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# Two-stage hospital efficiency analysis including qualitative evidence: A Greek case

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## ABSTRACT

**Background:** The European Union health policy agenda stresses the importance of environmental and qualitative factors in structural hospital reforms. In response to the economic crisis, both cost containment and performance improvements of the Greek hospital sector, have become a pertinent issue for overall reforms.
**Objective:** The study examines the efficiency of 112 Greek public hospitals, by applying bootstrapping techniques and investigating the effect of contextual factors on hospital efficiency. Furthermore, the effect of qualitative evidence, on hospital efficiency is explored by focusing on a subset of 28 large hospitals.
**Methods:** The quality aspects of the Greek hospitals are investigated by applying two models of Data Envelopment Analysis (DEA), augmented by bootstrapping techniques, in order to assess the importance of quality dimensions on the efficiency of hospital scores. In addition, two Tobit regression models are estimated assessing the contribution of contextual factors, in the efficiency and bias-corrected efficiency scores.
**Results:** Efficiency analysis indicated that only 23.2% of the hospitals are fully efficient (0.96-1.00), 37.5% are efficient (0.71-0.95) while 39.3% are inefficient (0.30-0.70). The Kolmogorov-Smirnov test, between the original and the bootstrap-corrected efficiency, indicates that their distributions are significantly different ($p$-value < .001). The environmental factors, influencing efficiency, are Occupancy Rate and the ratio between Outpatient Visits and Inpatient Days. Results indicate that the inclusion of Risk-Adjustment Mortality Rate significantly influences ($p$-value < .05) the efficiency of the hospitals.
**Conclusions:** In the era of economic crisis, the inclusion of quality variables and the use of bootstrapping techniques provide a vital framework in assessing the efficiency of the hospital sector.

**Key Words:** Hospital efficiency, Quality, Data envelopment Analysis, Tobit regression, Greece

## 1. INTRODUCTION

The ageing of the population, the increasing use of expensive health technologies and the inefficiencies in the health production process are the main factors that contribute to the rising of health expenditures.[1] Structural reforms in the hospital sector have become a vital part of the European Union's health policy agenda. Moreover, the EU has recognized the importance of qualitative evidence in the reform planning process, as well as the opportunity to improve health sector's long-term performance during the economic crisis.[2]

Greece is currently engaged in an economic adjustment program designed by the European Commission. However, to the best of our knowledge, there has been no effort to take

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under consideration both quantitative and qualitative aspects of the Greek hospital system in the reforms. The only dimension explored is the need of cost containment. Furthermore the Greek hospital's efficiency is based only in operational and financial evidence. In order to fill this gap, we decided to investigate the qualitative aspects of hospital performance.[3]

In Greece, the health expenditure ratio as a percentage of GDP has increased from 7.9% in 2000 to 10.03% in 2009, exceeding the respective European Union average. During the public debt crisis' period, spanning from 2009 to 2012, Greece confronted an endemic debt and was forced by its institutional lenders (European Union, European Central Bank and International Monetary Fund), among many other reforms, to reduce its public health expenditures. Health expenditure in Greece, as a percentage of GDP, was indeed decreased in comparison to the EU's average, which remained stable during the respective period. However, hospital expenditure, which represents almost half of the total health expenditure, remained relatively stable.[4]

Although the health facilities have been sufficient and the medical equipment excessive, Greek hospitals have been presenting long lasting problems related to spare capacity and absence of even the most basic managerial practices in the hospital sector.[3, 5] Healthcare funding is being distributed without taking into consideration the hospital efficiency or any quality indicator at all. This led to the burdening of the Greek households with the highest out-of-pocket medical expenses among the OECD countries.[6, 7]

The economic crisis brought significant deterioration of the population's health status and decline in the provision of health services. Despite its negative effects, it has often been argued by the OECD and other international organizations, that a crisis constitutes a "window opportunity" to launch new reforms in the health system. Within this framework several attempts have been made, in order to improve the efficiency and delivery aspects of hospital services in Greece. A new information management system (ESY.net), compatible with international standards, was established. Additionally, in an attempt to achieve a more efficient pooling of resources and to enhance the purchasing process of health services, through economies of scale, most of the main insurance funds were merged into a single provider of healthcare services, named "EOPYY". Moreover, the DRG-prospective reimbursement system was introduced, and an operational redeployment of 131 Greek public hospitals was partially made.[8]

There is a twofold purpose for this study: first is to examine the efficiency of 112 Greek public hospitals in 2009 by evaluating the importance of bootstrapping techniques and investigating the effects of contextual factors on hospital efficiency. Second, is to examine the magnitude of the effect that a quality output variable (mortality rate adjusted by the number of surgeries) imposes on the efficiency estimation. This is observed by applying efficiency estimation analysis based on a dataset consisting of 28 large public hospitals.

Despite our major effort to find the required information, they have been unavailable in many cases. More specifically, due to severe data collecting issues, we were unable to find qualitative indicators for the smaller hospitals. The same issue was also encountered concerning the time period that our data cover. We could not find any qualitative evidence after 2009. Despite the aforementioned difficulties, we took advantage of two well organized databases, merging them into one and making full use of all the available resources.

According to international practices, certain benchmarking criteria should be implemented in the managerial process of hospitals. This study attempts to provide such criteria, by exploiting qualitative evidence. To the best of our knowledge, there has been no other relevant study concerning Greek hospitals.

The rest of the study is divided in five sections. Section 2 contains a review on recent healthcare efficiency measurement studies implementing quality indicators. Section 3 shows a presentation of the mathematical background of DEA methodology, enhanced by bootstrapping techniques, as well as the respective theoretical basis of Tobit regression modeling developed. Likewise, we briefly present the statistical tests used in order to compare the efficiency score distributions. The relevant data and the estimated results are presented and discussed in section 4. Finally, the fifth section provides the conclusions and limitations of the current study.

## 2. Literature review

The measurement of efficiency is crucial for organizations and businesses because it allows performance comparison between themselves and their competitors. Furthermore, it aids in the establishment of a reciprocal policy of "best practices", providing incentive for improvement of their own performance. As far as hospitals are concerned, in order to contain their costs and verify the quality of their services, an efficient allocation and utilization of resources has to take place. Therefore, the concept of efficiency analysis is crucial for the potential improvement of hospital performance. Recent relative international studies are quoted below.

Silva[9] attempted to evaluate the worthiness of risk-adjustment methodology in technologically advanced healthcare environments. The research found that risk-adjustment becomes more complex and biased, as we add variables concerning the technological level of healthcare services. Furthermore, Silva argues that excluding these variables from the regression analysis would produce a less accurate risk-adjustment model.

Werner and Bradlow[10] attempted to find correlation among measures that show medical unit's quality of services and the ones that present risk's levels through adjusted mortality rates. They used cardiovascular data from 2004 to evaluate performance and Medicare claims data to calculate risk adjusted mortality. Results indicated that hospitals performing in the $1^{st}$ quality quartile have no significant difference, concerning risk-adjusted mortality rates (RAMRs), in comparison to the ones performing in the $3^{rd}$ quartile. Therefore, they propose the creation of new performance indicators tightly associated to mortality rates.

Forthman *et al.*[11] attempted to define a risk-adjustment method for validly comparing clinical outcomes among providers of healthcare and to describe its applications on documenting and monitoring hospital outcomes. They discovered that using risk-adjustment techniques on mortality rates create a useful guideline regarding the quantification of hospital quality of care. Resulting benefits are multi-layered since providers may use this tool to compare not only different healthcare units but, also to certify that quality standards remain high while experimenting with new treatment programs.

Glance *et al.*[12] tried to discover whether the regionalization of health care should be based on patient volume or on RAMRs. They found that RAMRs are more reliable on this topic when compared with hospital volume. Their results, based on 243,000 patients that underwent cardiac surgery, indicate that the latter's value is overrated and that volume as a measure of quality of care should be avoided, because its' results produce a lot of disruption. On the other hand risk-adjustment results are more accurate.

Share *et al.*[13] examined a collaborative program, funded by a private insurance company, among hospital units in Michigan that aimed to achieve better results by gathering collective resources from the hospitals and using them in a way that would be more efficient. Combining resources of different hospital units, under a joint management, seems to produce better outcomes in terms of mortality, and therefore quality, while, at the same time, gives the potential to reduce costs without affecting directly the overall hospital performance. Thus, stakeholders would be satisfied and simultaneously healthcare professionals will have no impact on their remunerations.

Joynt *et al.*[14] used Medicare patients suffering from Congestive Heart Failure (CHF) to find out whether or not experienced healthcare units provide higher quality services. Their results indicate that higher volume units seem to have lower mortality rates, due to experience and better management techniques. However, at the same time, such units also produce higher costs of care. Meanwhile, smaller, in terms of volume, hospitals, lack the required equipment and staff to provide prime quality services.

Birkmeyer *et al.*[15] examined connections to hospital outcomes and expenditures in the US Medicare population. Using the 100% national claims' files, they identified all US hospitals performing coronary artery bypass (CABG), total hip replacement (THR), abdominal aortic aneurysm (AAA) repair, or colectomy procedures between 2005 and 2007. Medicare payments concerning inpatient surgery are substantially higher at hospitals with high complications. These findings suggest that local, regional, and national efforts aimed at improving surgical quality, may ultimately reduce costs as well as improve outcomes. Hospital mortality was not associated with expenditures.

Last, Bilsel and Davutyan,[16] analyzed the operational performance of 202 Turkish rural general hospitals. They adopted a directional distance approach and treated a mortality based measure as a "needs indicator". They derived pure technical scale and output congestion inefficiency measures and show how they vary across size classes, showing that "reducing mortality" involves sacrificing some good outputs.

Moreover, several Greek studies have been conducted in the field of hospital efficiency. They are solely based on operational and financial evidence. Kontodimopoulos *et al.*[17] measured the technical efficiency of 17 small-sized hospitals, located in rural areas that cover approximately 20,000 people. The findings showed that their efficiency score ranged at about 75 per cent. In another study, Tsekouras *et al.*,[18] measured, using Bootstrap DEA, the productive efficiency of 39 intensive care units (ICUs) of the Greek Healthcare system in 2004. The purpose of the study was to reveal if new medical technology investment into ICUs had a positive impact. The findings demonstrated that technical efficiency was indeed improved but, scale efficiency remained the same. Androutsou *et al.*[7,19] measured the performance in seven homogenous specialty clinics across all National Health System hospitals in the Regional Health Authority of Thessaly, over the period 2002-2006 with Malmquist Index.

In the following section Data Envelopment Analysis (DEA) method as well as the bootstrap resampling technique are briefly presented.

## 3. METHODOLOGY

In the international literature there are mainly two approaches for efficiency measurement. These are the parametric and the non-parametric. The parametric approach employs two classes of econometric techniques for efficiency analysis: Corrected Ordinary Least Squares (COLS) and Stochastic Frontier Analysis (SFA).[1] Respectively, the non-parametric approach uses DEA which is based on linear programming. Although the latter is considered simplistic and criticized for being sensitive to outliers, we opted for it because it enables us to use a multiplicity of inputs and outputs and there is no need to be aware of the specific form of the production's function.[1,5]

### 3.1 DEA

Based on the work of Charnes *et al.*,[20] Banker *et al.*[21] introduced the so-called BCC (Banker, Charnes and Cooper) model of efficiency measurement. This model assumes a production technology of variable returns to scale, implying that any proportional change in inputs usage will result in variable proportional change in outputs. We assume that each DMU$_k$ has multiple inputs $X_{i,k}$ and multiple outputs $Y_{r,k}$. The input-oriented BCC model is formulated as follows (see Equation 1):

$$\begin{aligned} &\min E_0 = \theta_0 \\ &s.t. \sum_{k=1}^{n} \lambda_k X_{ik} \le \theta_0 X_{i0}; \\ &\sum_{k=1}^{n} \lambda_k Y_{rk} \ge Y_{r0}; \\ &\sum_{k=1}^{n} \lambda_k = 1. \end{aligned} \tag{1}$$

According to Simar and Wilson,[22] unless corrected by a bootstrapping procedure the DEA results are inconsistent and biased parameter estimates (*e.g.* as a result of the dependence of the DEA efficiency scores on each other). Thus, the bootstrapped DEA approach was applied in this study, by performing repeated sampling.

### 3.2 Tobit regression analysis

In a two-stage analysis of hospital efficiency, it is desired to shed more light on the issue of possible impact on efficiency of contextual factors beyond the control of the hospitals, *i.e.* the operating status of the hospital, the location *etc*. The Tobit model is employed because of the lower tail censoring of the distribution that DEA creates. Thus, the use of OLS estimations is not an appropriate method of determining the desired factors of hospital efficiency, since the dependent variable is constrained in the 0-1 interval.

Green[23] proposed a censoring point at zero for computation purposes and transformed DEA efficiency scores into inefficiency scores left-censored at zero using the equation as follows (see Equation 2):

$$ineff\ score = \frac{1}{DEA\, eff \cdot score} - 1 \tag{2}$$

Consider the linear regression model:

$$\begin{aligned} &y_i^* = \beta x_i + u_i,\ u_i \sim N(0, \sigma^2) \\ &y_i = y_i^*\ if\ y_i^* > 0; \\ &y_i = 0\ if\ y_i^* \le 0. \end{aligned} \tag{3}$$

For *i* = 1, ... ,*n*, $\beta$ is the vector of unknown parameters. $x_i$ is the vector of explanatory variables. The observed data $y_i^*$, represent possibly censored versions of $y_i$, where "ineff" is the inefficiency score and $x_i$ are the contextual factors.

### 3.3 Comparison of distributions between models

In order to compare the distributions of efficiency scores between two groups, different statistical tests are conducted in the non-parametric literature. The Mann-Whitney and the Kolmogorov-Smirnov tests are applied to explore inefficiency differences between different models.[24,25] Following the Mann-Whitney test, the test statistic is given by the following formulas where W is the sum rank for the first group of hospitals:

$$T_{MW} = \frac{U_1 - (N_1 N_2/2))}{\sqrt{N_1 N_2 (N_1 + N_2 - 1/12))}} \tag{4}$$

$$U_1 = N_1 N_2 + \frac{N_1(N_1+1)}{2} \tag{5}$$

The distribution of the Mann-Whitney test statistic is approximated well by the standard normal distribution for sufficiently large values of $N_1$ and $N_2$ (*e.g.*, $N_1$, $N_2$ > 10). In the case of the Kolmogorov-Smirnov test, the test statistic is given by the maximum vertical distance between $F^{G_1}(ln(\hat{\theta}_j))$ and $F^{G_2}(ln(\hat{\theta}_j))$ and the empirical distribution of the group $G_1$ and $G_2$. This Kolmogorov-Smirnov statistic, by construction, takes values between 0 and 1, and a high value for this statistic is indicative of significant differences in the distribution of inefficiency between the two groups. Whereas the Mann-Whitney statistic is more sensitive to variations of a distribution's median.

## 4. RESULTS

Our data set consists of year 2009, obtained from the web-based facility (ESY.net) of the Greek Ministry of Health and contains information on 112 public hospitals. The aforementioned facility, established a framework, as was agreed by the Ministry of Health and the so called "troika" (European Union, European Central Bank, International Monetary Fund), in order to collect data for financial and utilization evaluation of the NHS. It has been compatible with the international standards of organizations such as World Health Organization (WHO), OECD and Eurostat. However, the official grant of access to researchers was given in 2011.

The selection of inputs and outputs was based on international literature on hospital efficiency[1] and on the availability of relevant data concerning the Greek Hospitals. We measured outputs by: (1) the number of patient discharged adjusted for case-mix with Roemer Index and (2) the number of diagnostic procedures. Inputs were measured by (3) the number of doctors, (4) nurses, (5) beds and (6) non-labour expenditures (*i.e.* pharmaceutical supplies, *etc.*). We respected the DEA convention that the minimum number of DMUs (Decision Making Units: hospitals in this case) is three times the number of inputs plus outputs.[26] Table 1 presents summary descriptive statistics of input and output variables used in the models.

**Table 1.** Descriptive statistics of Input-Output variables for 112 Greek hospitals

| | Inputs | | | | Outputs | |
|---|---|---|---|---|---|---|
| | **Doctors** | **Nurses** | **Beds** | **Expenditures (€)** | **Patients** | **Diagnostic Tests** |
| Min | 8 | 13 | 18 | 259,007 | 4,717 | 3,940 |
| Max | 831 | 1,010 | 936 | 135,739,663 | 85,383 | 410,804 |
| Mean | 183 | 293 | 258 | 21,165,057 | 17,625 | 102,519 |
| St. Dev. | 174 | 234 | 217 | 27,694,096 | 20,120 | 73,029 |

**Table 2.** Distribution of Efficiency Values, 112 Greek hospitals

| Efficiency level | Efficiency Scores Range | Corrected Scores Range | Percentage |
|---|---|---|---|
| Fully Efficient | 0.96 - 1.00 | 0.72 - 0.89 | 23.21% |
| Very Efficient | 0.81 - 0.95 | 0.60 - 0.86 | 18.75% |
| Efficient | 0.71 - 0.80 | 0.45 - 0.68 | 18.75% |
| Inefficient | 0.51 - 0.70 | 0.24 - 0.50 | 30.36% |
| Very Inefficient | 0.30 - 0.50 | < 0.24 | 8.93% |

**Table 3.** Statistical tests of equality of distributions

| Statistical Test | *p*-value | Value of the test statistic |
|---|---|---|
| Kolmogorov-Smirnov | < .0001 | 2.290* |
| Mann-Whitney | < .0001 | 3.469* |

* Significant at the .001 level

Table 2 presents the original Efficiency Scores Range, the corresponding Bootstrap-corrected Efficiency Scores as well as the frequency percentages for each efficiency level.

Twenty-six (23.21%) hospitals were technically efficient. Twenty-one (18.75%) scored between 0.81 and 0.95. Twenty-one (18.75%) scored between 0.71 and 0.80. Thirty-four (30.36%) scored between 0.51 and 0.70 and ten (8.93%) scored less than 0.50. However, the respective bias-corrected efficiency scores were relatively lower for each efficiency level.

Table 3 shows the statistical tests used in order to evaluate the difference between the bias corrected and the original model distributions. The results of the tests indicate that the differences between the distributions are statistically significant.

Both tests are conducted under the null hypothesis that the two sets of scores are drawn from the same distribution. The Kolmogorov-Smirnov test statistic (2.290) reveals statistically significant differences in efficiency scores between the two models ($p$-value < .001). The Mann-Whitney test confirms that the differences in the two distributions are statistically significant ($p$-value < .001).

### 4.1 Regression results

As mentioned in the methodology section, Tobit regression relates the (in)efficiency scores, as the dependent variable, to a number of explanatory variables. In the context of this study, the following factor variables were investigated: (1) the catchment area population (CAP), (2) the three dummy variables concerning hospital size based on the number of beds (Large hospitals are the ones with more than 400 beds [L], medium hospitals have 100 to 400 beds [M] and small hospitals are all the rest, having less than 100 beds [S]), (3) the proportion of outpatient visits to inpatient days, (4) the bed occupancy rate (OCP), (5) the average length of stay (ALS), the two dummy dichotomous variables, Urban (Athens Metropolitan Area, Thessaloniki) and Rural (all other areas), representing the population density around the hospitals, and (6) the two dummy variables, Teaching or Non-Teaching, representing the academic status of the hospital.

**Table 4.** Tobit results for Inefficiency factors, 112 hospitals

| Model A (Inefficiency) | Coefficient | *t*-ratio | *p*-value |
|---|---|---|---|
| CAP | 1.02e-08 | 0.16 | .877 |
| Large | -0.044 660 5 | -0.25 | .802 |
| Medium | -0.104 641 5 | -0.85 | .398 |
| Small | (omitted) | | |
| OutPat/InPat Days | -0.134 530 2** | -3.62 | .000 |
| OCR | -1.509 689** | -4.94 | .000 |
| ALS | -0.058 097 1* | -2.06 | .042 |
| Urban | 0.098 378 5 | 0.46 | .649 |
| Rural | (omitted) | | |
| Teaching | 0.114 524 4 | 0.55 | .587 |
| Non-teaching | (omitted) | | |
| Constant | 1.783 901 | 7.66 | .000 |
| Sigma | 0.425 160 7 | | |
| | 24 left-censored observations at Inefficiency ≤ 0 | | |
| | 88 uncensored observations | | |
| Observations Summary | 0 right-censored observations | | |
| Number of Observations | 112 | | |
| $\chi^2$ (8) | 38.07 | | |
| Prob > $\chi^2$ | 0.000 | | |
| Pseudo $R^2$ | 0.214 3 | | |

*Significant at the .05 level; **Significant at the .001 level

Tables 4 and 5 summarize the main findings of two Tobit models referring 112 hospitals, in which the dependent variables are the Inefficiency score, mentioned above, and its bias-corrected counterpart. In both estimated models the explanatory ability is significant at a high statistical level (Prob > $\chi^2$ = 0.0001).

The environmental factors that seem to significantly influence Efficiency (Model A) are the ratio between outpatient visits and inpatient days, occupancy rating, and ALS. The Coefficient column indicates that the aforementioned factors have a positive relationship with efficiency, while the strongest among the significant coefficients is assigned to occupancy rating (1.51).

Respectively, concerning Model B, the most significant factors influencing the bias-corrected efficiency scores, are the ratio between outpatient visits to inpatient days and occupancy rating. The latter, while exhibiting marginal significance in the .05 level, has an extremely positive effect on efficiency (22.16), as shown in the coefficients column.

### 4.2 Effect of qualitative evidence on efficiency

Following the results of Bilsel & Davutyan,[16] the current study utilized information concerning clinical results, namely the number of surgeries, as it is considered an indicator of hospital's quality. More specifically, we combined the number of surgeries performed with the number of in-hospital deaths, thus creating a RAMR, as shown in Equation 6:

$$RAMR = 1 - \frac{Number\ of\ Deaths}{Number\ of\ Surgeries} \quad (6)$$

At the time that the study took place, we exploited the latest up-to-date database provided by the Greek Statistical Authority (ELSTAT), which was from the year 2009 and contained relevant information concerning 28 large public hospitals.

The risk adjusted mortality rate (RAMR), which was derived by the merging of the two aforementioned databases (ESY.net and ELSTAT), was the only available qualitative indicator at the time.

**Table 5.** Tobit results for bias-corrected Inefficiency factors, 112 hospitals

| Model B (Corrected Inefficiency) | Coefficient | *t*-ratio | *p*-value |
|---|---|---|---|
| CAP | 3.29e-06 | 1,29 | .199 |
| Large | 1.779 245 | 0,26 | .792 |
| Medium | 0.105 481 | 0,02 | .982 |
| Small | (omitted) | | |
| OutPat/InPat Days | 4.258 826 | 3,34 | .001** |
| OCR | -22.1583 | -2,04 | .044* |
| ALS | -0.447 58 | -0,62 | .539 |
| Urban | -4.5545 | -0,54 | .589 |
| Rural | (omitted) | | |
| Teaching | 4.990 986 | 0,63 | .533 |
| Non-teaching | (omitted) | | |
| Constant | 9.373 766 | 1,15 | .254 |
| Sigma | 16.849 39 | | |
| | 1 left-censored observations at Inefficiency ≤ 0 | | |
| | 111 uncensored observations | | |
| Observations Summary | 0 right-censored observations | | |
| Number of Observations | 112 | | |
| $\chi^2$ (8) | 26.32 | | |
| Prob > $\chi^2$ | 0.000 9 | | |
| Pseudo $R^2$ | 0.027 2 | | |

*Significant at the .05 level; **Significant at the .001 level

Two different models (Models I & II) were generated to compare the efficiency results between the cases that included and did not include the RAMR. Output was measured by: (1) the number of patients discharged, adjusted for case-mix with Roemer Index, (2) the number of diagnostic procedures, and (3) the RAMR mentioned above (only in Model I). Input was measured by (4) the number of doctors, (5) nurses, (6) beds and (7) non-labour expenditures (*i.e.* pharmaceutical supplies, *etc.*). Table 6 below, presents the basic descriptive measures for input and output variables .

**Table 6.** Descriptive Statistics of Input-output variables for 28 hospitals

| | Inputs | | | | Outputs | | |
|---|---|---|---|---|---|---|---|
| | Doctors | Nurses | Beds | Expenditures | Patients | Diagnostic tests | RAMR |
| Min | 215 | 212 | 312 | 23,128,917 | 8,905 | 37,204 | 1,892 |
| Max | 831 | 1,010 | 949 | 135,739,663 | 114,989 | 410,804 | 19,529 |
| Mean | 433 | 545 | 585 | 56,533,132 | 39,950 | 165,765 | 7,821 |
| St. Dev. | 123 | 184.5 | 139 | 24,535,737 | 20,946 | 70,540 | 3,924 |

**Table 7.** Differences in efficiency with and without quality variable in 28 hospitals

| Model | Efficiency | Corrected Efficiency | Confidence Interval at 5% | |
|---|---|---|---|---|
| | | | Lower | Upper |
| Model I (incl. qual. var) | 0.875 | 0.793 | 0.698 | 0.871 |
| Model II | 0.895 | 0.814 | 0.708 | 0.890 |

Table 7 sums up the results of the two different DEA models, represented by their respective mean values. The analysis was executed twice, once in order to generate the original efficiency scores and once using bootstrap resampling in order to generate the respective bias-corrected efficiency.

Subsequently, after observing the differences between the various models, we executed statistical tests to investigate their significance. The test results, shown in Table 8, indicate that for the bootstrap corrected models, there is a significant distance between the distributions of Models I and II. The value of the Kolmogorov-Smirnov test statistic (1.47), under the null hypothesis that the two models have the same distribution, is statistically significant in the .05 level are efficient (*p*-value = .027), revealing that the two distributions are indeed different.

**Table 8.** Statistical tests of equality of distributions

| Statistical Test | *p*-value | Value of the test statistic |
|---|---|---|
| Kolmogorov-Smirnov | | |
| Efficiency | .938 | 0.535 |
| Bootstrap-Corrected Efficiency | .027 | 1.47* |
| Mann-Whitney | | |
| Efficiency | .498 | 352.5 |
| Bootstrap-Corrected Efficiency | .127 | 299 |

*Significant at the .05 level

## 5. Conclusions and limitations

This study analyzed hospital technical efficiency using the DEA method for 112 public hospitals in Greece. The results show that the majority of the hospitals (30.4%) score between 0.51 and 0.7, while less than a quarter (23.2%) operate on the efficiency frontier. The main determinants of hospital efficiency are occupancy rating and the ratio between the outpatient visits and the inpatient days. Additionally, the use of bootstrap resampling, in efficiency analysis, imposes a statistically significant effect on the distribution of efficiency scores (*p*-values < .05).

Moreover, the addition of the quality indicator significantly affected the distribution of the bias-corrected efficiency scores, for a subset of 28 large hospitals (*p*-values < .05).

The practical policy conclusion of this study is that, despite the difficulties in the healthcare sector in Greece, certain public hospitals are leading the way to high productivity and efficiency. Their “best practices” should be identified and adapted by the less productive hospitals.

Moreover, identifying almost 10% of hospitals as totally inefficient is a major argument concerning the reconsideration of these hospitals’ operating status. Possible suggestions include the managerial and financial merging of those hospitals in order to achieve better efficiency outcomes or even their transformation into outpatient centers. Thus lifting some of the outpatient burden off from more efficient hospitals. The aforementioned suggestions should not be uncritically incorporated in the current decision making process but rather, regional and social issues should be taken under consideration as well.

Pine *et al.*[27] argued that risk adjustment models should contain enough clinical data such as clinical and laboratory evidence, in order to produce sufficiently accurate hospital quality indices. Therefore, we consider a limitation for the present study the fact that only the number of surgeries is implemented as a qualitative indicator.

Furthermore, recognizing that the efficiency of large urban hospitals may not be easily affected by indicators such as hospital deaths and surgeries, it would be of particular interest to include relevant indices concerning small or medium sized hospitals. Also, when the registry system of the Greek Statistical Authority will be completely updated, a dynamic approach in the measurement of Greek hospitals efficiency, during the years of economic crisis (2009-2015), could be pursued providing useful policy recommendations

## Conflicts of Interest Disclosure

The authors declare that they have no competing interests.

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