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PERFORMANCE OF THE HEALTH CARE INDUSTRY: THE ITALIAN CASE STUDY

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Performance of the health care industry: the Italian case study

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ABSTRACT: Considering the Italian healthcare system, the present study analyzes the aspects that might affect the efficiency of Italian hospitals. In this work, the authors analyze what influences a specific definition of efficiency, which is calculated maximizing healthcare production but minimizing potential financial losses. 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. Hence, the results of this paper are two-fold: from the organizational point of view and from the technical one.

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

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SUMMARY

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 innovative 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.

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 (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 (Malmquist, 1953; Burgess and Wilson, 1995; Färe *et al.*, 1994; Hollingsworth and Thanassoulis, 1999; McCallion, 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). 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.

The main aim of this work is to analyze the performance of the Italian healthcare industry in terms of efficiency, calculated considering financial losses as bad output and health production as good outcome.

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

In the environmental field, the problem of bad outputs was firstly considered by Pittman (1983), extending the framework by Caves *et al*. (1982)[1] and assuming a negative shadow price for each pollutant. This estimation, based on the quantification of prevention costs, might be source of big distortions, as underlined later by Färe *et al.* (1989) and Boyd and McClelland (1999). This creates the need for a direct estimation method able to consider bad output quantities without price information. A fundamental step forward came from Färe *et al.* (1989), who proposed a non-parametric efficiency analysis framework focused on taking into account undesirable outputs using quantities. They combine classical characterization of the production possibility set with two additional hypotheses of weak disposability and null jointness, which are now largely accepted in the literature. They propose a hyperbolic concept of efficiency to asymmetrically treat bad outputs: an extension of the classical DEA methodology, based on a non radial concept of distance where non linearity is introduced and estimation is possible only under certain conditions. Färe *et al*. (1989) also developed a proxy of total regulation impact by applying hyperbolic productivity indexes under the two different disposability assumptions. Still within the hyperbolic framework, Zofio and Prieto (2001) introduced production limits and analyzed the manufacturing industries of 14 OECD countries considering only CO2 emissions as bad output and Rio’s quantitative goals as standards. Ball *et al.* (2004) derived hyperbolic productivity indexes for the case of agricultural outputs, when there exists a relevant environmental impact in terms of human health and aquatic life. Cuesta and Zofio (2005) introduced a parametric distance function based on a translog form to estimate the hyperbolic efficiency for a sample of Spanish saving banks.

To overcome non-linearity problems, intrinsic to the hyperbolic assumptions, other approaches have been proposed in the literature, as summarized by Tyteca (1996) or Tyteca (1997). Scheel (2001) tried to sum up the most widely used DEA frameworks to take account of emissions[2] in a particular linear transformation of bad output data such as:

$$f(b) = -b$$

or

$$f(b) = -b + K$$

with K sufficiently large to ensure that f(b)>0. However, this leads to a production function that is not representative of reality. Another kind of transformation,

$$f(b) = 1/b$$

[1] In Caves et al.(1982), the multilateral superlative index is defined as the difference between the translog multilateral output index and the translog multilateral input index.

[2] After this transformation bad output data are inserted among the input in a standard DEA model and the program provides productivity and efficiency indexes which imply a minimization of all inputs, hence also of pollution.

introduces problems of non linearity and then the classical DEA approach is no longer sufficient.[3]

This paper follows the approach introduced by Chambers et al. (1996), which is based on a new concept of non radial distance, named directional distance function, and derives from the benefit function proposed within a consumer framework. The theoretical properties of this generalization of the output and input distance functions were analyzed by Chambers *et al*. (1998) and Färe *et al*. (2000). The power of this tool is the possibility to modify the direction in which to search for an efficient counterpart of each firm, which allows changing the concept of productivity without modifying technology representation via data transformation.

The applications of this concept using pure linear programming method are growing, especially in the environmental field: Chung *et al*. (1997) analyze paper and pulp mills; Boyd *et al*. (2002) study a small sample of US glass manufacturing firms; Picazo-Tadeo and Prior (2009) and Picazo-Tadeo *et al*. (2005) consider the Spanish ceramic industry; and McMullen and Noh (2007) focus on transit buses firms. Furthermore, this methodology is applied at the aggregate level, when whole industrial sectors are analyzed, like in Domazlicky and Weber (2004) who analyze the chemical sector using different digit specifications. Weber and Domazlicky (2001) apply the DODF at the US states level and Kumar (2006) at the country level. In some recent papers, such as Färe *et al*. (2005), Kumar and Managi (2010), and Bellenger and Herlihy (2010), some semiparametric versions of the directional distance also appear.

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

$$x = (x_1,...x_N) \in R_+^N$$

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

$$y = (y_1,...y_N) \in R_+^M$$

and, finally, a vector of bad outputs

$$b = (b_1,...b_N) \in R_+^N$$

which could be seen as the hospitals' financial loss. 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

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

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

[3] For a complete review of the literature on DEA models in environmental field see Zhou *et al*. (2008).

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

$$\begin{aligned} &(x, y, b) \in P(X) \Rightarrow (x, y, \alpha b) \notin P(X), \\ &\Rightarrow (x, \alpha y, b) \in P(X) \end{aligned} \qquad (3)$$

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:

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

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, the following linear problem after defining a particular directional vector *g = (y,-b):*

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

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

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

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

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).

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;

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

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 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”).

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: Descriptive statistics of explanatory variables

Variable	Obs.	Mean	Std. Dev.	Min	Max	Source
Case Mix Index	67	1.06075	0.18030	0.68000	1.56000	
Entropy Index	67	2.22895	0.16284	1.38000	2.42000	
North-west	67	0.43284	0.49921	0.00000	1.00000	
North-east	67	0.08955	0.28769	0.00000	1.00000	
Center	67	0.08955	0.28769	0.00000	1.00000	
South	67	0.17910	0.38633	0.00000	1.00000	
Islands	67	0.20896	0.40963	0.00000	1.00000	
Purchase of goods (cod. b0010) *	67	10.51452	0.88163	7.28756	11.95480	
Purchase of services (cod. b0210) *	67	10.16600	0.89281	7.71200	11.63862	
Ordinary repairs (External) (cod. b0700) *	67	8.50142	0.94201	4.14313	9.97203	Italian national healthcare system
Leasing and rental (cod. b0750) *	67	7.47787	1.18562	3.36730	9.81684	
Health Employees (cod. b0800) *	67	11.29100	0.76719	7.22402	12.34468	
Professional Employees (cod. b0810) *	63	5.81237	0.76333	3.52636	8.53346	
Technical Employees (cod. b0820) *	65	9.46446	0.74859	7.18992	10.74290	
Administrative Employees (cod. b0830) *	67	8.77401	0.81710	5.71703	10.19481	
Other operating costs (cod. b0840) *	67	8.13081	0.73863	4.99043	9.54831	

** If a log transformation is applied*

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).

The Case Mix index indicates the complexity of the medical treatments supplied by each observation, in relation to the average of the considered sample; whereas the Entropy Index represents the level of specialization of the medical centers. Taking the supply of medical treatments into account, these two variables 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.

The other variables are extracted from the hospitals' financial statements and they refer to the costs borne by said hospitals to produce medical treatments. At this stage, the work tries to establish a potential correlation between hospitals' inefficiency (i.e. their inability to maximize health production while minimizing potential financial loss) and the main costs borne by these institutions to supply medical treatments. In details, the following costs are proposed:

- The purchase of goods (cod. b0010), which is the cost of all goods necessary to provide healthcare (e.g. drugs, vaccines);
- The purchase of services (cod. b0210), which is the cost of all services supplied by other medical centers through their physicians and/or general practitioners;
- Ordinary repairs (cod. b0700), which is the cost of ordinary repairs supplied by external companies (e.g. repairs to motor vehicles, buildings, etc.);
- Leasing and rental (cod. b0750), which is the cost of using goods belonging to a third party (e.g. leasing of medical instruments);
- Health Employees (cod. b0800), which is the cost of all workers involved in healthcare (both physicians and nurses);
- Professional Employees (cod. b0810), which is the cost of all workers with professional skills (e.g. lawyers, engineers);
- Technical Employees (cod. b0820), which is the cost of workers with technical skills (e.g. statisticians, programmers);
- Administrative Employees (cod. b0830), which is the cost of administrative workers (at both the managerial and lower levels).

The use of aggregate accounts is affected by data availability, since some single sub-accounts are not included in the hospitals' financial statement. Moreover, 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

The next tables try to support the proposed thesis using a multiple regression model in the first step (Table 5), and a truncated regression model in the second step (Table 6). Considering the number of potential explanatory variables (Table 4), an automatic selection method is proposed in the first step (i.e. stepwise option with a p-value of 0.200). The stepwise option is essentially a combination of the *forward selection* and the *backward elimination*. The forward selection procedure is used to add variables to an existing model and, after each addition, a backward elimination step is introduced to assess whether variables entered earlier might now be removed because they no longer contribute significantly to the model (Rabe-Hesketh and Everitt, 2004). In the second step, following Simar and Wilson (2007), the truncated regression model is performed, applying the bootstrap option with 200 replacements, a lower level equal to 0, and a higher one equal to 2. Obviously, only the significant variables obtained in the first step will be considered in the second one.

Table 5 is a multiple regression model with the stepwise option. If all the regression coefficients in the fitted model are zero, the statistic tests are both jointly zero and thus the hypothesis is rejected. In other words, the F test shows that the associated *p*-values are both equal to zero and thus the models are statistically significant. Moreover, the squares of the multiple correlation coefficients (R-sq) are good. Taking the adjusted R-square into account, the model shows that 81% of the variance of the efficiency scores is

Table 5:Multiple regression model with stepwise option (0.2)

VARIABLES	Efficiency Scores
North-west	-0.849***
	(0.0756)
North-east	-0.871***
	(0.105)
Center	-0.580***
	(0.109)
South	-0.185**
	(0.0824)
Entropy Index	-0.408**
	(0.170)
Purchase of goods	-0.231***
	(0.0695)
Professional Employees	0.0976**
	(0.0399)
Administrative Employees	0.209***
	(0.0656)
Constant	1.983***
	(0.416)
F(8,54)	34.10
Prob > F	0.0000
Observations	63
R-squared	0.8348
Adj R-squared	0.8103

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

accounted for by the explanatory variables of interest. Obviously, considering the *pairwise* correlation coefficients between the explanatory variables, acceptable values with high significance levels have been obtained.

The model confirms Italy's geographical differentiation, that is to say, how the South is more inefficient than the Center and the North. Moreover, the results suggest that the Entropy Index can increase the efficiency scores, whereas the Case Mix Index is not significant (dropped by the stepwise option). Finally, the cost of administrative and professional employees increases the hospitals' inefficiency.

In the second step, the dependent variable and the key explanatory variables are tested with the more appropriate truncated regression model, applying the bootstrap option.

Table 6: Truncated regression model with bootstrap option (200 replacements)

	Efficiency Scores	
VARIABLES	eq1	sigma
North-west	-0.962***	
	(0.114)	
North-east	-1.078***	
	(0.219)	
Center	-0.597***	
	(0.120)	
South	-0.181	
	(0.115)	
Entropy Index	-0.433	
	(0.342)	
Purchase of goods	-0.310**	
	(0.121)	
Professional Employees	0.132**	
	(0.0662)	
Administrative Employees	0.273**	
	(0.131)	
Constant	2.116***	0.186***
	(0.725)	(0.0278)
Wald chi2(8)	149.80	
Prob > chi2	0.0000	
Log likelihood	35.40944	
Observations	63	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6 is a truncated regression model, applying the bootstrap option with 200 replacements, a lower level equal to 0, and a higher one equal to 2. According to the proposed approach, the explanatory variables are the statistically significant variables obtained in the first step. Even if the estimator changes (log likelihood, in this case), the model suggests the same results. Only the Entropy Index and the South macro-area are not significant now. The purchase of goods is still negative and significant, which means that, by increasing this specific expenditure, the hospitals' efficiency grows. A potential explanation could be related to the quality of these goods. In other words, an increase in the quality of goods (i.e. their cost) might boost the hospitals' output (i.e. health production).

Obviously, this potential explanation should be further investigated to be validated, but disaggregate data are necessary.

Another interesting result, which is confirmed by this second step, concerns the cost of workers. Results suggest the idea that the cost of administrative and professional employees is the main cause of hospital inefficiency or, at least, the main potential target for public managers to improve efficiency (since the geographic area cannot be changed). It is quite clear that these employees represent a substantial cost for hospitals, without direct positive financial feedback. Nevertheless, they are fundamental since they deal with all bureaucratic aspects, which must unavoidably be faced. Now the issue is the following: how can this result be interpreted? Is it simply a matter of numbers (i.e., there are too many employees in this specific sector), or is there another explanation?

Although it is quite clear that the number of professional employees has a negative impact on the hospitals' financial statements, considering the administrative sector, inefficiency should not be ascribed to the number of employees but to how they are organized within medical centers.[5] Hence, to understand the real cause of hospitals' inefficiency, their internal administrative organization must be analyzed.

The next sub-section aims to answer these questions, suggesting the most appropriate approach in terms of management and organization of public hospitals. In other words, the authors try to determine whether inefficiency is linked to the number of administrative workers or to the hospitals' administrative organization.

[5] Notice that the professional employees are not organized in the same way as the administrative ones. Indeed, we can find single professional workers (e.g. architects or lawyers) within departments that mainly include administrative employees.

4. CONCLUSIONS

This work suggests a close relationship between inefficiency and two main costs, those of professional and administrative employees. As far as the former are concerned, hospitals should prefer targeted consultancies, when needed, over employing full-time professionals, thus managing to reduce costs and keep within their budget. About the latter, to understand the real cause of hospitals' inefficiency, their internal administrative organization must be analyzed. 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.

Another interesting result deserving further investigation is the positive relation between the purchase of goods and hospitals' efficiency. More data should be collected to understand whether the proposed explanation is appropriate. If these data become available, there might be an opportunity to develop this work and to suggest a new thesis on the spending review of this specific public sector.

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.

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