An Empirical Comparison of DEA and SFA Method to Measure Hospital Units' Efficiency

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Abstract: Although frontier techniques have been used to measure healthcare efficiency, their utility in decision making process is limited by both methodological questions concerning their application. The present paper aims to examine the data envelopment analysis (DEA) and stochastic frontier analysis (SFA) results in order to facilitate a common understanding about the adequacy of these methods. A two-stage bootstrap DEA method and the Translog formula of the SFA were performed. Multi-inputs and multi-outputs were used in both of the approaches assuming two scenarios either including environmental variables or not. Thirty-two Greek public hospital units constitute the sample. The main output of the analysis was that the efficiency scores increased with the incorporation of environmental variables. Moreover, environmental variables being hospital status and geographical position were found significantly correlating with inefficiency, while patient mobility was not found strongly correlating. DEA and SFA were found to yield divergent efficiency estimates due to the nature of the environmental variables and the measurement error. The analysis concludes that there is a need for careful attention by stakeholders since the nature of the data and its availability influence the measurement of the efficiency and thus it is necessary to be specific when choosing the mathematical form.

1 INTRODUCTION

1.1 Background

Governments all over the world face the difficult task of managing the complexities of controlling healthcare costs while at the same time ensuring that patients receive not only a high quality of care, but also that this care is delivered as efficiently as possible (Katharaki, 2008). As a result, payers and purchasers have begun to use frontier efficiency measurement techniques in order to measure the performance of the healthcare sector with the aim of supporting their decisions on healthcare units' performance. More commonly used techniques are data envelopment analysis (DEA) and stochastic frontier analysis (SFA) which employ quite distinct methodologies for frontier estimation and efficiency measurement, each with associated strengths and weaknesses. Specifically, "…non-statistical approaches such as DEA have the disadvantage of assuming no statistical noise, but have the advantage of being non-parametric and requiring few assumptions about the underlying technology. SFA models on the other hand have the attraction of allowing for statistical noise, but have the disadvantage of requiring strong assumptions as to the form of the frontier" (Jacobs, 2001, p.3). DEA is favored where measurement error is unlikely to pose much of a threat and where the assumptions of neoclassical production theory are in question. Conversely, SFA should have the advantage in coping with severe measurement error and where simple functional forms provide a close match to the properties of the underlying production technology. Gong and Sickles (1992) report findings along similar lines so that "...as mis-specification of functional form becomes more serious, DEA's appeal (vis-à-vis SFA) becomes more compelling" (p.259).

Hospital units evaluations have to date been carried out using mostly DEA-based methodologies. During the last twenty years, non-parametric and parametric methods have been increasingly

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employed to measure and analyze the productive performance of healthcare services. The healthcare sector is a unique area of application, and one in which the measurement of efficiency has burgeoned over the past few years. Mortimer (2002) highlighted the need for parallel application of competing methods for frontier estimation and efficiency measurement.

Thereby, in the efficiency analysis literature there has been considerable interest in reconciling SFA and DEA (Mutter et al., 2011). Both studies of Chirikos and Sear (2000) and Jacobs (2001) that compared SFA and DEA methods found divergent estimations between the results. Linna (1998) examined cost efficiency of Finish hospitals and found that SFA and DEA generated similar results. The last 5 years Desaia et al., (2005), Assaf and Matawie (2008), Lee et al., (2009) share the same prospect that neither DEA nor SFA can be regarded as clearly dominant. Likewise, more recent studies, Nedelea and Fannin (2012), Ippoliti and Falavigna (2012) suggest that SFA and DEA approaches along with other techniques are viable alternatives for analyzing the impact of environmental variables and dynamic effects on hospital cost efficiency, generating similar but more consistent results in empirical application to the efficiency analysis of healthcare units. Moreover, the majority of the researchers agree on the need of being aware of using both DEA and SFA methods, along with determining the sources of productivity factors by regressing the efficiency scores against a set of environmental variables.

1.2 Aim and Scope

Under this context, an empirical application of both two-stage bootstrap DEA approach of Simar and Wilson (2007) and SFA with the Translog functional form ($SFA_{translog}$) on a sample of Greek public hospital units has been conducted in order to analyze cost efficiency estimations comparatively. Based on the fact that SFA is mostly used in literature under one input and many outputs or the opposite (Bryce, Engberg and Wholey, 2000; Chirikos and Sear, 2000; Giuffrida and Gravelle, 2001; Jacobs, 2001; Ondrich and Ruggiero, 2001; Assaf and Matawie, 2008; Lee et al., 2009), in this paper, multi-inputs and multi-outputs are used in both of the approaches assuming two scenarios, either including environmental variables or not. Thus, the analysis is focused on discussing the results derived by the models' applications.

Therefore, the main purpose of our study is to examine the “behavior” of the two-stage bootstrap DEA approach and $SFA_{translog}$, and how the two methods can be used to make valid inferences about the effects of environmental variables on estimated cost efficiency. Nevertheless, the present study aims to highlight the importance of the information derived with regard to the functional forms of the DEA and SFA method and therefore what should be taken into account when applying them in a larger sample of health units. Hospital managers and policymakers can become more effective decision makers by understanding the relationships between efficiency and these environmental variables.

2 LITERATURE SURVEY

Many researchers have applied methods in order to evaluate hospital efficiency, such as Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). These frontier methods use an efficient frontier to identify the efficiency of hospital units relative to a reference set of healthcare units. DEA is a non-parametric approach that uses mathematical programming to identify the efficient frontier. SFA is a parametric approach that hypothesizes a functional form and uses the data to econometrically estimate the parameters of that function using the entire set of DMU's. However, the two methods differ in some key theoretical aspects. DEA measures efficiency relative to a nonparametric estimate of an unobserved true frontier, conditional on observed data (Simar and Wilson, 2007). On the other hand, SFA requires the specification of a functional form for the frontier, and assumptions about the distributions of the random error and inefficiency error terms, which might be very restrictive (Newhouse, 1994).

In their systematic literature review regarding the investigation of the results derived from at least one pair-wise comparison of the DEA/SFA methods, Katharakis and Katostaras (2012) highlighted that both approaches of DEA and SFA were found to yield divergent efficiency estimates due to many factors such as statistical noise and inputs and outputs definition, as well as data availability. Nevertheless, different modeling approaches have advantages and disadvantages and the choice of the most appropriate estimation method should depend on the type of organizations under investigation, the perspective taken and the quality of the available data as Hollingsworth (2008) also highlights. The issue of testing whether an environmental variable has a significant influence on the production process and any resulting efficiency estimates has been also reviewed. Jacobs (2001) note that the literature provides several different recommendations on how to handle such variables. Katharakis & Katostaras (2012) points out that researchers, besides the combination of models to measure efficiency, introduce environmental variables in the analysis, aiming at better understanding the relationship of these factors to efficiency and thus at better decision making.

The most commonly used SFA method is the Cobb-Douglas functional form and Quadratic formula or Translog formula, using one input or one output most of the time, along with existing environmental factors which are analyzed separately. DEA has the advantage that it is able to manage complex production environments with multiple inputs and outputs, but as a non-statistical method it does not produce the usual diagnostic tools with which to judge the goodness-of-fit of the model specifications. While SFA can discriminate between efficient units, DEA has a limited ability to do this, although both techniques can discriminate between inefficient hospitals (Jacobs, 2001). Considering the above and the purpose of the study, the choice of multi-inputs and multi-outputs was adopted for the SFA Translog formula, indicating the innovation suggested by this paper.

3 MATERIAL AND METHODS

3.1 Sample Synthesis and Variables Definition

Following Katharaki (2008) research work, both DEA and SFA model was applied on the sample of 32 Obstetrical and Gynecological (O&G) units located in five of the ten geographical Greek NHS regions. Below, hospital units are referred to by number (N1–N32), for confidentiality reasons. The evaluation is focused on DEA and SFA methods that allow initial comparisons to be made and some early conclusions to be reached. Based mainly on the data fit to the model, the following are used in this study as inputs:

- number of beds (KL);
- number of medical personnel (PR);
- total expenditure for the provision of care (SD).

Regarding the selected inputs, hospital size and capacity were measured by the number of beds. Most studies exclude the number of physicians because independent contractors exist who may admit patients. For the purpose of the current study, it is important to include them as an input since wide discrepancies exist between the numbers of specialized physicians in different regions of the country which largely determine the volume of the O-G services that a hospital can perform (Katharaki, 2008). The input “total expenditure”, refers to the grand total expenditure and not to the individual resource component costs (doctors’ salaries, nurses’ salaries, etc.). The introduction of “operating expenses” into the set of inputs aims at an estimate of the degree of utilization of the financial resources in relation to the "services" produced.

It should be mentioned that quantitative expression of factors determining services provided by healthcare units display significant difficulties referring to both the factors’ identification and their functional relationship to the health product. According to this the "health product" of healthcare units is expressed through:

- the number of female patients treated (NOS);
- the number of outpatient examinations (EIA);
- the number of lab tests (ERG).

The use of the number of O&G lab tests and patient days as outputs of the study was selected in order to become criteria for efficiency assessment of units as proxy factors of the degree of resource utilization. These criteria have been utilized in a plethora of related studies (Chilingerian and Sherman, 2004).

In this analysis, the environmental variables in order to analyze the efficiency are the same for both the stochastic frontier model and the second stage truncated regression of DEA model. For the specification of environmental variables, we followed Rosko and Mutter (2011) along with Nedelea and Fannin (2012). The primary variable of interest is Geographical Position (GP) dummy (one if the hospital is an urban and zero if it a rural one) which is used to test whether rural O&Gs are more or less cost efficient than non-rural hospitals. Two more dummy variables that define the reputation of the hospital, indicated by:

- Hospital Status (HS) (one with high status, referring to tertiary and university hospitals and zero with lower status, referring to secondary and non-university hospitals) and
- Patient Mobility (PM) to seek healthcare services in well-known hospitals (one referring to hospitals that accept patients from other geographical regions and zero otherwise)

are included to control the internal pressure associated with efficiency estimation. The HS variable was introduced to our analysis based on the fact that it explains the organizations’ structure.

Following Assaf and Matawie (2008), and Chen, Hwang and Shao (2005) the status of the hospital depends on the position of the hospital (university hospital or not), the experience of the doctors and the technological infrastructure of the hospital. Moreover, the PM is a variable which gives the patients' mobility to well-known tertiary hospitals for their better treatment. PM variable has also been used by Ippoliti and Falavigna (2012) who argue that patient mobility may be due to a previous personal experience or to remarks by someone closer to the patient and that the perception mechanism is linked to reputation. In this study the classification of each hospital of the sample regarding PM was based on Katharaki (2008) research work who describes the mobility of patients through regions in order to seek healthcare services.

3.2 Data Analysis

The empirical research was conducted using two scenarios: the application of DEA and SFA model either with environmental variables or without them. The programming language R environment version 2.15 was used for the data analysis, along with the software package FEAR 1.15 of Wilson (2010) and the software package FRONTIER 4.1 of Coelli (2007).

The SFA Translog and the DEA CRS approaches were used to conduct the empirical analysis of the first scenario which was not investigated the environmental effect on inefficiency. With regard to the method used, DEA, a method originating from Farrell's 1957) seminal work, popularized by Charnes, Cooper and Rhodes (1978) and Banker, Charnes and Cooper (1984), provides a non-parametric alternative to parametric frontier production function analysis. This non-parametric method allows the calculation of technical efficiency measured that can be either input or output oriented (Charnes, Cooper and Rhodes, 1978; Charnes and Cooper, 1985; Cooper, et al., 2004; Katharaki, 2008). To estimate the efficiency of the Greek public units used in the sample, the CCR (Charnes, Cooper and Rhodes) input oriented model was used (1978). With the help of input and output variables, the cost-minimizing input vector for each hospital is calculated using linear programming (Nedelea and Fannin, 2012). Next, cost efficiency is measured as the ratio of minimum cost to observed cost and takes a value between 0 and 1, where a value of 1 indicates a cost efficient hospital (Coelli et al., 2005).

Regarding SFA, this parametric method was based on the quantitative economy theory. According to Farrell (1957) theory of efficiency measurement, Aigner et al., (1997) and Meeusen and van den Broeck (1977) independently constructed an error structure of stochastic frontier analysis to measure productive efficiency of firm. SFA is a parametric approach, and is suited to measure efficiencies of stochastic industry for input/output information. To complete the model estimation, it is important to specify and use the suitable functional form. Translog and Cobb-Douglas cost functions are the most well known formulas for research, especially in evaluating the efficiency of units. Translog function is very commonly used. It is a generalization of the Cobb-Douglas function and it's a flexible functional form providing a second order approximation. Cobb-Douglas and Translog functions are linear in parameters and can be estimated using least squares methods. For the purpose of our empirical research the Translog function has been used since we had multi-inputs and multi-outputs of the O&G units. In this paper, we use the Translog form (formula embedded in the package frontier 4.1 for multi-inputs and outputs) with three inputs and three outputs provided in the following equation (equation 1), respectively:

$$\begin{aligned} ln(y_{it}) = \beta_0 + \beta_1 ln(KL_{it}) + \beta_2 ln(SD_{it}) + \\ \beta_3 ln(PR_{it}) + \tfrac{1}{2}\beta_4 ln(KL_{it}^2) + \\ \tfrac{1}{2}\beta_5 ln(SD_{it}^2) + \tfrac{1}{2}\beta_6 ln(PR_{it}^2) + \beta_7 ln(KL_{it}) * \\ ln(SD_{it}) + \beta_8 ln(KL_{it}) * ln(PR_{it}) + \\ \beta_9 ln(SD_{it}) ln(PR_{it}) + V_{it} - U_{it} \end{aligned} \tag{1}$$

where

y_{it}= the variables of the outputs (NOS= Patients hospitalized, EIA=Patients examined in outpatient clinics, ERG=Lab tests) for the i^{th} healthcare unit at time t

KL_{it}= Beds for the i^{th} healthcare unit at time t

SD_{it}= Total expenditures (€) for the i^{th} healthcare unit at time t

PR_{it}= Medical personnel for the i^{th} healthcare unit at time t

V_{it}= Random error

U_{it}= Non-negative random variable (or technical inefficiency)

Data analysis of the second scenario was based on the two-stage bootstrap DEA method and the Translog formula of the SFA including the explanatory variables that have been defined (see section 3.1). The differences between the SFA and the DEA approaches are that the SFA requires functional forms on the production frontier, and assumes that firms may deviate from the production frontier not only due to technical inefficiency but also from measurement errors, statistical noise or other non-systematic influences (Admassie, Matambalya, 2002). For this purpose, in the formula of the SFA Translog frontier, the second non-negative random variables U_{it} which are assumed to be independently and identically distributed normal random variables as truncations at zero with $Z_{it}\delta$ means and variances σ_u^2 ($U_{it} \sim iid\ N(0, \sigma_u^2)$) are known as the technical inefficiency effects and in our model was formed under the environmental factors, which were earlier defined. Thus equation 2 represents the inefficiency effects model and is the following for the second scenario:

$$U_{it} = \sigma_0 + \sigma_1\, GP_{it} + \sigma_2\, HS_{it} + \sigma_3\, MP_{it} + W_{it} \qquad (2)$$

where

GP_{it}= dummy variable of geographical position (0, 1) for the i^{th} healthcare unit at time t

HS_{it}= dummy variable of hospital status (0, 1) for the i^{th} healthcare unit at time t

MP_{it}= dummy variable of moving patient (0, 1) for the i^{th} healthcare unit at time t

W_{it}=Random error ($W_{it} \sim N(0, \sigma_w^2)$)

This research focus on how the environmental variables influence hospital cost efficiency. From the first stage of the DEA approach the efficiency scores are estimated, then regressed in the second stage by the three environmental variables in order to investigate if the hospital inefficiency is changed by these explanatory variables.The second stage of the two-stage DEA model is conducted by regressing environmental variables on the healthcare units' CRS technical inefficiency scores which are predicted from the first step of the two-stage DEA model. The units' technical inefficiency scores are used as the dependent variable. The set of environmental variables are used as independent variables for the two-stage DEA model. The estimated inefficiency scores are normally bounded between zero and one. Applying the method of truncated regression with such a dependent variable that its values are bounded between zero and one will lead to biased and inconsistent estimators, since the truncated method is likely to predict inefficiency scores which are greater than one (Coelli et al., 2005). A disadvantage of DEA is that it has no statistical properties. Simar and Wilson (2007) have recently addressed this problem and showed that it is possible to obtain statistical properties for DEA via the use of the ''bootstrap'' approach. The bootstrap approach can also be extended to account for the impact of environmental variables on efficiency. These variables are viewed as possibly affecting the production process but not under the control of managers. Determining how these variables influence efficiency is thus essential for deriving performance improvement strategies. The procedure used in this study follows that of Simar and Wilson (2007). A comprehensive discussion of the bootstrap procedure and its advantages are also provided in Simar and Wilson (2007).

Both of these approaches have been popular the last years among researchers in order to explain valid inferences about the impact of environmental variables on hospital cost efficiency. What is clear from the existing literature is that none of the existing papers (to our knowledge) have adopted the bootstrapped DEA procedure comparing it with an SFA model for multi-inputs and multi-outputs.

4 RESULTS

Table 1 shows summary of efficiency scores (per unit and per geographical area) estimated by both DEA CRS, DEA bootstrap and SFA Translog model under the two scenarios of the analysis, with and without determinants. Efficiency intervals in two methods DEA and SFA are respectively between zero and one. Moreover with regard to the first scenario, the DEA CRS mean efficiency score was 81.56% while the mean efficiency estimated using SFA_{Eq1} was 85.07%. Note the increased score of approximately 120% for the SFA_{Eq1} estimation of units N9, N16, and N29, something that can be explained by the structure of the hospital organization since they have a small amount of O&G beds and of which the two are regional hospitals.

From table 1 it is derived that the efficiency scores obtained from DEA CRS and SFA_{Eq1} without determinants differ, which is consistent with Chirikos and Sear (2000). The Spearman's Rank Correlation between the mean of efficiencies calculated in different methods was then estimated. The results are listed in Table 2; as it is seen there is no significant correlation in the different methods.

Subsequently, results of the Maximum Likelihood Estimation of equation 1 of the SFA Translog model are provided in Table 3. All variables of the stochastic frontier regression proved significant.

Table 1: The efficiency score of the units of the sample using DEA and SFA model under the two scenarios.

Hospital units	DEA CRS efficiency score	SFA efficiency score (Eq_1)	% change	DEA bootstrap efficiency score (bias corrected)	SFA efficiency score (Eq_{1+2})	% change
N1	0.9512	0.76038	-20.06%	0.7716	0.8917	15.57%
N2	1.0000	0.96840	-3.16%	0.8096	0.9762	20.58%
N3	1.0000	0.93015	-6.99%	0.8108	0.9621	18.66%
N4	0.7196	0.88657	23.20%	0.6199	0.9452	52.48%
N5	0.7794	0.72841	-6.54%	0.6922	0.8027	15.96%
N6	0.5038	0.52935	5.07%	0.4327	0.9456	118.53%
N7	0.5916	0.75046	26.85%	0.5093	0.6842	34.34%
N8	1.0000	0.90595	-9.41%	0.8145	0.9596	17.81%
N9	0.4162	0.91890	120.78%	0.3701	0.8966	142.26%
N10	0.8463	0.66225	-21.75%	0.7516	0.7293	-2.97%
N11	1.0000	0.98596	-1.40%	0.8482	0.9810	15.66%
N12	0.8891	0.82467	-7.25%	0.8034	0.8810	9.66%
N13	1.0000	0.71870	-28.13%	0.8078	0.8244	2.05%
N14	0.4777	0.87582	83.34%	0.4167	0.9336	124.05%
N15	1.0000	0.79965	-20.04%	0.8691	0.8669	-0.25%
N16	0.4337	0.96563	122.65%	0.3552	0.9322	162.44%
N17	0.6852	0.86720	26.56%	0.5947	0.9693	62.99%
N18	0.6603	0.84691	28.26%	0.5840	0.8745	49.74%
N19	0.7634	0.83798	9.77%	0.6597	0.8867	34.41%
N20	0.8084	0.67411	-16.61%	0.7135	0.7988	11.96%
N21	1.0000	0.83900	-16.10%	0.8458	0.9071	7.25%
N22	0.6024	0.73069	21.30%	0.4965	0.8009	61.31%
N23	1.0000	0.97582	-2.42%	0.8572	0.9843	14.83%
N24	1.0000	0.95069	-4.93%	0.8223	0.8961	8.97%
N25	0.9818	0.87170	-11.21%	0.8705	0.9164	5.27%
N26	1.0000	0.96252	-3.75%	0.8669	0.9730	12.24%
N27	0.9096	0.97093	6.74%	0.8232	0.9854	19.70%
N28	1.0000	0.92440	-7.56%	0.8318	0.8966	7.79%
N29	0.4348	0.89203	105.16%	0.3572	0.9201	157.59%
N30	0.8590	0.87164	1.47%	0.7764	0.8572	10.41%
N31	1.0000	0.87509	-12.49%	0.8369	0.8857	5.83%
N32	0.6343	0.97526	53.75%	0.5392	0.9669	79.32%
Mean	*0.8156*	*0.8507*	*4.30%*	*0.6945*	*0.8924*	*28.49%*

Table 2: DEA CRS vs. SFAEq1 Spearman's Rank Correlations rho.

coefficient = 0.241759
p-value = 0.1825 >0.05

Note: coefficient was insignificant at 0.05% level.

Table 3: SFA Results without determinants.

	Coefficient	Std. Error	t value
Intercept	-4.5136e+03	9.8655e-01	-4575.185***
LogKL	-3.5771e+02	9.5342e-01	-375.191 ***
LogSD	3.4379e+03	9.0588e-01	3795.058 ***
LogPR	-1.6328e+02	9.4125e-01	-173.477 ***
σ^2	4.5061e-02	3.7098e-03	12.146 ***
γ	9.9025e-01	4.5601e-02	21.715 ***
Log Likelihood function			23.2629

Note: ***denotes significance at 1% level, **significance at 5% level, *significance at 10% level

Provided that DEA models incorporate only discretionary inputs and the fact that environmental factors that may influence efficiency are not taken into consideration in the analysis, scenario 2 was introduced and under the null hypothesis of positive effect of the environmental variables GP, HS and PM on inefficiency, SFA Translog under equation 1 and 2 was performed. In other words, GP, HS and PM dummies were included into the SFA Translog model as shifted variables or else variables that explain the inefficiency level. Table 1 summarizes the estimated efficiency scores that are likely to substantially increase, while Table 4 outlines the significance of the introduced variables of the MSE estimation of $SFA_{Eq(1+2)}$. In particular, the two environmental variables GP and HS found to explain inefficiency as significant. This is also derived from

Ippoliti and Falavigna (2012) and Chen, Hwang and Shao (2005).

Moreover, the coefficients of the KL and PR variables found to be negatively correlating with inefficiency before and after the explanatory variables introduction (Table 3 & 4). According to Chen, Hwang and Shao (2005) hospitals with a large bed size, experience a lower inefficiency score. On the other hand, the variable SD was found to be significantly correlating with inefficiency in both scenarios. This finding is in line with Katharaki (2008) results, indicating the need for more rational utilization of economic resources.

Table 4: SFA Results with determinants.

	Coefficient	Std. Error	t value
Intercept	-4.7798e+03	9.8891e-01	-4833.3560***
LogKL	-3.7874e+02	9.6128e-01	-393.9903***
LogSD	3.4567e+03	9.2055e-01	3755.0573***
LogPR	-1.5535e+02	9.4804e-01	-163.8625***
GP	-7.9177e-01	1.8268e-01	-4.3341***
HS	6.9518e-01	1.4319e-01	4.8551***
MP	2.2101e-01	1.1332e-01	1.9504
σ^2	1.9973e-02	1.0085e-02	1.9805*
γ	9.6286e-01	3.4351e-01	2.8030**
Log Likelihood function			32.87449

Note: ***denotes significance at 1% level, **significance at 5% level, *significance at 10% level

Following Simar and Wilson (2007), a DEA bootstrap was conducted. The results are also presented in Table 1. The Spearman's Rank Correlation between the mean of efficiencies scores of DEA bootstrap and SFA_{Eq1+2} were also calculated. The results are listed in Table 5; as it is seen, there is still no significant correlation in the different methods.

Table 5: Boootsrap DEA CRS vs. $SFAEq_{1+2}$ Spearman's Rank Correlations rho.

coefficient = 0.21004
p-value = 0.2475>0.05

Note: coefficient was insignificant at 0.05% level.

Considering that the most common approach in testing the impact of environmental variables on efficiency involves the use of two-stage analysis, where according to McDonald (2009) ‘‘*Stage 1 is used to use nonparametric DEA to calculate the efficiency with which output is produced from physical inputs. Stage 2, on the other hand, uses regression to relate efficiency scores to factors seen to influence*’’ (p. 792), and that Simar and Wilson (2007) have recently criticized this approach, and suggested instead of a bootstrap approach in which it is possible to improve the accuracy of the regression estimates, we regressed the derived bias corrected bootstrap efficiency scores on the environmental variables GP, HS and PM (following the methodology presented in section 3.2). Note that 2000 bootstrap replications (B=2000) was used, following Simar and Wilson (1999) who highlighted the adequate coverage of the confidence intervals by choosing the appropriate number of replications.

At the last step of our analysis, the effect of determinants on inefficiency was estimated through the model of the truncated regression. Results of the Maximum Likelihood Estimation for the parameters on DEA CRS initial scores and on the bias corrected bootstrap scores are provided in Table 6. Comparing the results with those from the SFA method (Table 3 and 4) all variables proved significant and likely similar. The estimated coefficients and standard errors for the models are also presented in Table 6.

Table 6: Estimated effects of environmental variables in both approaches.

DEA results without the effect of determinants			
	Coefficient	Std. Error	t value
Intercept	0.6604	0.05347	12.352 ***
KL	-0.0001643	0.002434	-0.007
SD	2.467e-07	8.526e-08	2.893**
PR	-0.01773	0.006159	-2.880**
Log Likelihood function			13.694348
Two- stage DEA results with determinants after bootstrap			
	Coefficient	Std. Error	t value
Intercept	0.5664788	.0458635	12.35***
KL	-0.000144	.0018592	-0.08
SD	2.23e-07	6.72e-08	3.31**
PR	-0.0170342	.0052943	-3.22**
GP	-0.3272004	.1759237	-3.86***
HS	0.2450065	.1442114	3.70***
MP	0.1418569	.1156827	1.23
Log Likelihood function			18.57163

Note: ***denotes significance at 1% level, **significance at 5% level, *significance at 10% level

Furthermore, Table 6 outlines the positive and highly significant coefficient of GP, and negative and highly significant coefficient of HS dummy, suggesting that the geographical position of a healthcare unit, as well as the hospital status of the unit influence their performance.

5 DISCUSSION

This paper has proposed a framework to measure the efficiency of hospital units, aiming to examine the adequacy of two different methods that are commonly used in literature. Both DEA and SFA approaches are efficiency frontier analysis, and provide a suitable way of approaching the measurement of hospital efficiency. Hospitals are aimed to minimize inputs and operating efficiently. Under this context, this paper applies the two methods to evaluate the efficiency of 32 hospital units. In particular, a two-stage bootstrap DEA method and the Translog formula of the SFA were performed. Multi-inputs and multi-outputs were used in both of the approaches assuming two scenarios either including environmental variables or not.

The main output of the analysis was that the efficiency scores increased with the incorporation of environmental variables in the SFA model and decreased when bootstrap is applied. Specifically, the analysis shows that the average efficiency scores of SFA_{Eq1} model is the highest (0.85), followed by DEA_{CCR} model (0.81), while the $SFA_{Eq(1+2)}$ model increased (0.89) when environmental variables were taken into consideration. This result is in line with Prochazkova (2011), and Nedelea and Fannin (2012). In addition, when applying the bootstrap approach and regressing the bias corrected estimations on the same environmental variables, the average score decreases to 0.69. Considering the bootstrapped results, none of the healthcare units appear to be close to full efficiency and even the rankings are not preserved. This confirms previous results from Simar and Wilson (1998; 1999) who argued that traditional DEA models tend sometimes to present firms as efficient, when they are actually not. Consistent to Cordero, Pedraja and Santin (2009) who outlines that one stage approach overestimates efficiency especially in the small sample due to the loss of discrimination power in DEA after including additional variables (non-discretionary inputs), the above finding could be further justified from the small sample of our analysis.

Moreover, the significant correlation of environmental variables GP and HS with the inefficiency are in line with the findings of Ippoliti and Falavigna (2012) and Chen et al., (2005), indicating that future research would include a more detailed study of organizational factors (Minvielle et al., 2005; Minvielle et al., 2008). In addition, the present study provides valuable information regarding deployment of medical staff and beds and the utilization of financial resources. SFA results indicate the need for measures taken regarding the more rational utilization of economic resources.

With regard to the methodology used, a large number of efficiency analysis studies use SFA with cross-sectional data. However, the cross-sectional stochastic frontier model has been shown to have some limitations. First, in cross-sectional stochastic frontier models, firm-specific efficiency is unidentified and researchers typically estimate expectations of efficiency conditional on a composite residual. Second, cross-sectional stochastic frontier models require specific distributional assumptions for each error component in order to estimate efficiency.

Alternatively, one can use the two-stage approach along the line of Simar and Wilson (2007) with cross-sectional data. From the results, it is clearly that the DEA and SFA approach have many advantages and disadvantages as well. Both techniques constitute two alternatives solutions for analyzing the effects of the environmental variables on hospital efficiency. It is shown that similar and consistent results have been obtained in our empirical application from the two methods considering the efficiency analysis of O&G units.

6 CONCLUSIONS

Different methods have been utilized for adjusting efficiency scores to control the environmental factors (Cooper, Seiford and Zhu, 2004). The purpose of our work was to reach a wide variety of stakeholders, each of which faces different pressures and values in the selection and application of efficiency measures. Moreover, this paper is intended to create a common understanding among these stakeholders about the adequacy of tools to measure healthcare efficiency. Given the limitations of frontier techniques, it may be that they are best employed in tandem, when possible, and if different methods suggest similar directions for results then the validity of such findings is enhanced. Since the healthcare industry is one area where efficiency measurement may have a direct policy impact, a cautious approach is necessary. The use of models with restrictions placed upon the weight given to variables, in order to reflect underlying production models or policy values, is also an interesting area requiring further research to justify the use of such restrictions. The quality of data available for use may also be a problem to be addressed. Notwithstanding the caveats mentioned earlier regarding making comparisons across studies, and that perhaps work needs to be undertaken to think of ways of making efficiency studies comparable, these findings may have important policy implications for the organizational structure of healthcare delivery.

Besides that, the paper has a number of other limitations. The panel has been restricted to one year of observations in an unbalanced form with a small sample of the healthcare units. According to Coelli et al. (2005) SFA models should be applied in much bigger samples. Furthermore, focusing solely on the improvement of the overall inefficiency, a policy maker or a manager may opt to alter a specific decision variable. It is thus necessary to carefully address issues regarding improving the managerial decision-making process through quantitative analysis.

To sum up, careful attention should be paid to the purpose of the analysis and to how results are to be used. In particular, if they are to be used to influence economic behavior - for example in the form of setting targets, or identifying candidates for inspection - then the potential costs of making incorrect inferences should be recognized. The results of this analysis should not serve as a background for immediate policy responses. It rather points out special circumstances and provides motivation for further research. At the same time, it is fully acknowledged that economic analysis of Greek hospitals is not telling the whole story. It should be supplemented by surveys of satisfaction with the quality of care or surveys of patient criteria for choosing the hospital unit, and thus include quality of care, other managerial factors and even clinical research and political change, as exogenous variable factors, in order for the analysis to provide an overall picture.

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