospital operations by comparing its performance achievements for each model. Then we study in a second stage how these efficiencies are affected from factors that concern the performance of hospitals services. Determining how these variables influence on efficiency is essential for determining performance improvement strategies.

As discussed in Simar and Wilson [1, 2] the simple DEA model is subjected to statistical limitation, and might not lead to accurate efficiency inference. For this reason some of the recent DEA studies on hospitals evaluation, address this limitation by applying bootstrap correction techniques. These techniques provide valid inference on DEA assessments have been applied either to the standard DEA models and/or to the second stage assessment concerning the effect of environmental variables.

We apply these methods in order to evaluate 96 general hospitals of the Greek national health system. The results indicate that even if the average efficiency scores in both models have remained relative stable compared to past assessments, there are internal changes in hospitals performance.

The DEA methodology

Data envelopment analysis (DEA) is a linear programming methodology to measure the efficiency of multiple decision-making units (DMUs) when the production process presents a structure of multiple inputs and outputs. The DEA has been validated through studies and its use in health services management applications has raised many questions about the efficiency of individual units. More specifically, the efficiency concerns the achievement or not of the objective of maximizing the health improvements produced by a given level of public expense. Efficiency involves therefore the relation cost-effectiveness. In healthcare, the term efficiency describes the degree of utilization of available resources to produce outputs-results which may begin with intermediate output-results (patients who were hospitalized, days of hospitalization, clinic visits, number of diagnostic tests, etc.) and reach the final goal that is to restore people's health as it can be expressed in positive health indicators or health indicators relevant to the quality of life. The efficiency is generally greater when a given quantity of product-output is produced at minimum cost and best quality, or when having a given cost the maximum amount of product output is achieved. In addition for every inefficient DMU, DEA identifies a set of corresponding efficient units that can be utilized as benchmarks for improvement. Since the introduction of DEA methodology, a considerable number of researchers have applied it in the health service sector. For a review of this literature see [3, 4].

Charnes et al. [5] first introduced a mathematical programming formulation of the problem of estimating the relative efficiency of operating units such as Hospitals that produce multiple outputs from a given set of multiple inputs. They analyze the performance of operating units when the technology exhibits constant returns to scale (CRS). The CRS orientation efficiency scores of each hospital can be obtained by solving the following linear programming problem:

$$\theta_{CRS}=\min \left\{\theta > 0 \,\middle|\, y \leq \sum_{i=1}^{n} \lambda_i y_i ,\ \theta x \geq \sum_{i=1}^{n} \lambda_i x_i ,\ \lambda_i \geq 0,\ i = 1,\ldots n \right\} \qquad (1)$$

In Eq. (1) the efficient level of input is defined by θx, which is the projection of an observed hospital (x, y) on to the efficient frontier, while θ is a scalar and λ is a non-negative vector of constants specifying the optimal weights of inputs/outputs. The value of θ_{crs} obtained is the Technical Efficiency score for the i^{th} hospital. In order to become efficient, technical efficiency gives the decrease of inputs, which an observed hospital at location (x, y) could undertake. In the case where $\theta_{crs}=1$, the hospital is considered fully efficient. The CRS assumption is only appropriate when all measured units are operating at an optimal scale. Financial or other input constraints, public sector central planning procedures, etc., may prevent a unit from operating at an optimal scale.

Banker et al. [6] have adopted a set of assumptions different from Charnes et al. [5]. They have introduced an extension of the CRS DEA model to account for variable returns to scale (VRS). The use of a CRS specification in cases when not all measured units operate at the optimal scale results in a measure of Technical Efficiency which is biased by Scale Efficiency. The use of the VRS specification permits the calculation of Technical Efficiency scores free of Scale Efficiency effects. The CRS linear programming problem can be easily modified to account for VRS by adding in equation (1) the convexity constraint:

$$\sum_{i=1}^{n} \lambda_i = 1 \qquad (2)$$

This approach forms a convex hull of intersecting planes which envelop the data points more tightly than the CRS conical hull and thus provide technical efficiency scores which are greater than or equal to those obtained using the CRS model. The convexity constraint essentially ensures that an inefficient unit is only “benchmarked” against units of a similar size.

In this paper, there a priori reasons to assume that hospital operations would be subject to VRS due to the heterogeneous sample of hospitals. As discoursed in the next section the hospitals in our sample vary widely in size, treatment capabilities and workload.

3.2 First stage analysis: Bootstrapping DEA scores

Since DEA has statistical limitations we use the bootstrap procedure smoothed bootstrap approach of Simar and Wilson [1]. Bootstrapping DEA is an approach that simulates the original sample B times, each time recalculating the parameter of interest which is the DEA efficiency score. This will allow B estimates of the parameter, and thus makes it possible to generate an empirical distribution for the parameter of interest. The empirical distribution can then be used to be used to construct confidence interval of the efficiency scores calculated via DEA, and also obtain other statistical properties. The VRS and CRS efficiency measures are estimated in each bootstrap replication according to the following algorithm:

a) Calculate the DEA input-orientated efficiency score θ_i for each hospital i=1,2,..n using DEA with either a CRS or VRS specification.
b) Using a smooth bootstrap generate from θ_1, θ_2,… θ_n a random sample size of

n: $\theta_{1,b}*,\ \theta_{2,b}*, \ldots \theta_{n,b}*$, b=1,…B where b is the b[th] iteration of the bootstrap.

c) Smooth the sampled values using the following equation: $\tilde{\theta}_i * = \begin{cases} \theta_{1,b} * + h\varepsilon_i * & \text{if } \theta_{1,b} + h\varepsilon_i * \geq 1 \\ 2 - \theta_{1,b} * + h\varepsilon_i * & \text{if } \theta_{1,b} + h\varepsilon_i * < 1 \end{cases}$

Were h is the smoothing parameter of the Kernel density of the original efficiency estimates, $\varepsilon_i *$ are random draws for the standard normal distribution. Note that we obtain h for our bootstrapping application by maximizing the likelihood cross-validation function in the Gaussian kernel estimation. The Kernel density estimation is a nonparametric technique for density estimation in which a known density function (the kernel) is averaged across the observed data points to create a smooth approximation.

d) Calculate the final value θ* by adjusting the smoothed sample value using the following equation:

$$\theta_i * = \overline{B} + \frac{\tilde{\theta}_i - \overline{B}}{\sqrt{1 + h^2/\sigma_\theta^2}}$$

were: $\overline{B} = \left(\frac{1}{n} \sum_{i=1}^{n} \theta_{i,b} * \right)$ b=1,…B and $\sigma_\theta^2 = \frac{1}{n} \sum_{i=1}^{n} (\theta_{i,b} - \overline{\theta_\iota})^2$,

e) Adjust the original outputs for each hospital i=1,..n using the ratio: $\theta_i / \theta_i *$.

f) Resolve the original DEA model using the adjusted outputs to obtain $\theta_{i,b} *$, b=1,…B.

g) Repeat steps b-f, B times to provide for B sets of estimates and compute the estimated confidence intervals for the efficiency scores. For this analysis 2000 samples were generated for each hospital. Bias corrected estimates of original technical efficiency scores are derived through:

$$\text{bi}\hat{\text{a}}\text{s}_i = \left(\frac{1}{B} \sum_{b=1}^{B} \theta_{i,b} * \right) - \theta_i = \tilde{\theta}_i - \theta_i .$$

A bias-corrected estimator of the true value of θ_i can then be computed using the following equation: $\hat{\theta}_i = \theta_i - \text{bi}\hat{\text{a}}\text{s}_i$.

3.3 Second stage analysis: bootstrapped truncated regression

In the empirical literature on efficiency assessment, it has been common practice to perform analyses aimed at investigating the determinants of efficiency. Simar and Wilson [2] have pointed out that, previous studies involving such two-stage semi-parametric models of production processes fail to describe a coherent data-generating process and are invalid because of the complicated nature of serial correlation among the estimated efficiencies. A main reason for this problem is the well-known fact that the DEA efficiency score is a relative efficiency index, not an absolute efficiency index. Therefore the second stage of our analysis is to carry out a regression model to determine the influence of environmental variables on the bias-corrected efficiency scores. In doing so, we make use of the procedure proposed by Simar and Wilson [2], based on truncated regression and bootstrapping techniques. The importance of this procedure is the demonstration of valid estimates for the parameters in the regression model, using the bias corrected estimates of θ. To illustrate the procedure that we followed we apply the following regression model:

$$\theta_i = \beta_i z_i + \varepsilon_i \qquad (3)$$

where z_i is a vector of environmental variables that explain the efficiency between the hospitals under consideration and β_i refers to a vector of parameters with some statistical noise ε_i. A common method in the literature is to use the OLS regression to estimate this relationship. However, as described in [5], this might lead to estimation problems due to the correlation and dependency problems of the efficiency scores which violate the regression assumption that ε_i are independent of z_i. This bootstrap algorithm described briefly in the following steps:

a') Calculate the DEA input-orientated efficiency score θ_i for each hospital i=1,2,..n using the DEA method.

b') Maximum likelihood is used in the truncated regression of θ_i on z_i, to provide an estimate $\hat{\beta}$ of β and an estimate $\hat{\sigma}_\varepsilon$ of σ_ε.

c') For each hospital i=1,…n, the next four steps (1-4) are repeated B times to yield a set of bootstrap estimates $\{\theta_{i,b}*, b=1,\ldots B\}$.

1) Drown ε_i from the N(0, $\hat{\sigma}_\varepsilon^2$) distribution with left-truncation at $(1-\hat{\beta}z_i)$.

2) Compute $\theta_i* = \hat{\beta}z_i + \varepsilon_i$.

3) Construct a pseudo data set (x_i*, y_i*), where $x_i* = x_i$ and $y_i* = y_i\theta_i / \theta_i*$.

4) Compute a new DEA estimate θ_i* on the set of pseudo data (x_i*, y_i*), i.e. Y and X are respectively replaced by $Y* = \{y_i*, i=1,\ldots n\}$ and $X* = \{x_i*, i=1,\ldots n\}$.

d') For each hospital i=1,…n, compute the bias-corrected estimate $\hat{\theta}_i = \theta_i - bi\hat{a}s_i$, where $bi\hat{a}s_i$ is the bootstrap estimator of bias obtained as $bi\hat{a}s_i = \left(\frac{1}{B}\sum_{b=1}^{B}\theta_{i,b}*\right) - \theta_i$.

e') Use the Maximum likelihood method in the truncated regression of $\hat{\theta}_i$ on z_i, to provide an estimate $\hat{\hat{\beta}}$ of β and an estimate $\hat{\hat{\sigma}}$ of σ_ε.

f') Repeat the next three steps (1-3) are repeated B times to yield a set of bootstrap estimates $\left\{(\hat{\hat{\beta}}_b*, \hat{\hat{\sigma}}_b*, b=1,\ldots,B)\right\}$.

1) For each hospital i=1,…n, ε_i is drawn from the N(0, $\hat{\hat{\sigma}}$) distribution with left truncation at $(1-\hat{\hat{\beta}}z_i)$.

2) For each hospital i=1,…n, $\theta_i** = \hat{\hat{\beta}}z_i + \varepsilon_i$ is computed.

3) The Maximum likelihood is again used in the truncated regression of θ_i** on z_i, providing estimates $\hat{\hat{\beta}}*$ of β and an estimate $\hat{\hat{\sigma}}*$ of σ_ε.

g') Construct the confidence intervals for the efficiency scores. The estimated $(1-\alpha)$ per cent confidence interval of the *j*-th element β_j of the vector β, is: $\mathrm{Prob}(Lower_{\alpha,j} \le \beta_j \le Upper_{\alpha,j}) = 1-\alpha$

where $Lower_{\alpha,j}$ and $Upper_{\alpha,j}$ are calculated using the empirical intervals:

$$\mathrm{Prob}(-\hat{b}_\alpha \le \hat{\hat{\beta}}_j* - \hat{\hat{\beta}}_j \le -\hat{a}_\alpha) \approx 1-\alpha$$

where $Upper_{\alpha,j} = \hat{\hat{\beta}}_j + \hat{b}_\alpha$ and $Lower_{\alpha,j} = \hat{\hat{\beta}}_j + \hat{a}_\alpha$.

4. Data sources

The present study has been based on data provided by the Greek Ministry of Health concerning 96 Greek general hospitals for the year 2005. The total number of Greek public hospitals is 134. In order to ensure general comparability we select a more homogenous sample which contains hospitals that provide the full range of general services. Therefore we exclude the rest of 38 very specialized hospitals (dermatological, orthopedic, gynecological, psychiatric ect). The descriptive information that is presented in table 1 indicates also the inputs and outputs that were used for assessing hospital efficiency in economic and production models.

Table1: Descriptive information concerning the hospitals of the study.

	Variable	Mean	S.D.
Inputs: Economic Model	The expenses for the human resources	18,562,003	15,429,949
	The expenses for supplies	35,312,382	46,703,583
	The operational cost	6,979,521	6,798,164
Inputs: Production Model	Number of doctors	185	145
	Number of laboratorial doctors	58	49
	Number of nurses	288	241
	Number of administrative staff	70	66
	Number of beds	268	214
Outputs for both models	Introduction in pathologic clinic	7,723	7,508
	Introduction in surgical clinic	6,825	5,185
	Number of surgeries	4,313	4,739
	Number of outpatient visits	105,213	65,736
	Laboratorial examinations	1,291,205	1,417,416
Explanatory variables	Occupancy	0.64	0.15
	Length of Stay	4.20	1.29
	Medium size hospitals (Vs. small ones)	64.6	-
	Large size hospitals (Vs. small ones)	22.9	-

Note: All prices are measured in Euro's. For dummy variables the mean value gives the proportion of hospitals in that class.

In the second stage of the analysis three explanatory variables were regressed. These variables are among the most employed in the literature with respect to DEA studies about hospital evaluation. First, we chose the size of the facilities (i.e. the number of beds). Three size categories were selected: less than 100 beds; 100-400 beds; and, 400 or more beds. These size categories are commonly used by national organizations to classify hospitals for comparison. The next two variables represent service indicators that can be used to assess how hospital resources are utilized and whether hospitals are operate according to their full capacity. For example, patients that stay in hospital longer than necessary are using resources that could be allocated to other patients. Commonly used ratios that measure service characteristics of hospital performance include (1) bed occupancy rates and (2) average length of stay. Bed occupancy rate: refers to the average number of patients per bed per year is used to represent hospital capacity utilization. Average length of stay is the average amount of time spent in hospital and is defined as the mean number of days that an inpatient stays in hospital from the time of admission to discharge and is often used to represent the intensity and efficiency with which individual patients are treated and is therefore an important quality indicator.

Results

The results that were estimated with the DEA-bootstrapping procedure described previously, suggest an average bias–corrected VRS efficiency of 72% in economic model and 81% in production model. The average score in production model seem to be very similar with the bias-corrected results of the other studies in the literature which is near 80% [7, 8, 9], in contrast to the economic model which produces a sufficient lower average score. These results indicate that the Greek hospitals face more difficulties in using their economic resources, than in the usage of the human resources. Another interesting aspect comparing the cost and production models occur when we observe their average bias correction. In economic model the average bias in CRS and VRS is much larger than of those observed in production model. This effect indicates that the economic model present greater heterogeneity than the production model, due to the large variation in hospitals expenditures. The above analysis of the efficiency scores provides an overview of the general cost and production efficiency in the Greek hospitals. The variability of performance, however, may be due to environmental and organizational factors beyond the manager's control.

The truncated regression analysis provides more general information about hospital efficiency in Greece. The estimation results of the truncated regression models presented in Equation (3) are shown in Table 3. This table include the value of each estimated coefficient, the z-statistic and the corresponding p-value as well as the lower (LB) and the upper bound (UB) of each estimated coefficient. The estimation results for the production model and economic model are displayed in the left and right part of the table 3 respectively.

In production model the coefficient in both medium and large size hospitals is negative and statistically significant with the level of efficiency. The coefficient of occupancy is positive however it is not statistically significant. In contrast, the length of stay coefficient is negative and statistically significant. Longer lengths of stay appear to hurt the level of production efficiency.

On the other hand in economic model the effects from their operational size characteristics are not statistically significant. The coefficient of occupancy is positive and their effect is now statistically significant. Hence, hospitals that maximize their bed uses or having fewer empty beds could be able to improve their cost efficiency. This was an expected result since a hospital spread their fixed cost according to their occupancy rates. Ferrier and Valdmanis [10] indicate also a positive impact of occupancy rate on hospital cost efficiency.

Table 3: Sources of VRS technical in production model and economic model

	production model				**economic model**			
Variable	Coefficient	t-statistic (p-value)	95% Confidence Interval		Coefficient	t-statistic (p-value)	95% Confidence Interval	
			LB	UB			LB	UB
Constant	0.926	11.29 (0.000)	0.765	1.086	0.711	8.34 (0.000)	0.544	0.878
Medium	-0.115	-3.34 (0.001)	-0.183	-0.047	-0.080	-1.52 (0.129)	-0.184	0.023
Large	-0.118	-2.25 (0.025)	-0.221	-0.015	-0.058	-0.83 (0.407)	-0.196	0.079
Occupancy	0.189	1.64 (0.101)	-0.037	0.416	0.303	2.52 (0.012)	0.067	0.539
Length of stay	-0.024	-2.15 (0.032)	-0.047	-0.002	-0.025	-2.10 (0.036)	-0.049	-0.001
Log-L	88.02				65.91			
Wald X^2	15.52				10.76			

Number of iterations=2000

Additionally, the impact of the length of stay variable is negative and statistically significant. Hence, the cost efficiency in a similar manner with production efficiency appeared to be harmed with longer lengths of stay, meaning that the hospitals spend more on patients who stay longer. As it noted in [11] the average length of stay in hospitals is often regarded as an indicator of efficiency, since a shorter stay may reduce the cost per discharge and shift care from in-patient to less expensive post-acute settings. Here, it must point out that the complex tertiary cases are referred to large hospitals, for that reason the average length of stay would be expected to be relatively short in small and medium hospitals. Results of the Mann-Whitney test indicate statistically significant differences in average length of stay between small and large hospitals ($p=0.02$) and medium and large hospitals ($p<0.001$). These differences on the complexity of care provided to patients may also explain a part of the inefficiencies obtained in large hospitals [12].

Conclusions

This study provides a clear framework for policy implications to increase the overall efficiency of general hospitals. Although public hospital services were integrated into national health system and many resources were consumed for their improvement, significant problems in hospitals still remain and there is substantial public dissatisfaction with the hospital services. Evaluating the hospitals operation we observe that cost containment polices concentrate to horizontally cut off the human resources. Consequently, all levels of public health services organization and provision are severely understaffed. On the other hand the cost of hospitals supplies has risen uncontrollably over the past 10 years, leading to an excessive increase in hospital expenditures. This is partly due to the fact that new treatments are in general, more expensive than older ones, however in Greek hospitals until now there is not any reliable mechanism to quantify and monitor their supplies. In several cases the absence of Enterprise Resource Planning (ERP) tools to monitor and control hospitals inventory, cause the abuse or the expiration of expressive consumables.

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