Title: The performance of Italian hospitals and their hierarchical structure of administrative employees.

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Type: Original article

Keywords: Hospital efficiency; Directional Distance Function (DDF); Hierarchical organization; Healthcare management

Abstract

Object: considering the Italian health-care system, the present study analyzes what might affect the efficiency of hospitals.

Methodology: in this work, authors propose the Directional Distance Function (DDF) to analyze hospitals' performance, considering efficient each medical center which is able to maximize the production of medical treatments (good output) while complying, at the same time, with budget constraints (i.e. minimizing the expected bad output: financial loss).

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Results: the empirical analysis suggests that an excessive allocation of employees at the highest level of the hierarchical pyramid can affect the hospitals’ performance.

Conclusions: a redistribution of employees among hierarchical levels is necessary to increase the hospital’s efficiency.

1. Introduction and theoretical background

Considering the Italian healthcare system, the present study analyzes the aspects that might affect the efficiency of Italian hospitals. Even if this paper presents an application to the Italian case, the methodology to compute efficiency is well known in environmental field but its application in healthcare industry is very recent – as shown afterwards – and the results could be useful in terms of healthcare management. Indeed, in this work the authors analyze what might affect a specific definition of efficiency, which is calculated maximizing the healthcare production but minimizing the potential financial loss. In other words, this work considers efficient each hospital which is able to maximize the production of medical treatments while complying at the same time, with budget constraints. Considering the current era of austerity and the redefinition of the European welfare systems, as well the related national spending review, this work is even more interesting and necessary. Indeed, even if this work is focusing on Italy, the policy implications could be extended to other European countries, which are facing the same spending reviews and the redefinition of their national welfare systems.

In the last decades the frontier methodology has been widely adopted to compute the efficiency of healthcare management (Gattoufi *et al.*, 2004). In particular, many authors have focused on distinguishing between non-parametric and parametric measures in order to define the best methodology to apply to the healthcare field (Hollingsworth *et al.*, 1999; Hollingsworth, 2003). Parametric techniques, such as the regression model, assume a specific functional form in defining the frontier and they are susceptible to model misspecification, whereas non-parametric approaches are not (Rosko, 1999). Moreover, another significant point about frontier methodology, i.e., Data Envelopment Analysis (DEA) or Stochastic Frontier Analysis (SFA), concerns the distinction between deterministic and stochastic approaches. The former do not contain a random error component and then they can be sensitive to outliers; the latter can separate inefficiency from random effect (Banker, 1993). Nevertheless, the problem linked to the impact of extreme observations on the frontier can be solved through the *envelopment map* (Cooper *et al.*, 2002), the boostrap methodology (Simar and Wilson, 2004), and the sensitivity analysis (Cooper *et al.*, 2004).

In the literature, the most popular technique used to compute technical efficiency scores is the DEA methodology, which is a deterministic and non-parametric approach. This model does not require information on relative prices – differently from cost function models – and it is flexible and versatile. In addition, the DEA methodology can easily consider multiple inputs and outputs; whereas the SFA approach typically uses only one input (total cost) or output (total revenue). When the multivariate SFA is used, another problem occurs: how to combine residuals from different models (O'Neill *et al.*, 2008). Based on these considerations, many authors have applied the DEA approach to the healthcare field.

Sherman (1984) was the first to apply the DEA methodology in order to measure the efficiency of seven US hospitals and his research has been followed by many applications considering other healthcare providers, i.e., physicians (Chilingerian and Sherman, 1990; Chilingerian, 1994), nursing homes (Chattopadhyah and Ray, 1996) and health maintenance organizations (Siddharthan *et al*., 2000).

As for Europe, the first analysis on efficiency was carried out by Färe *et al.* (1994) on Swedish hospitals and, in few years, researches on this topic have increased.

Obviously, from then on, applications have been addressed to study adaptations and/or modifications of classical models in order to define the most representative framework to be applied. Referring to the survey by O'Neill *et al.* (2008), the standard DEA model (Ozcan and McCue, 1996; O'Neill and Dexter, 2005; Charnes *et al.*, 1989; Thompson *et al.*, 1986; Färe *et al.*, 1985) and its extensions are the most commonly applied in the literature (i.e., DEA with congestion: Grosskopf *et al.*, 2001; multifactor efficiency: O'Neill, 1998; scale efficiency: Maindiratta, 1990; DEA in combination with SFA: Chirikos and Sear, 2000; Giokas, 2001; Jacobs, 2001; Retzlaff-Roberts and Morey,1993; DEA in conjunction with the Single Price Model: Ballestero and Maldonado, 2004).

These researches have often been linked to the measure of technical efficiency over time through Malmquist indexes (Caves *et al.*, 1982; Burgess and Wilson, 1995; Färe *et al.*, 1994; Maniadakis *et al.*, 1999; McCallion *et al.*, 2000; Quellette and Vierstraete, 2004; Solá and Prior, 2001; Sommersguter-Reichmann, 2000).

As mentioned above, the DEA models have been used extensively in order to obtain a simple efficiency score representing the ability of firms (or units) to maximize outputs, keeping the inputs fixed (output-oriented model), or to minimize inputs, keeping the outputs fixed (input orientation).

Nevertheless, in different fields, such as the environmental industry, there is a problem linked with outputs, because one output might be desirable (called "good", i.e., production in the environmental field) and one output might be undesirable (called "bad", i.e., pollution). For this reason, a specification of the standard DEA model has been created. The Directional Distance Function (DDF) is a non-parametric and deterministic methodology, more flexible and able to consider good and bad outputs (output approach). The possibility to introduce two categories of outputs with opposite meanings allows us to consider a more thorough concept of efficiency because the production of a firm – hence, also of a hospital – is not always good. There are different strategies to consider bad outputs, for example by turning them into good outputs (Scheel, 2001, Prior, 2006). Thanassoulis *et al.* (2008, pp. 301-304) demonstrate that the production possibility set obtained by treating the bad output as input and the set obtained by converting the bad output into good by subtraction from a large positive number are the same. Nevertheless, as explained in the following section, a specification of the DEA methodology, i.e. the Directional Distance Function (DDF), has been adopted in this paper. This technique allows us to build a frontier that considers the two categories of outputs with free and weak disposability assumptions. The literature has already considered this point and some applications of the DDF to the hospital field can be found. An interesting work is provided by Bilsel and Davutyan (2011), who consider mortality as bad output and find that reducing mortality means sacrificing some good outputs: there is a trade-off between quality and quantity. In the recent study of Wu *et al.* (2012), authors adopt the non-radial output-oriented directional distance function in order to analyze Taiwan's hospital productivity considering the number of readmissions as bad output. They confirm the need to consider quality factor while measuring hospital's efficiency/productivity, as previously proposed by Arocena and Garcia-Prado (2007). Nevertheless, the directional distance function in the healthcare industry has been often used without considering bad outputs, as in the studies of Dervaux *et al.* (2009) and Barros *et al.* (2008). In these works, the DDF methodology allows authors to jointly maximize outputs and minimize inputs. Also in these cases, results are related to efficiency as a measure of healthcare production, so much so that authors consider productivity indexes in order to evaluate hospitals' performance. In opposing trend, this study proposes to think about hospitals' performance as a measure of cost efficiency, taking both good and bad outputs into account but simultaneously. This is the main potentiality of the proposed methodology, which might be considered alternative to the DEA approach. Recalling the analysis proposed by Ferrier *et al.* (2006), in which authors apply the output-based data envelopment analysis with two different assumptions (i.e. strong disposability of outputs and weak disposability of outputs) to a sample of Pennsylvania hospitals introducing the uncompensated care as bad output and the health production as good ones; the DDF approach would give the possibility to consider jointly both outputs (i.e. bad and good outputs) instead of separately. This could be thought as the plus value given by the DDF approach: the possibility to consider the uncompensated care as a bad output simultaneously to the suggested good outputs, proposing an alternative option for the performance estimation. For this reason, the DDF technique appears an interesting approach for estimating hospitals’ efficiency performance.

This work proposes a two stage methodology, as suggested by Simar and Wilson (2007). The number of employees and beds are considered as input, whereas the health production is ‘good’ output and financial loss is ‘bad’. In the first stage, efficiency scores are computed using input, good output and undesirable output through linear programming. In the second stage, these scores have been regressed for some key explanatory variables to test if the allocation of employees at a higher level can negatively influence the hospital’s performance.

This is exactly the main aim of this work: analyzing the impact of the hierarchical administrative organization on the performance of the Italian healthcare industry in terms of efficiency, calculated considering financial losses as bad output and health production as good outcome. Recalling the hierarchical structure suggested by Simon (1947), the authors will find that, by reducing the relative frequency of administrative workers involved in the controlling group (the highest levels of the hierarchical administrative organization), the efficiency grows. In other words, considering several hierarchical levels, the allocation in the lower level, instead of the higher one, could be a strategy to increase the medical centres’ efficiency, as well proposed in this paper (with good and bad outputs).

In the second section, the data and methodology of this paper are proposed; whereas in the third one the empirical analysis is presented. Finally, in the last section, some conclusions about the main results are discussed.

2. Data and methodology

There are two main phases in this work. In the first stage efficiency scores are calculated, introducing the directional output distance function; whereas in the second stage these values are regressed for some key explanatory variables. In the next subsections the proposed methodology is presented along with descriptive statistics about inputs, outputs, and key explanatory variables.

2.1 Methodology: efficiency estimates considering bad outputs minimization

This work applies the proposed methodology to the healthcare sector, assuming:

- the following vector of inputs (*x*), which are the necessary inputs to produce medical treatments

  $x = (x_1, ...x_N) \in R_+^N$ (*N* = number of inputs)

- a vector of good outputs (*y*), which are exactly the financial value of those medical treatments

  $y = (y_1, ...y_M) \in R_+^M$ (*M* = number of good outputs)

- and, finally, a vector of bad outputs, which could be thought as the hospitals' financial loss

  $b = (b_1, ...b_J) \in R_+^J$ (*J* = number of bad outputs)

Starting from classical assumptions on technology and input-output sets, we assume that undesirable outputs are jointly produced with good outputs. In other words, with reference to the analyzed sector (i.e. medical care), a financial loss might be necessary to satisfy the demand of goods which have given prices (i.e. DRGs). This hypothesis, which is called null jointness, is written as

$$(y, b) \in P(x) \text{ and } b = 0 \rightarrow y = 0 \qquad (1)$$

where *P(x)* is the production possibility set.

Another largely accepted assumption is called the weak disposability assumption. If there are some undesirable outputs, it is reasonable to assume that the bad outputs cannot be reduced without also reducing the good outputs, provided that the inputs remain unchanged. Taking hospitals into consideration, the observed financial loss cannot be reduced without reducing health production if the input mix remains the same; moreover, the whole production process cannot be rethought. In other words, to respect budget constraints, an optimal amount of goods is needed and, over that level, financial losses are inevitable. Considering the current European financial crisis and related national policies (i.e. spending review and austerity), the idea of unavoidable financial losses to satisfy the demand of medical treatments seems the most interesting and realistic. Hence, the weak disposability option has been applied.

Moreover, the classical assumption of free disposability does no longer hold for all outputs, but only for the good ones, which can be reduced without costs. In notation, where $0 \leq \alpha \leq 1$ and *P(x)* is the production possibility set, we denote weak disposability in (y,b)

$$(x, y, b) \in P(x) \Rightarrow (x, \alpha y, \alpha b) \in P(x) \qquad (2)$$

whereas free disposability in y

$$(x, y, b) \in P(x) \Rightarrow (x, y, \alpha b) \notin P(x), \Rightarrow (x, \alpha y, b) \in P(x) \qquad (3)$$

Then, weak disposability implies that good and bad outputs can be proportionately contracted, but only good outputs can be freely reduced without costs.

The directional output distance function (DODF) gives the maximum feasible proportional contraction in bad outputs and expansion in good outputs. The DODF is defined on *P(X)*, which takes on a value equal to 0 for efficient firms (which contribute to frontier identification) and increases with inefficiency. Formally, the directional output distance function is defined as follows:

$$\vec{D}(x, y, b; g_y, g_b) = \max\{\beta : (y, b) + (\beta g_y, \beta g_b) \in P(x)\} \qquad (4)$$

where $g = (g_y, -g_b)$ is the directional vector and *P(x)* is the production possibility set estimated via the DEA by solving, for each firm (i.e., hospital in the paper), the following linear problem after defining a particular directional vector *g = (y,-b):*

$$\begin{aligned} \vec{D}_W(x_0, y_0, b_0; y, -b) &= \max \beta \\ \text{s.t.} \quad x_0 &\geq \mathbf{X}z \\ (1+\beta) y_0 &\leq \mathbf{Y}z \\ (1-\beta) b_0 &= \mathbf{B}z \\ z \geq 0, &\beta \geq 0 \end{aligned} \qquad (5)$$

Where, given K as the number of hospitals, **X** is the NxK matrix of inputs; **Y** is the MxK matrix of good outputs, and **J** is the JxK matrix of bad outputs

In practice, the directional output distance function re-scales the observed output vector *(y,b)* on the frontier following the direction of *g*, which is *(y,-b)* in our case.

Applying the DODF, production technology is represented in a way which immediately derives from reality, without transformations, and every constraint in the estimation of *P(x)* could be formulated in linear form; hence, DEA framework is immediately applicable. In our work, all the linear programs are written and solved using R software.

In the next subsection, the adopted data and relative descriptive statistics are proposed.

2.2 Data

Table 1 presents the variables adopted in the first stage. Health production is the *good output*, whereas financial loss is the *bad output*. This work proposes the following inputs: hospital beds (i.e. day, day surgery, and ordinary) and hospital workers (i.e. administrative and support staff, nurses and technicians, physicians, general healthcare personnel and specialists). Outputs are expressed in thousands of Euros, whereas inputs are proposed in single units.

Data about both technical inputs and financial outputs are collected in the database of the Italian national healthcare system (http://www.salute.gov.it) and they refer to public Italian hospitals in 2007.[4] This work considers only autonomous hospitals (which are known in Italy as AOs); thus not including all the medical centers linked to the Local Health Authorities (which are known in Italy as ASLs or AUSLs). Data about financial outputs are extracted from the hospitals' financial statements. The financial loss refers to the hospital result (i.e. code Z9999), assuming the value 0 if there is no loss or if there is a positive result. In the Italian system, the health production considers the reimbursements of medical treatments from Local Health Authorities (i.e. code A0060), both from the region of the hospital in question and from another region (i.e. patients' positive mobility). Some observations have been dropped from the dataset since there is no health production. These atypical observations concerns regions in the South of Italy: Calabria (2 hospitals), Sardinia (1 hospital) and Sicily (7 hospitals).

Table 1
Inputs and outputs, Italian public hospitals (2007)

	Variables	Obs.	Mean	Std. Dev.	Min.	Max.
Good output	Health Production	94	124617.70	106818.50	2	371700
Bad output	Financial loss	94	12458.37	27203.08	0	154534
Inputs	Day Hospital Beds	94	75.51	46.47	4	282
	Day Surgery Beds	94	19.48	21.89	0	88
	Ordinary Hospital Beds	94	695.00	360.77	61	1680
	Administrative and support staff	94	424.50	264.35	14	1288
	Nurses and technicians	94	1228.19	680.18	141	2842
	Physicians	94	447.80	250.33	49	1285
	General healthcare	94	282.27	210.50	12	1085
	Specialist healthcare	94	41.34	33.11	3	160

Source: Italian National Healthcare System

Taking Italian regions into account, table 2 presents descriptive statistics of efficiency scores, which have been obtained from the data proposed in the previous table and adopting the above-mentioned methodology.

According to this methodology, we can rank the various Italian regions. The most efficient one is Marche, in which two hospitals have a score equal to zero; whereas the worst regions are Sicily and Campania. However, there are only three hospitals with anomalous scores: A.O. "G. Rummo" and A.O. "S.G. Moscati" (Campania), and A.O. "Gravina e S. Pietro" of Caltagirone (Sicily), which will be dropped in the second stage.

Moreover, note that some Italian regions (i.e. Valle d'Aosta, Abruzzi and Molise) and the autonomous provinces of Trento and Bolzano have been dropped since there are no observations. In other words, the regional healthcare systems of these observations are shaped around medical centers linked to the Local Health Authorities.

Table 2
Efficiency scores, Italian regions (2007), weak disposability assumption

Region	Mean	Std. Dev.	Freq.
Basilicata[4]	0.009187	0.012992	2
Calabria[4]	1.000000	0.000000	2
Campania[4]	5.174808	9.774207	10
Emilia Romagna[2]	0.016396	0.036663	5
Friuli Venetia Giulia[2]	0.195734	0.046389	3
Lazio[3]	0.358458	0.327520	5
Liguria[1]	0.077128	0.118245	3
Lombardy[1]	0.149334	0.168133	29
Marche[3]	0.000000	0.000000	2
Piedmont[1]	0.222437	0.309571	8
Puglia[4]	0.206719	0.292345	2
Sardinia[5]	1.000000	0.000000	2
Sicily[5]	259.266710	931.193880	13
Tuscany[3]	0.203307	0.169660	4
Umbria[3]	0.000000	0.000000	2
Veneto[2]	0.052052	0.040912	2
total	36.557101	346.329860	94

[1] North-west; [2] North-east; [3] Center; [4] South; [5] Islands;

According to the classification of the Italian National Institute of Statistics (ISTAT), table 3 proposes the same descriptive statistics but in aggregate version, considering 5 geographical macro-areas (i.e. North-west, North-east, Center, South, and Islands).

Table 3 indicates the most efficient Italian macro-area (i.e. North-east), as well as the worst one (i.e. South of Italy), but without considering the above-mentioned anomalous values. In

[4] The choice of this specific year is affected by data availability. Indeed, data about technical inputs are currently proposed only for that year.

other words, the three anomalous observations are not considered in this table (A.O. "G. Rummo", A.O. "S.G. Moscati", and A.O. "Gravina e S. Pietro").

Table 3
Efficiency scores, Italian macro areas (2007), weak disposability assumption

Macro area	Mean	Std. Dev.	Freq.
Islands	1.00000	0.00000	14
South	0.74513	0.42951	14
Center	0.20042	0.25836	13
North-east	0.07733	0.09022	10
North-west	0.15854	0.19906	40
total	0.37530	0.41313	91

In the second stage, the authors try to explain what might affect hospital inefficiency by performing an empirical analysis, i.e. a regression analysis of efficiency scores (dependent variable) for some key explanatory variables (independent variables). Table 4 shows these explanatory variables but considering only inefficient hospitals, i.e. efficiency scores higher than zero (24 hospitals are efficient and they do not appear in the second stage).

Table 4
Descriptive statistics of explanatory variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
Entropy Index	67	2.22895	0.16284	1.38000	2.4200
North-west	67	0.43284	0.49921	0.00000	1.0000
North-east	67	0.08955	0.28769	0.00000	1.0000
Center	67	0.08955	0.28769	0.00000	1.0000
South	67	0.17910	0.38633	0.00000	1.0000
Islands	67	0.20896	0.40963	0.00000	1.0000
Administrative employees (*number*)	67	262.05970	170.76240	9.00000	798.0000
People in charge Index	67	1.50799	1.85756	0.33448	13.6477
D Index	67	1.00052	0.50030	0.00000	2.5333
C Index	67	0.87938	0.27142	0.22533	1.5796
B Index	67	1.02991	0.51600	0.04255	2.2127
A Index	67	2.04245	2.65957	0.00000	12.8596

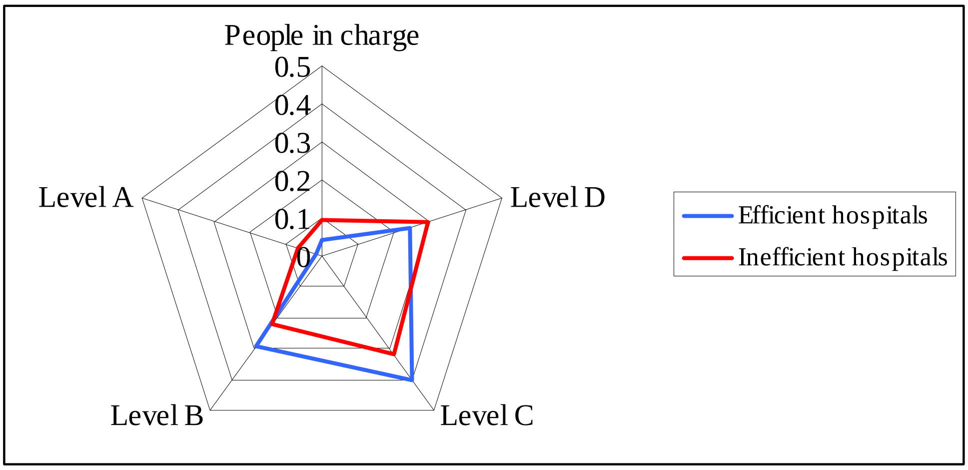
* *If a log transformation is applied*
Source: Italian national healthcare system

The Entropy Index represents the level of specialization of the medical centers. Taking the supply of medical treatments into account, this variable should normalize the considered sample. Moreover, according to the classification suggested in the previous tables, five dummy variables are adopted to capture the effect of the geographical macro-areas.

According to the current bibliography on management (Simon, 1947), the administrative structure of an institution should be shaped around a hierarchical pyramid with few people in charge at the top and many workers with lower skills at the bottom. As for Italy and its public management system, workers in the lowest positions are indicated by the letter A (i.e. *commesso*), followed by the B level (i.e. *coadiutore amministrativo*), whereas the middle levels are indicated respectively by the letters C and D (i.e. *assitente amministrativo* and *collaboratore amministrativo*).[5] Finally, the person in charge of each hospital's operating structure is an administrative employee of D level who is given specific responsibilities. Obviously, the wage for each level depends on the corresponding hierarchical position.

A potential explanation of hospital's inefficiency can be ascribed to this hierarchical pyramid rather than to the total number of employees. Figure 1 is the graphic interpretation of this thesis, taking hierarchical pyramids of efficient and inefficient hospitals into consideration.[6]

Figure 1: Italian administrative hierarchical pyramid: Efficient vs. inefficient hospitals



Indeed, if there is no significant relation between hospitals' inefficiency and the number of administrative employees, their distribution in this pyramid might be the real cause of bad performance. In other words, there could be a relation between hospitals' inefficiency and an excessive number of employees in the highest levels (i.e. too many individuals in charge and/or too many D-level workers). We can observe this situation in Figure 1. In efficient hospitals (i.e. the sub-sample of observations with score equal to 0) there are relatively more employees in the lower levels (B and C) than in the higher ones (i.e. people in charge and D); whereas inefficient hospitals (i.e. the sub-sample of observations with a score higher or equal to 1) display a bigger relative number of employees in the higher levels (i.e. people in charge

[5] Italy's public administrative structure within the Health Care System can be better understood by looking at the current national work contract, i.e. "Contratto Colletivo Nazionale di Lavoro del personale del comparto del servizio sanitario nazionale quadriennio normativo 2006-2009 e biennio economico 2006-2007". Notice that the same hierarchical structure is applied by all Italian hospitals since the cited national work contract is the common legal frame-work for the whole country. What can change is the allocation of employees in each level, according to the specific center's organization.

[6] Efficient hospitals are observations with a score equal to zero, whereas inefficient ones are observations with a score equal or higher than one. The values showed in the figure are the mean of these two sub-samples of observations.

and D) than in the lower ones (B and C). Table 5 proposes a descriptive statistic on administrative employees, considering both efficient hospitals and inefficient ones, but grouping between observations with scores lower than 1 and higher than 1. The proposed classification in these three main categories gives an idea of employees' allocation between levels.

Table 5
Descriptive statistics on administrative employees
(*a score equal to 0 denotes an efficient observation whereas a score higher than 0 denotes an inefficient one)*

Variable	Efficiency score	Obs.	Mean	Std. Dev.	Min.	Max
People in charge	Score = 0	24	0.0407068	0.0148677	0.019704	0.068966
	>0 Score <1	43	0.0401371	0.0332188	0.013616	0.241814
	>=1 Score <2	24	0.0994560	0.1097073	0.017647	0.555556
Level D	Score = 0	24	0.2416194	0.1004659	0.079137	0.493151
	>0 Score <1	43	0.2053904	0.1041013	0.080182	0.541562
	>=1 Score <2	24	0.3068807	0.1234694	0.000000	0.612108
Level C	Score = 0	24	0.4034484	0.0988070	0.240000	0.586207
	>0 Score <1	43	0.3714786	0.1089481	0.119718	0.637306
	>=1 Score <2	24	0.3248693	0.1062053	0.090909	0.584906
Level B	Score = 0	24	0.2959915	0.1380295	0.054795	0.577778
	>0 Score <1	43	0.3551303	0.1446547	0.012594	0.654930
	>=1 Score <2	24	0.2147493	0.1246167	0.018868	0.470588
Level A	Score = 0	24	0.0182340	0.0242771	0.000000	0.062500
	>0 Score <1	43	0.0278639	0.0389480	0.000000	0.139360
	>=1 Score <2	24	0.0540447	0.0593241	0.000000	0.234483

Obviously, both dependent and independent variables have been plotted in order to justify the normality assumption with acceptable results, along with the residuals of each empirical analysis, which is proposed in the next section.

3. *Empirical analysis*

Taking Italy's macro-areas and the Entropy Index into account, Table 6 presents the effects of administrative employees (total number) on efficiency scores. Column A proposes a multiple regression model whereas column B proposes a truncated regression model with a lower level equal to 0 and a higher one equal to 2. In both cases, the bootstrap option has been applied with 200 replacements. The model supports the thesis that there is no direct correlation between hospitals' inefficiency and the total number of administrative employees, taking geographical macro-areas and the Entropy Index into consideration. In the next model (Table 8), the real cause of this inefficiency is identified, i.e. the internal administrative organization of these public medical centers.

Table 6
Multiple regression model (A) and truncated regression model (B)
bootstrap option (200 replacements)

	Efficiency Scores		
	(A)	(B)	
VARIABLES		eq1	Sigma
North-west	-0.791***	-0.901***	
	(0.0514)	(0.112)	
North-east	-0.841***	-1.087***	
	(0.0874)	(0.231)	
Center	-0.547***	-0.564***	
	(0.116)	(0.123)	
South	-0.199*	-0.211*	
	(0.113)	(0.119)	
Entropy Index	-0.609**	-0.694*	
	(0.272)	(0.368)	
Administrative employees (*number*)	0.000167	0.000222	
	(0.000192)	(0.000300)	
Constant	2.325***	2.507***	0.205***
	(0.593)	(0.793)	(0.0354)
Observations	67	67	67
R-squared	0.813		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The hypothesis suggested in the previous section is tested in the next table (Table 7) on the whole population of observations (i.e. considering observations between 0 and 2). By looking at some parameters, the relation between inefficiency and the share of individuals in each administrative level is analyzed.[7]

Again, column A proposes a multiple regression model, whereas column B proposes a truncated regression model with a lower level equal to 0 and a higher one equal to 2. Also in this case, the bootstrap option has been applied with 200 replacements.

The model supports the thesis according to which there is a direct correlation between hospitals' inefficiency and the number of administrative employees, but considering their distribution among their various administrative levels. As confirmed by the results, the higher the number of employees in relation to the identified indexes (i.e. higher than 1), the higher the inefficiency. Similarly, the lower the number (i.e. lower than 1), the lower the hospital's inefficiency. The lowest level, i.e. that of clerical assistants, is not considered in this

[7] The parameters, extracted from the sub-sample of efficient hospitals and showed in Figure 1 and in Table 8, are proposed as a percentage of the total number of administrative employees. Specifically, the following parameters are considered: 4.07% for people in charge, 24.16% for level D, 40.34% for level C, and 29.60% for level B. The remaining 1.82% are clerical assistants, which means workers of level A. For each hospital, both the efficient and inefficient ones, the shares of administrative employees for each level are calculated and then compared with the above parameters. Obviously, values equal to 1 are coherent with the proposed distribution, whereas values higher than 1 indicate a number of employees higher than the proposed parameter.

regression, but, within a general reorganization, it should be enlarged, coming to include a higher share of a hospital's administrative employees.

Table 7
Multiple regression model (A) and truncated regression model (B)
bootstrap option (200 replacements)

	Efficiency Scores		
	(A)	(B)	
VARIABLES		eq1	Sigma
North-west	-0.809***	-0.914***	
	(0.0869)	(0.111)	
North-east	-0.845***	-1.068***	
	(0.102)	(0.179)	
Center	-0.557***	-0.569***	
	(0.0948)	(0.105)	
South	-0.186**	-0.199**	
	(0.0737)	(0.0797)	
Entropy Index	-0.550***	-0.629***	
	(0.149)	(0.168)	
People in charge Index	0.0413*	0.0511**	
	(0.0219)	(0.0255)	
D Index	0.254*	0.331**	
	(0.130)	(0.158)	
C Index	0.474**	0.592**	
	(0.224)	(0.266)	
B Index	0.295*	0.390*	
	(0.171)	(0.212)	
Constant	1.207**	1.100	0.194***
	(0.587)	(0.673)	(0.0217)
Observations	67	67	67
R-squared	0.827		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This is exactly the thesis proposed in this work: there are too many employees at the higher levels (especially D, B, and C), which leads to excessive administrative costs and, consequently, inefficiency. In other words, if a hospital chooses to allocate a larger share of employees to the higher levels of its administrative hierarchy, rather than to the lower ones, the hospital will display bad performance (i.e. a higher inefficiency).

4. *Conclusions*

This work suggests a close relationship between inefficiency and administrative employees. An interesting scenario could regard the administrative hierarchical organization. Indeed, a preliminary analysis of data suggests that, if the organization of a hospital is more geared toward the higher levels, its inefficiency will rise. This hypothesis could be coherent with the proposed approach, since both outputs (good and bad) are expressed in financial values: increasing the number of employees at the higher levels rather than clerical assistants means higher costs. However, for now this thesis is only an interesting hypothesis among several others.

Finally, in addition to interesting results, from the methodological point of view, this paper presents a still quite rare application of the directional distance function to the healthcare industry. Considering the weak disposability assumption, this methodology allows obtaining a global definition of efficiency, also based on necessary outputs that are strictly linked to good outputs. Indeed, hospitals are cost centers but, differently from firms, they do not have only revenues. On the one hand, they must provide basic services to patients and receive reimbursements on the basis of DRGs (hospitalizations). On the other hand, hospitals receive funds according to Regional policy but the amount of these funds might not be appropriate (i.e. inevitable financial loss).

Based on these considerations and in order to analyze the impact of the hierarchical organization of hospitals on their efficiency, the directional distance function with weak disposability assumption is the model that best fits the healthcare sector in this age of austerity.

Bibliography

Ball V. E., Lovell C. A. K., Luu H. and Nehring R. (2004), Incorporating environmental impacts in the measurement of agricultural productivity, *Journal of Agricultural and Resources Economics* 29 (3), 436-460

Ballestero E, Maldonado JA. (2004) Objective measurement of efficiency: applying single price model to rank hospital activities. Computers & Operations Research, 31:515–32.

Banker R., (1993) Maximum likelihood, consistency and data envelopment analysis: a statistical foundation. Management Science, 39:1265–73.

Bellenger M.J. And Herlihy A.T. (2010), Performance-based environmental index weights: are all metric created equal?, *Ecological Economics* 69, 1043-1050

Bilsel M. and Davutyan N. (2011), Hospital efficiency with risk adjusted mortality as undesirable output: the Turkish case, Annals of Operations Research, DOI: 10.1007/s10479-011-0951

Boyd G. A. and McClelland J. D. (1999), The impact of environmental constraint on productivity improvement in integrated power plants, *Journal of Environmental Economics and Management* 38, 121-142

Boyd G. A., Tolley G. and Pang J. (2002), Plant level productivity, efficiency and environmental performance of the container glass industry, *Environmental and Resource Economics* 23, 29-43

Burgess JF, Wilson PW. (1995) Decomposing hospital productivity changes, 1985–1988: a nonparametric Malmquist approach. The Journal of Productivity Analysis, 6:343–63.Maniadakis N, Hollingsworth B, Thanassoulis E. (1999) The impact of the internal market on hospital efficiency, productivity and service quality. Health Care Management Science, 2:75–85

Chambers R. G., Chung Y. and Färe R. (1996), Benefit and distance function, *Journal of Economic Theory* 70, 407-419

Chambers R. G., Chung Y. and Färe R. (1998), Profit, directional distance function and Nerlovian efficiency, *Journal of Optimization Theory and Applications* 98 (2), 351-364

Charnes A, Cooper W, Wei Q, Huang Z. (1989) Cone ratio data envelopment analysis and multi-objective programming. International Journal of Systems Science, 20:1099–111.

Chattopadhyah S, Ray CS. (1996) Technical, scale, and size efficiency in nursing home care: a non-parametric analysis of Connecticut homes. Health Economics; 5:363–73.

Chilingerian J, Sherman D. (1990) Managing physician efficiency and effectiveness in providing hospital services. Health Services Management Research, 3:3–15.

Chilingerian J. (1994) Exploring why some physicians’ hospital practices are more efficient: taking DEA inside the hospital. In: Charnes A, Cooper W, Lewin A, Seiford L, editors. Data envelopment analysis: theory, methodology, and applications. Boston: Kluwer Academic Publishers. p. 167–94.

Chirikos TN, Sear AM. (2000) Measuring hospital efficiency: a comparison of two approaches. Health Services Research, 34:1389–408.

Chung Y. H., Färe R. and Grosskopf S. (1997), Productivity and undesirable outputs: a directional distance function approach, *Journal of Environmental Management* 51, 229-240

Cooper W, Seiford L, Tone K. Data envelopment analysis: a comprehensive text. Boston: Kluwer Academic Publishers; 2002.

Cooper W, Seiford L, Zhu J. (2004) Handbook on Data Envelopment Analysis. Boston: Kluwer Academic Press.

Cuesta R. A. and Zofio J. L. (2005), Hyperbolic efficiency and parametric distance function: with application to Spanish saving banks, *Journal of Productivity Analysis* 24, 31-48

Domazlicky B. R. and Weber W. L. (2004), Does environmental protection lead to slower productivty growth in the chemical industry?, *Environmental and Resource Economics* 28, 301-324

Färe R, Grosskopf S, Lindgren B, Roos P. (1994) Productivity developments in Swedish hospitals: a Malmquist output index approach. In:Charnes A, Cooper WW, Lewin AY, Seiford LM, editors. Data envelopment analysis: theory, methodology, and applications. Boston: Kluwer Academic Publishers; p. 253–72.

Färe R, Grosskopf S, Lovell C. (1985) The measurement of efficiency of production. Boston: Kluwer Academic Publishers

Färe R. and Grosskopf S. (2000), Theory and application of directional distance function, *Journal of Productivity Analysis* 13, 93-103

Färe R., Grosskopf S., Lovell C.A.K. and Pasurka C. (1989), Multilateral productivity comparison when some output are undesirable: a non parametric approach, *The Review of Economics and Statistics* 71 (1), 90-98

Färe R., Grosskopf S., Noh D. and Weber W. (2005), Characteristics of a pollution technology: theory and practice, *Journal of Econometrics* 126, 469-492

Gattoufi S, Oral M, Kumar A, Reisman A. (2004), Epistemology of data envelopment analysis and comparison with other fields of OR/MS for relevance to applications. Socio-Economic Planning Sciences;38:123–40.

Giokas DI. (2001) Greek hospitals: how well their resources are used. Omega, 29:73–83.

Grosskopf S, Margaritis D, Valdmanis V. (2001) The effects of teaching on hospital productivity. Socio-Economic Planning Sciences, 35:189–204.

Hernandez-Sancho F., Picazo-Tadeo A. and Reig-Martinez E. (2000), Efficiency and environmental regulation. An application to Spanish wooden goods and furnishings industry, *Environmental and Resource Economics* 15, 365-378

Hollingsworth B, Dawson P, Maniadakis N. (1999), Efficiency measurement of health care: a review of non-parametric methods and applications. Health Care Management Science, 2:161–72.

Hollingsworth B. (2003) Non-parametric and parametric applications measuring efficiency in health care. Health Care Management Science, 6:203–18.

Jacobs R. (2001) Alternative methods to examine hospital efficiency: data envelopment analysis and stochastic frontier analysis. Health Care Management Science, 4:103–15.

Kumar S. (2006), Environmentally sensitive productivity growth: a global analysis using Malmquist-Luenberger index, *Ecological Economics* 56, 280-293

Kumar S. and Managi S. (2010), Sulfur dioxide allowances: trading and technological progress, *Ecological Economics* 69, 623-631

Maindiratta A. (1990) Largest size-efficient scale and size efficiencies of decision-making units in data envelopment analysis. Journal of Econometrics, 46:57–72.

Malmquist S. Index numbers and indifference surfaces. Trabajos de Estatistica 1953;4:209–42.

McCallion G, Glass JC, Jackson R, Kerr CA, McKillop DG. (2000) Investigating productivity change and hospital size: a nonparametric frontier approach. Applied Economics, 32:161–74.

McMullen B. S. and Noh D. (2007), Accounting for emission in the measurement of transit agency efficiency: a directional distance function approach, *Transportation Research* Part D 12, 1-9

O'Neill L, Dexter F. (2005) Methods for understanding super-efficient data envelopment analysis results with an application to hospital inpatient surgery. Health Care Management Science, 8:291–8.

O'Neill L. (1998) Multifactor efficiency in data envelopment analysis with an application to urban hospitals. Health Care Management Science; 1:19–27

O'Neill L., Rauner M., Heidenberger K. and Kraus M. (2008), A cross-national comparison and taxonomy of DEA-based hospital efficiency studies, Socio-Economic Planning Sciences, 42, 158-189.

Ozcan YA, McCue MJ. (1996) Development of a financial performance index for hospitals: DEA approach. Journal of the Operational Research Society, 47:18–26.

Picazo-Tadeo A. J. and Prior D. (2009), Environmental externalities and efficiency measurement, *Journal of Environmental Economics and Management* 90, 3332-3339

Picazo-Tadeo A., Reig-Martinez E. and Hernandez-Sancho F. (2005), Directional distance functions and environmental regulation, *Resources and Energy Economics* 27, 131-142

Quellette P, Vierstraete V. (2004) Technological change and efficiency in the presence of quasi-fixed inputs: a DEA application to the hospital sector. European Journal of Operational Research, 154:755–63.

Retzlaff-Roberts DL, Morey RC. (1993) A goal-programming method of stochastic allocative data envelopment analysis. European Journal of Operational Research, 71:379–97.

Rosko M. (1999), Impact of internal and external environmental pressures on hospital inefficiency. Health Care Management Science; 2:63–74.

Scheel, H. (2001). Undesirable outputs in efficiency evaluations.European Journal of Operational Research, 132(2), 400–410

Schell H. (2001), Undesirable outputs in efficiency valuations, *European Journal of Operational Research* 132, 400-410

Sherman HD. (1984) Hospital efficiency measurement and evaluation. Empirical test of a new technique. Medical Care; 22:922–38.

Siddharthan K, Ahern M, Rosenman R. (2000) Data envelopment analysis to determine the efficiencies of health maintenance organizations. Health Care Management Science; 3:23–9

Simar L, Wilson P. (2004) Performance of the bootstrap for DEA estimators and iterating the principle. In: Cooper WW, Seiford L, Zhu J, editors. Handbook on data envelopment analysis. Boston: Kluwer Academic Publishers; p. 265–98.

Simar L. e Wilson P.W. (2007), Estimation and inference in two-stage, semi-parametric models of production process, Journal of Econometrics 136, 31-64

Solá M, Prior D. (2001) Measuring productivity and quality changes using data envelopment analysis: an application to Catalan hospitals. Financial Accountability and Management, 17:219–45.

Sommersguter-Reichmann M. (2000) The impact of the Austrian hospital financing reform on hospital productivity: empirical evidence on efficiency and technology changes using a non-parametric input-based Malmquist approach. Health Care Management Science, 3:309–32.

Sophia Rabe-Hesketh and Brian Everitt (2004). A handbook of statistical analyses using Stata. CRC Press LLC, 3rd ed. .

Thanassoulis, E., Portela, M. C. S., & Despic, O. (2008). DEA: the mathematical programming approach to efficiency analysis. In H. Fried, C. A. Knox Lovell, & S. S. Schmidt (Eds.), The measurement of productive efficiency and productivity growth. New York: Oxford University Press

Thompson R, Singleton F, Thrall R, Smith B. (1986) Comparative site evaluation for locating a high-energy physics lab in Texas. Interfaces, 16:35–49.

Tyteca D. (1996), On the measurement of the environmental performance of firms -a literature review and a productive efficiency perspective, *Journal of Environmental Management* 46, 281-308

Tyteca D. (1997), Linear programming models for the measurement of environmental performance of firms -concept and empirical results, *Journal of Productivity Analysis* 8, 183-197

Weber W.L. and Domazlicky B. (2001), Productivity growth and pollution in state manufacturing, *The Review of Economics and Statistics* 83 (1) 195-199

Zhou P., Ang B. W. And Poh K. L. (2008), A survey of data envelopment analysis in energy and environmental studies, *European Journal of Operational Research* 189, 1-18

Zofio J.L. and Prieto A.M. (2001), Environmental efficiency and regulatory standards: the case of CO2 emission from OECD industries, *Resources and Energy Economics* 23, 63-83