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Partitioning input cost efficiency into its allocative and technical components: an empirical DEA application to hospitals

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Abstract

The study presents an empirical analysis of best practice production and cost frontiers for a sample of 94 acute care hospitals by applying Data Envelopment Analysis (DEA) and a regression model, in a two-stage approach. This paper contributes to the DEA and efficiency measurement literature by adding results from a homogeneous method of partitioning cost efficiency into its allocative (or price) and technical components, and by decomposing technical efficiency into scale, congestion and pure technical efficiency. Allocative efficiency is calculated using a DEA assurance approach. It introduces constraints with lower and upper bounds on the admissible values of weights of the CCD DEA model that computes technical efficiency. We thus obtain scores unbiased by the lack of precise information on input prices. In the second stage, a log-regression model is employed to test a number of hypotheses involving the role of ownership, market structure, and regulation in terms of differences amongst the various efficiency concepts measured. Results highlight the relevance of market concentration and public finance in explaining these differences. © 2000 Elsevier Science Ltd. All rights reserved.

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1. Introduction

The purpose of this paper is to obtain empirical and complementary measures of hospital

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performance rooted in the principles of production economics, and to evaluate the factors that contribute to performance. The method is applied to 94 acute care hospitals operating in the context of a National Health Service in Catalonia (Spain)[1]. Assessing performance is a necessary step in the design and implementation of privatization of ownership and management policies, and in fostering competition and other deregulating measures in health and hospital services. In this regard, health care purchasers in all systems are now seeking ways to improve hospital efficiency.

Hospital performance is proxied in this paper using measures of Farrell's [1] definition of technical and allocative efficiency. These are partial, but theoretically rooted, indicators of hospital performance. A hospital is said to be technically efficient if a reduction in any input requires an increase in at least one other input or a decrease in at least one output. A hospital is allocatively inefficient if it does not select the optimal mix of inputs given the available technology and the input prices it faces. Technical efficiency has been advocated as a measure to compare performance of firms having different ownership regimes or legal statuses. It is particularly useful in evaluating the performance of public sector and nonprofit activities, which are predominant in the hospital sector. Technical efficiency may be achieved independently of allocative efficiency.

1.1. Measuring hospital efficiency

Empirical measurement of inefficiency has been accomplished using two classes of methodologies: stochastic parametric regression-based methods and nonstochastic nonparametric mathematical programming methods. Data envelopment analysis (DEA) is the most used family of linear programming models.

A number of papers have measured hospital efficiency on the basis of the *best-practice frontier* by using both methodologies. Inefficiency provided by hospital cost frontiers is the result of technical and allocative inefficiency combinations in unknown proportions [2]. Eakin [3] is an exception, computing allocative efficiency scores. Some advances in frontier regression analysis allow one to obtain differentiated measures of technical and allocative inefficiencies by introducing restrictions equalizing marginal productivity ratios and price ratios in the cost function. Nevertheless, computational difficulties in panel data aside, some problems exist in ruling out X-inefficiency when separating both types of inefficiency in cost frontier regression analysis. These are due to the assumption that maximizing behaviour is present [4] since it uses the so-called Shepard cost share equations to estimate model parameters. In response to this situation, several DEA models are proposed here to partition cost efficiency into its allocative and technical components within a multiple input multiple output production process.

An increasing number of researchers have applied DEA to hospital efficiency analysis. Some recent examples include: Burgess and Wilson [5], Valdmanis [6], Ozcan and Luke [7], Magnussen [8], and Dalmau and Puig-Junoy [9]. The hospital DEA literature has restricted its

[1] Catalonia is a region with six million inhabitants. The hospital system in Catalonia may be summarized as acting in a National Health Service with the following measures: 99% of population with public insurance, 73% public financing and 39% public production

attention to technical efficiency, although cost-minimizing efficiency includes both technical and allocative efficiency. To our knowledge, only two papers calculate hospital allocative efficiency [10,11] using nonparemetric models. Calculation of allocative efficiency requires accurate information on prices of inputs. Morey et al. [10] and Byrnes and Valdmanis [11] use average prices to calculate allocative efficiency for public and nonprofit hospitals in California in the period 1982–83. However, in both cases, average input prices involve an unreasonably wide range of variation between hospitals, which is not justified by the authors. In this regard, we suggest that less quality of cost data are available than physical input data in self-reported sources of information. As might be expected, a major difficulty is encountered in securing the price information needed to implement the concept of allocative efficiency.

This paper's contribution to the DEA applications literature involves the use of this method to derive both allocative and technical efficiency scores for hospitals, thus overcoming the traditional confinement to technical efficiency in earlier efforts. The use of DEA provides the opportunity to partition cost efficiency into its allocative and technical efficiency (and the latter into pure technical, congestion and scale efficiency), and to subsequently obtain comparable measures of the different theoretical efficiency concepts. Results should cast light on the relative importance of the different types of inefficiency for hospitals under analysis. Additionally, a DEA assurance approach is applied to the calculation of allocative efficiency in order to obtain scores unbiased by the lack of precise information on input prices.

1.2. Explaining variations in hospital measured efficiency

According to Pestieau and Tulkens' [12] theoretical and empirical revision, three categories of factors might be distinguished in assessing and explaining the performance of public and nonprofit enterprises: ownership (and firm objectives), competition, and regulation. In order to assess the expected effects of projected and in-course hospital policies, it is thus of crucial importance to ascertain the potential impact of ownership, market structure and regulation on the explanation of differences in efficiency scores.

Evidence from empirical analyses of hospital inefficiency using DEA several times on the same set of data, Grosskopf and Valdmanis [13] and Valdmanis [6] suggest that public hospitals are more technically efficient than are nonprofit and private ones. Register and Brunning [14], also using DEA, found no differences between nonprofit and public hospitals when comparing technical efficiency. Ozcan et al. [15] and Ozcan and Luke [7] observed that US government hospitals tend to be more efficient, and for-profit hospitals less efficient, than other hospitals. Chirikos and Sear [16] conclude that for-profit hospitals are technically less efficient when they perform in less competitive markets.

A number of earlier papers have documented a positive relation between costs per admission or per patient-day and more competitive markets [e.g. 17,18], usually attributed to the effects of nonprice competition. Nevertheless, only a few of these papers have addressed the relation between efficiency and competition. Recent empirical research estimating a frontier cost function found weak evidence to sustain the notion that competition from other hospitals is related to inefficiency [2, 3]. A positive relation between competition and higher average cost or cost inefficiency does not necessarily imply technical inefficiency. It might, for example, be a case of exclusively allocative inefficiency, or both technical and allocative inefficiency in different, unknown proportions. Two studies explicitly address the effect of competition on technical inefficiency by explaining differences in DEA scores. Register and Brunning [14] did not find any relation between DEA scores and market concentration. Chirikos and Sear's [16] results showed that inefficiency scores are higher in markets with more vigorous inter-hospital competition, the relation being more intense in highly competitive markets.

Analysis of the relation between regulation and hospital efficiency has focused nearly exclusively on Medicare Prospective Payment System evidence (PPS). Zuckerman et al. [2] thus found that profit rates are significantly higher among relatively less cost inefficient hospitals subject to PPS. Chirikos and Sear [16] found no significant relation between technical efficiency and an index of early PPS pressures.

In this paper, an evaluation of the effects of *observed present* market structure, ownership and regulation on hospital allocative and pure technical efficiency for 94 Catalan acute care hospitals is developed. In reference to the relation between hospital performance and factors explaining performance, this paper adds to the preceding literature in three aspects. Firstly, it does not restrict attention to larger or urban hospitals since all acute care hospitals are considered. It uses a Herfindahl–Hirschman index [19] of concentration calculated for every hospital using patient origin data, and it expands evidence to hospitals in a European National Health Service context. Secondly, it encompasses the analysis of a wider range of environmental variables considered simultaneously as factors explaining efficiency, and it also considers some control variables for efficiency scores. Ratios partially measuring inefficiency are ruled out as factors explaining efficiency (i.e. occupancy rate, length of stay, etc.). And, thirdly, it sheds separate light on the effects of environmental variables on allocative and technical efficiency (rather than on *average* production/cost functions).

The paper is organized as follows. Section 2 lays out the general framework for the application of Data Envelopment Analysis to the measurement of cost and technical efficiency. Variable definitions and descriptions are presented in Section 3. Section 4 presents DEA allocative and technical inefficiency results. A regression analysis of the DEA efficiency scores is presented in Section 5, while section 6 concludes.

2. The performance evaluation methodology

As noted previously, hospital performance is proxied in this paper by allocative and technical efficiency. In this section, we provide definitions of efficiency used and their methods of measurement.

2.1. Efficiency definition

To characterize production technology relative to which efficiency is measured, each hospital uses variable inputs $x=(x_1,\dots,x_N)\in {R^N}_+$ to produce variable outputs $y=(y_1,\dots,y_M)\in {R^M}_+$. Inputs are transformed into outputs using a technology that can be described by the graph $\mathrm{GR}=\{(x,y)\text{: } x \text{ can produce } y\}$. Corresponding to the graph, there is a family of input sets $L(y)=\{x\text{:}(x,y)\in \mathrm{GR}\}$, $y\in {R^M}_+$. Input sets are assumed to be closed and bounded above, and to satisfy strong disposability of inputs. The input sets contain isoquants Isoq $L(y)=\{x\text{:}x\in$

$L(y), \theta x \in L(y), \theta \notin (0,1)\}$, $y \in R^M{}_+$. Also corresponding to the graph of the technology is a family of output sets $P(x)=\{y:(y,x)\in \mathrm{GR}\}, x \in R^N{}_+$. Output sets are assumed to be closed and bounded above, and to satisfy the properties of convexity and strong disposability of outputs.

A Farrell–Debreu radial measure of the technical efficiency of input vector x in the production of output vector y is given by: $\mathrm{TE}(x,y)=\min\{\theta:\theta x \in L(y)\}$, where $\theta=1$ indicates radial technical efficiency and $\theta < 1$ shows the degree of radial technical inefficiency. According to Farrell's concept, the cost efficiency of a hospital using input vector x to produce output vector y when input prices are w is measured by the ratio of minimum cost to actual cost: CE $(x,y,w)=c(y,w)/w^{\mathrm{T}}x$, where $c(y,w)$ is the cost function (the minimum expenditure required to produce y when input prices are w), where CE $(x,y,w)=1$ indicates cost efficiency and CE $(x,y,w) < 1$ shows the degree of cost inefficiency.

2.2. Efficiency measurement

Assuming strong input and output disposability, the input cost efficiency measure (CE) may be decomposed into its input allocative efficiency (AE), scale efficiency (SE), input congestion (C), and pure technical efficiency (PTE) components [20, p. 80]: CE $(x,y,w)=\mathrm{AE}(x,y,w)\cdot\mathrm{SE}(x,y)\cdot\mathrm{C}(x,y)\cdot\mathrm{PTE}(x,y)$. As Färe et al. [20] state "*the input cost inefficiency must be due to selection of the wrong input mix, to the adoption of an inefficiently small or large scale, to input congestion, or to purely technical inefficiency*". Scale inefficiency thus occurs because the hospital is not operating at the scale of operation consistent with long-run competitive equilibrium. Also, technical efficiency (TE) is defined as the product of the scale efficiency, input congestion, and pure technical efficiency components: $\mathrm{TE}(x,y)=\mathrm{SE}(x,y)\cdot\mathrm{C}(x,y)\cdot\mathrm{PTE}(x,y)$. The Farrell input allocative efficiency of a hospital is measured as the ratio of cost efficiency to overall technical efficiency: $\mathrm{AE}(x,y,w)=\mathrm{CE}(x,y,w)/\mathrm{TE}(x,y)$, where AE $(x,y,w)=1$ indicates input allocative efficiency and AE $(x,y,w) < 1$ shows the degree of input allocative inefficiency.

Assume the hospital under evaluation as having data (x^0,y^0,w^0), and consider the *input-oriented CCR DEA model* [21] in the primal (envelopment) formulation, where $x^i \in R^N{}_+$ and $y^i \in R^M{}_+$, and $i = 1\ldots I$, where I indicates the number of hospitals in the sample:

$$\mathrm{TE}(x^0,\, y^0) = \min_{\theta,\, \lambda} \theta$$

subject to

$$\theta x^0 - X\lambda \geqslant 0$$

$$-y^0 + Y\lambda \geqslant 0$$

$$\lambda \geqslant 0$$

where X is an $N \times I$ input matrix with columns X^i, Y is an $M \times I$ output matrix with columns y^i, and λ is an $i \times 1$ intensity vector. The optimal value of θ provides a technical efficiency measure of the hospital under evaluation. Input-oriented radial efficiency requires $u^{\mathrm{T}}y^{\circ}=\theta=1$.

A hospital is judged to be technically inefficient if, at optimum, $\theta < 1$, and technically efficient if, at optimum, $\theta = 1$. The *input-oriented CCR DEA model* incorporates the assumption of constant returns to scale in production.

Banker et al. [22] (BCC) generalized the CCR formulation to allow variable returns to scale. The *input-oriented BCC DEA model* computes, exclusively, a pure technical efficiency measure (W) by introducing an additional restriction to the input-oriented CCR DEA model: $e^{\mathrm{T}}\lambda = 1$, where e^{T} is an $I \times 1$ row vector of ones. This pure technical efficiency measure is obtained under the restriction of weak input disposability but allows for variable returns to scale. The above decomposition of input cost efficiency requires PTE to be computed by relaxing the strong input disposability restriction, to allow for an input congestion component. The congestion component is due to production on a backward-bending segment of the isoquant that is in the region where marginal product is negative. Pure technical efficiency with weak disposability of inputs may be computed from the following problem in the primal (envelopment) formulation:

$$\mathrm{PTE}(x^0, y^0) = \min_{\theta, \lambda, \sigma} \theta$$

subject to

$$\theta\sigma x^0 - X\lambda = 0$$

$$-y^0 + Y\lambda \geqslant 0$$

$$e^{\mathrm{T}}\lambda = 1$$

$$0 < \sigma < 1$$

$$\lambda \geqslant 0$$

Then, the congestion measure is obtained as:$C = W/\mathrm{PTE}$.

Input cost efficiency can be measured for hospital (y^0, x^0, w^0) by solving the following linear programming problem, under the assumption of constant returns to scale [20]:

$$c(y^0, w^0) = \min_{x} \; w^{0\mathrm{T}}x$$

subject to

$$x - X\lambda \geqslant 0$$

$$-y^0 + Y\lambda \geqslant 0$$

$$\lambda \geqslant 0$$

The proposed cost efficiency DEA model has similar constraints to those of the CCR DEA model, but it differs in the objective function (cost) and in the number of input units (x), which must be determined by the model. The cost efficiency linear problem previously defined is similar to the applied models of Morey et al. [10] and Ferrier and Lovell [23], which differ in constraints relating to returns to scale assumptions[2], and of Byrnes and Valdmanis [11]. However, usually data requirements to compute allocative efficiency cannot be satisfied because prices of hospital inputs are not accurately observed, thus severely limiting actual applications. When it is not possible or difficult to ascertain exact knowledge of prices, input cost efficiency cannot be measured. One solution to this problem involves a recourse to average prices, this being the approach used in hospital applications [10,11]. Two problems may appear in this case. First, average prices can be a misrepresentation if: (i) inputs are not completely individualized and defined with some degree of aggregation in the DEA problem; (ii) there exists price variability during the period under analysis; and (iii) there are reasonable doubts about data reliability on resource quantity or costs, especially when data come from self-reported sources of information. Second, prices can be (and often are) subject to variation in very short periods so that additional choices and assumptions are involved concerning their pertinence.

An alternative to computing input cost efficiency, as suggested by Cooper et al. [24], is to introduce constraints with lower and upper bounds on the admissible values of weights of the CCR DEA problem. It is known that as increasingly severe constraints are placed on weights, so the measure of efficiency derived moves from one of relative technical efficiency to one of relative overall efficiency. In this way, knowledge of exact price information could be replaced by knowledge of upper (UL) and lower (LB) bounds within which relative prices are expected to vary using the Assurance Region (AR) approach first developed by Thompson et al. [25]. The AR approach introduces separate linear homogeneous restrictions on input (and output) weights of the multiplier (dual) DEA problem. We specify a Cone-Ratio Assurance Region (CR-AR)[26]. Let the h-tieth input (X_h) be a numeraire for the inputs. Then, an assurance region may be specified as follows: $a_i \cdot v_h \leqslant v_i \leqslant b_i \cdot v_h$, $i = 1,\ldots,N$, where $a_i = \mathrm{LB}_i/\mathrm{UB}_h$ and $b_i = \mathrm{UB}_i/\mathrm{LB}_h$, and where v_i is the weight given to the ith input.

Usually, the application of CCR and BCC DEA models place no constraints on weights attributed to each input (v) and each output (u) in the dual (multiplier) problem, thus allowing absolute weight flexibility. Then, outlier or extreme units will be automatically classified as technically efficient units by assigning a zero weight (i.e., weights of very small magnitude) to some of the inputs or outputs. This represents a contradiction in itself because if such inputs or outputs are not important, they would not be included in the analysis [27, p. 218–20]. Absolute weight flexibility may result in an overestimation of technical efficiency, and, consequently, may also result in an overestimation of allocative inefficiency when cost efficiency is decomposed into its technical and allocative components. The solution could be the imposition of restrictions on the weights in the multiplier DEA problem. This would suggest the formulation of value judgments about the relative importances of the inputs and/or outputs. In this paper,

[2] Morey et al. [10] define a constraint not allowing decreasing returns to scale ($e^{\mathrm{T}}\lambda \geqslant 1$) in hospital cost efficiency estimation. Ferrier and Lovell [23] limit efficiency measurement in banking to variable returns to scale ($e^{\mathrm{T}}\lambda = 1$).

however, technical efficiency is computed from CCR and BCC unbounded DEA models, and a DEA Assurance Region approach which constrains input weights to compute allocative efficiency scores. We do this for two reasons. First, using simulated data from a Cobb–Douglas production function with constant returns to scale, Pedraja-Chaparro et al. [27] showed that, as sample size increases, the overestimation of efficiency is lowered in unbounded DEA models[3]. Importantly, overestimation represents a problem only when the size of the sample is relatively small. And, second, the only implicit hypothesis in the unbounded CCR and BCC DEA models is that the weights adopted by the hospital under scrutiny are acceptable. This may be an acceptable principle when no judgment on allocative efficiency is required. When constraints on the weights are introduced, however, the measure of efficiency derived moves from one of relative technical efficiency to one of relative overall efficiency, confusing the partition of input cost efficiency into its allocative and technical components.

3. Data and variables

We now apply the DEA models defined previously to calculate technical efficiency, pure technical efficiency, scale efficiency, congestion efficiency and cost efficiency for 94 Catalan acute care hospitals[4]. Resolution of the implied mathematical programming problems requires definition of input and output variables, and input prices. Input and output variables were selected among those that had been used primarily in the DEA hospital efficiency literature. One of the most important issues in DEA applications is that computed efficiency scores may be influenced by the model specification of input and output variables. The magnitude of this problem has been illustrated for output specification in hospital applications by Magnussen [8]. Input and output sets used in this paper are very close to those more often employed in the literature on hospital efficiency. (In a previous paper [9], some alternative model specifications showed high correlations amongst the obtained efficiency scores.)

Output is defined in this paper as health services or intermediate outputs (*throughputs*). Eight separate direct hospital outputs were specified: Case-mix adjusted discharged patients (Y_1); In-patient days in acute and subacute care services, except intensive care units (medicine, surgical, obstetrical, gynaecological and paediatric services) (Y_2); In-patient days in intensive care units, including intensive neonatal and burn units (Y_3); In-patient days in long-term (psychiatric[5], long stay, and tuberculous services) and other hospital services (Y_4); Surgical interventions (Y_5); Hospital daycare services (Y_6); Ambulatory visits (Y_7); and Resident

[3] Note that DEA models always overestimate efficiency when the production function is convex.

[4] Data (circa 1990) came from the Estadística de Establecimientos Sanitarios con Régimen de Internado, a survey conducted annually by the Department of Health and Social Security of the autonomous government in cooperation with the Instituto Nacional de Estadística (National Institute of Statistics). This data set is unique in that it allows one to employ accurate information on case-mix of public, nonprofit and private hospitals as well as a Herfindahl–Hirschman index of market concentration for the Catalan hospital market previously estimated in Dalmau and Puig-Junoy [9].

[5] All hospitals included in the study are acute care hospitals in order to make comparisons between homogeneous decision making units. Although being acute care hospitals, in some cases, they have small psychiatric facilities.

physicians (Y_8). Selected output variables represent both in-patient (admissions and in-patient days) and out-patient hospital services (visits and day care), as well as teaching activities (residents).

On the input side, four variables representing resource consumption are defined: Full-time equivalent (FTE) physicians, including residents (X_1); FTE nurses and equivalents (X_2); FTE other non-sanitary personnel (X_3); and In-patient beds (X_4). A summary of all variable definitions appears in Table 1.

Note that the first three inputs are labour while the last one is a proxy for net capital assets, as suggested by Grosskopf and Valdmanis [13]. Input and output quantities and input prices represent average measures during the period under study. Descriptive statistics for all input and output variables appear in Table 2.

The Assurance Region (AR) approach to cost efficiency requires the introduction of restrictions on the input weights. Because input prices are imperfectly known, in the AR

Table 1
Variable definitions

Variable	Definition
Outputs	
Y_1	Case-mix adjusted discharged patients
Y_2	In-patient days in acute care medicine services, except intensive care units (medicine, surgical, obstetrical, gynaecological and paediatric services)
Y_3	In-patient days in intensive care units, including intensive neonatal and burn units
Y_4	In-patient days in long-term (psychiatric, long stay, and tuberculosis) services, as well as other services
Y_5	Surgical interventions
Y_6	Hospital daycare services
Y_7	Ambulatory visits
Y_8	Resident physicians
Inputs	
X_1	Full time equivalent (FTE) physicians, including residents
X_2	FTE nurses and equivalents
X_3	FTE other nonsanitary personnel
X_4	In-patient beds
Explanatory variables	
Z_1	Nonprofit hospitals
Z_2	For-profit hospitals
Z_3	Herfindahl–Hirschman index of market concentration
Z_4	Number of competitors in the local market
Z_5	Proportion of service revenues from NHS
Control variables	
W_1	More than one hour surgical intervention per one hundred patients
W_2	Teaching status
W_3	Proportion of recovered discharged patients
W_4	Number of beds
W_5	Number of square beds

Table 2
Descriptive statistics of input, output, explanatory and control variables (N = 94)

	Mean	Standard deviation	Min	Max
Input variables				
X_1	79.6	132.6	3.5	721.0
X_2	230.6	335.7	6.6	1765.5
X_3	132.2	175.2	0.3	951.5
X_4	200.0	203.6	14.0	949.0
Output variables				
Y_1	6210.4	6346.0	224.4	32,268.5
Y_2	49,868.7	57,925.1	1133.0	285,308.0
Y_3	1597.9	3864.0	0.0	22,512.0
Y_4	6075.1	13,991.0	0.0	95,449.0
Y_5	3761.4	3431.7	61.0	15,050.0
Y_6	1190.9	4315.1	0.0	32,021.0
Y_7	49,993.5	71,379.5	0.0	520,591.0
Y_8	10.0	31.5	0.0	163.0
Explanatory variables				
Z_1	0.263	0.443	0.0	1.0
Z_2	0.474	0.502	0.0	1.0
Z_3	3139.3	2917.8	459.0	10,000.0
Z_4	16.3	16.2	0.0	36.0
Z_5	61.8	40.9	0.0	100.0
Control variables				
W_1	22.8	18.4	0.0	86.2
W_2	0.05	0.23	0.0	1.0
W_3	92.5	10.2	10.6	99.9
W_4	200.2	203.6	14.0	949.0
W_5	81,075.5	178,047.1	196.0	900,601.0

approach they are replaced by the bounds within which prices are expected to vary. Specification of upper and lower limits ("*assurance region*") of input prices used in this paper come from market prices and expert opinion. First, information on wages for full time hospital physicians, nurses and other personnel were obtained from those officially established for hospitals belonging to Social Security, and from public agreements between trade unions and the principal hospital associations[6]. Second, this information has been revised by three experts in order to estimate potential variations around obtained wages. Third, upper and lower limits for the cost per in-patient bed were established from average prices revised by expert opinion. And fourth, lower and upper bounds were set for all inputs allowing for possible variations in relative input prices from 1990 to 1997. This, we felt, helped to guarantee the continued relevance of the prices used. Indeed, major changes have not been detected during this period[7].

[6] *Consorci Hospitalari de Catalunya* and *Unió Catalana d'Hospitals*.

[7] The values used in this paper are as follows: for h = 1: $a_1=0.79$, $a_2=0.48$, $a_3=0.34$ and $a_4=0.16$; and $b_1=1.30$, $b_2=0.75$, $b_3=0.55$ and $b_4=1.45$.

4. Evaluating hospital performance

Under a DEA formulation, the performance of a hospital is evaluated in terms of its ability to contract its input vector given its output vector subject to constraints imposed by best observed practice. For the hospital being evaluated, the positive elements of λ identify that set of dominating hospitals located on the constructed frontier (best observed practice), against which the hospital is evaluated. Given the input and output data sets, DEA identifies the efficient hospitals or constructs a linear combination of them in the sample as those representing the best observed practice. The constructed production frontier is then used as a reference for inefficient hospitals. DEA is a nonparametric approach, which is less prone than econometric approaches to misspecification of the functional form of the production function (the relation between inputs and outputs). The way in which DEA falls short of modelling a hospital depends primarily on the appropriateness and measurement of the inputs and outputs. However, our cost and technical efficiency measures are relative measures in the sense that inefficient hospitals are compared with the *best* observed practice in the sample of hospitals being analyzed. A change in the analyzed hospitals may thus shift the frontier and result in lower efficiency scores for some hospitals. What can be predicted is that hospitals identified as inefficient may decrease their inputs without decreasing their outputs, until they reach the frontier, given the sample of references and the input and output vectors.

DEA models presented in previous sections allow us to compute relative measures of cost, allocative, technical, pure technical, scale and congestion efficiencies. Table 3 summarizes the average scores for the five efficiency concepts measured in this paper.

Results show an average technical inefficiency of 10.1%. That is to say, hospitals would need to lower inputs 10.1% if all were operating on the production efficiency frontier. The average overall efficiency scores range from 0.545 to 1. Pure technical inefficiency scores show a lower level of inefficiency, the average being 2.9%. Average scale inefficiency is 4.6% while congestion efficiency is 2.8%. For technical efficiency, the percentage of hospitals operating on the frontier is 36.2. The average efficiency score for nonfrontier hospitals is 0.841, implying that nonefficient hospitals use, on average, 18.9% more inputs per unit of output than do efficient hospitals. According to the pure technical efficiency criterion, 69 of the hospitals

Table 3
DEA efficiency scores[a]

Efficiency definition	Mean	Standard deviation	Min	Median	Number efficient	% Efficient
CE	0.803	0.152	0.395	0.894	15	16.0
AE	0.891	0.095	0.528	0.906	15	16.0
TE	0.899	0.124	0.545	0.941	34	36.2
PTE	0.971	0.069	0.584	0.998	69	73.4
SE	0.954	0.094	0.545	0.993	34	36.2
C	0.972	0.066	0.577	0.999	56	59.6

[a] Note: CE = Cost efficiency; AE = Allocative efficiency; TE = Technical efficiency; PTE = Pure technical efficiency; SE = Scale efficiency; C = Congestion efficiency. Sample size: $N = 94$.

operate efficiently, with an average efficiency score of 0.971 for nonfrontier hospitals. The distribution of all scores is summarized in Table 4.

The decomposition of technical efficiency shows that, on average, scale inefficiency accounts for over 45% of technical inefficiency. However, only in seven of the 25 hospitals showing pure technical inefficiency is scale inefficiency the primary source of technical inefficiency. Nearly two-thirds of the inefficient hospitals, according to TE, are operating under decreasing returns to scale. However, 23 other inefficient hospitals show increasing returns to scale.

Average cost inefficiency for all hospitals under analysis is significantly higher than overall technical inefficiency. Hospital cost is, on average, 24.5% higher than would be necessary if all hospitals were operating on the best-practice cost efficiency frontier. Cost efficiency scores range from 0.395 to 1. Only 15 hospitals (16%) are on the cost frontier, i.e, operating at minimum cost. The average cost efficiency score for nonfrontier hospitals is 0.766, implying that excess cost in these hospitals is 23.4%.

Cost efficiency is decomposed into allocative (or price) efficiency and technical efficiency. A technically efficient hospital may show cost inefficiency because, given input prices, it does not minimize cost. According to our results, average allocative inefficiency is 10.9%, ranging from 47.2% to zero. While a hospital may be technically efficient, it may be at the same time allocatively inefficient, and vice versa. Then, the primary source of inefficiency is allocative inefficiency. Given the lower and upper bounds of input prices, cost inefficient hospitals employ a nonoptimal mix of inputs. Here, their costs are 30.5% higher than the cost-minimizing level.

Table 5 shows summary statistics on the possible savings as obtained from the analysis of overall technical efficiency. For each input, more than half the hospitals show no possible savings; the other half have input slack. Possible savings represent a complementary dimension of technical inefficiency. Table 5 suggests that if it were possible for the 60 inefficient hospitals to perform like the *best-practising* 34, savings of 7.38% in the number of physicians would be possible. The larger slacks occur in the nurses input, which could be reduced by more than 14% in inefficient hospitals. At the same time, potentially increased outputs can be observed. Acute care patient-days and ambulatory visits thus show a very low potential for increase, as do the number of residents and discharged patients. Potential increases arise in the augmented

Table 4
Distribution of DEA socres[a]

Score value	CE		AE		TE		PTE		SE		C	
	Number	%	Number	%	Number	%	Number	%	Number	%	Number	%
Less than 0.500	3	3.2	–	–	–	–	–	–	–	–	–	–
0.500–0.599	9	9.6	2	2.2	5	5.3	1	1.1	2	2.1	1	1.1
0.600–0.699	10	10.6	3	3.2	3	3.2	–	–	3	3.2	–	–
0.700–0.799	19	20.2	7	7.4	9	9.6	3	3.2	1	1.1	2	2.2
0.800–0.899	25	26.6	29	30.9	19	20.2	8	8.5	7	7.4	5	5.2
0.900–0.999	13	13.8	38	40.4	24	25.5	13	13.8	47	50.0	30	31.9
1.000	15	16.0	15	16.0	34	36.3	69	73.4	34	36.2	56	59.6

[a] Note: CE = Cost efficiency; AE = Allocative efficiency; TE = Technical efficiency; PTE = Pure technical efficiency; SE = Scale efficiency; C = Congestion efficiency. Sample size: $N = 94$.

Table 5
Potential savings derived from technical efficiency scores

Input	Hospitals with zero slack	Total slack as % of total input for inefficient hospitals
X_1 physicians	67	7.38
X_2 nurses	49	14.12
X_3 other labor	62	8.42
X_4 beds	91	0.00

number of surgical interventions, days of stay in intensive care units, and the number of daycare services. The latter could be more than doubled in the inefficient hospitals.

To discriminate between relatively efficient hospitals, a Cross Efficiency Matrix[8] has been employed. In this structure, the number of efficient hospitals appears in the peer groups of inefficient hospitals. An indication of robustly efficient hospitals is the number that appears in the peer groups of inefficient ones. Five of the 34 hospitals showing technical efficiency appear in 30 or more comparison groups of inefficient hospitals (more than half of them). On the other side, seven efficient hospitals do not appear in any comparison group of inefficient hospitals.

5. An econometric analysis of performance

What causes a hospital to produce by using more than the minimum quantity of inputs for a specific vector of outputs? What causes a hospital to spend more than the minimum for a specific vector of outputs? What are the factors associated with efficiency?

In order to determine the influence of environmental variables on efficiency, we adopt a two-stage approach. Let $z_j \in R_+$, $j = 1,\ldots,I$ be a discrete or continuous environmental variable. z_j represents variables over which the hospital has no control during the time period under consideration; z_j and the input variables should be uncorrelated. In the first stage, inefficiencies are calculated using a DEA model in which the environmental variables are ignored. In the second stage, variation in calculated efficiencies is attributed to variation in operating environments by means of a regression model. It is hypothesized that the DEA efficiency measures are some function of the vector z and a random disturbance ε^i:

$$\theta_i = \mathrm{f}(z_{ij})\varepsilon^i.$$

Some authors, such as Rosko et al. [28], Chilingerian [29] and Kooreman [30], have conceptualized DEA efficiency scores as a censored normal distribution; that is, those values of the dependent variable in the regression model above a threshold are measured by a concentration of observations at a single value. We would thus suggest that ordinary least squares, as used by Chirikos and Sear [16], was not an entirely appropriate method. Some

[8] A Cross Efficiency Matrix is a table that conveys information on how a hospital's relative efficiency is rated by other hospitals using their DEA optimal weights.

authors [9, 30] have therefore concluded that a censored Tobit model is appropriate in order to avoid biased estimates from ordinary least squares. The Tobit model is based on normally distributed latent variables. However, DEA scores do not fit the theory of censored sampling that gives rise to Tobit models; i.e., accumulation of sample observations at the highest level of efficiency.

Importantly, Tobit, and also Probit, estimates are inconsistent in the cases of nonnormality of error terms and/or error term heterogeneity. To overcome this problem, several alternatives have been proposed in the literature: Luoma et al. [31], for example, used a test statistic sensitive for linear fit; in particular, the type of heteroscedasticity which is related to fit and excess skewness of the error terms. González and Barber [32] estimated their model assuming different probability distributions of disturbance. Burgess and Wilson [33] removed the censoring problem directly through the addition of information on the distance of each observation from all other observations in the sample.

Further to these studies, Banker and Johnson [34] proposed a consistent, nonmaximum-likelihood estimator in an empirical application based on the theoretical conditions established by Banker [35]. Given the implausibility of normally distributed latent efficiency as required by Tobit models, and according to Banker and Johnson [34], we make the assumption that inefficiencies are log-normally distributed, and define the following transformations:

$$\bar{\theta}_i = 1/\theta_i - 1 + \omega$$

where ω is some very small number. Then, inefficiency can be posited to be a multiplicative function of the explanatory variables and random error term:

$$\bar{\theta}_i = \beta_0 \Pi_j z_j^{\beta_j} e^{v_j}$$

where β_j are parameters capturing the relationships between the explanatory variables and input and output inefficiency, respectively; and $\exp\{v_i\}$ is a random error term that is assumed to be independently and identically distributed and log-normally distributed with mean 1.

As noted earlier, factors explaining the performance of hospitals, as measured by productive efficiency, may be conceptualized in three categories: ownership, market structure and regulation. In order to test the empirical impact of market concentration on efficiency it is necessary to consider other relevant factors. Partial tests, as those of Valdmanis [6] and limited to the effect of ownership, may present statistical biases due to possible misspecifications of the regression model.

Ownership is considered here by classifying hospitals in three types: public, nonprofit, and for-profit. Market structure or competition is proxied by two variables: the Herfindahl–Hirschman index of local market concentration, calculated for admission data, and the number of competitors in the local market. The Herfindahl–Hirschman index is specifically used for testing the hypothesis that there is more efficiency in less concentrated markets. The presence of regulation influences hospital behaviour through the payment system and patient flows. The proportion of hospital revenues received from the NHS may be a proxy for the relative importance of regulation in hospital activities. These monetary flows are influenced by the NHS payment system as it pertains to patients subject to NHS regulated flows.

The explanatory factors of efficiency are defined here as: Nonprofit hospitals (Z_1), For-profit hospitals (Z_2), Herfindahl–Hirschman index of market concentration (Z_3), Number of competitors in the local market (Z_4), and Proportion of service revenues from NHS (Z_5).

The control variables are present to test the influence of input or output characteristics omitted or imperfectly measured in the DEA model. Here, they are designed to reflect differences in severity of treated cases, teaching status and differences in outcome quality. There is no direct measure available on severity of illness. In this situation, severity is proxied by the number of surgical interventions with more than one hour per admitted patient. Outcome quality, the direct measure of which is not available, is proxied here by the proportion of discharged patients with a recovered health status.

Additionally, efficiency scores are controlled for by the potential influence of hospital dimension (scale economies). We accomplished this by including the number of beds and square beds. Since overall technical efficiency scores assume that the efficient frontier exhibits constant returns to scale, hospital size is likely an explaining factor.

According to the preceding arguments, control variables are empirically defined as: More than one hour surgical interventions per one hundred patients (W_1), Teaching status (W_2), Proportion of recovered discharged patients (W_3), Number of beds (W_4) and Number of square beds (W_5).

Inefficiency scores obtained in this paper were regressed against the explanatory and control variables. The data were examined for evidence of collinearity and the residuals for evidence of nonlinearity, nonnormality and heterocedasticity. Correlations between the explanatory variables were not statistically significant and collinearity was not considered a problem, except in the case of the Herfindahl–Hirschmann index of market concentration (Z_3) and number of competitors in the local market (Z_4). Given the high correlation between these two variables, and the fact that both measure the degree of market concentration, regression models were estimated using these two variables separately. Also, nonlinearity was not apparent. Kolmogorov–Smirnov and Shapiro–Wilks test [36] statistics for normality of the residuals did not reject normality for the six equations. Finally, the Breusch–Pagan test [36] did not reject homoscedasticity.

Regression results for DEA efficiency scores as dependent variables are presented in Table 6. The results were obtained using a stepwise method that identifies only one signifcant explanatory variable for each equation. We found that the explanatory factors do not show statistical significance in explaining any of the calculated scores. Econometric results indicate that only the Herfindahl–Hirschman index in the local market (market share) presents a significant contribution in explaining differences in technical, pure technical, scale and congestion inefficiency scores. In all four cases, as the level of market concentration decreases (lower Herfindahl–Hirschman index), the inefficiency level is lower. Hospitals operating as local monopolies, i.e., those with very few local competitors, are less technically efficient than hospitals operating in a more competitive environment. From the econometric point of view, models with the Herfindahl–Hirschmann index of market concentration (Z_3) as an explanatory variable are preferred to those with the number of competitors in the local market (Z_4). These results are in contrast with those obtained from a Tobit estimation in a previous paper [9]. The earlier work indicated that efficiency was influenced by the number of competitors rather than by the degree of concentration. Factors apart from market structure did not show any relevance in explaining observed levels of technical and pure technical inefficiency.

Market structure did not appear to influence cost and allocative efficiency in contrast to technical efficiency. Allocative efficiency was significantly explained by the proportion of service revenues from NHS (level of public financing). Hospitals with a higher proportion of revenues from public financing realized a higher allocative inefficiency score than did those with a lower proportion. That is, a low relative importance on public financing source apparently contributes to the use of input factors according to their relative prices in a more accurate manner than in public hospitals or in hospitals receiving a higher proportion of revenues from the NHS. These results highlight the potential for improving hospital performance through reforms in the public payment system that provide incentives to minimize cost. It is noteworthy that the greatest part of inefficiency variation was not explained by the models presented in this section.

In closing, we analyze correlation coefficients of traditional partial indicators of efficiency with the different efficiency measures (Table 7). Partial ratios considered here are length of stay, occupancy rate, labor intensity per case, average cost per case, average cost per patient-day, and proportion of costs covered by grants. These indicators should not be considered as explaining factors of efficiency scores because they only partially measure the relation between some inputs and outputs.

Length of stay shows no statistical correlation with any efficiency score. But then, length of stay is a poor indicator of efficiency. In contrast, the occupancy rate is positively and highly correlated with all efficiency scores, except for those of allocative efficiency. The lower the occupancy rate, the higher the technical inefficiency level. If there is no reason to consider capacity excess as valued additional output, the occupancy rate may be related to performance.

Labor intensity per case is not correlated with pure technical efficiency but is highly and negatively correlated with scale and allocative scores. This coefficient might indicate, in

Table 6
Factors explaining DEA inefficiency scores[a]

Inefficiency measure	Constant	Z3	Z5	Adjusted R square	F
CE	−1.47973		0.15153	0.048	5.66
	(−0.7199)		(2.2380)		
AE	−1.75006		0.16104	0.065	7.40
	(−9.158)		(2.721)		
TE	−6.4296	1.14214		0.043	5.17
	(−3.882)	(2.274)			
PTE	−8.4473	1.15075		0.061	6.96
	(−5.873)	(2.638)			
SE	−6.5797	1.01253		0.0412	5.06
	(−4.432)	(2.249)			
C	−9.6381	1.67810		0.131	14.85
	(6.714)	(3.854)			

[a] Note: Total observations: N = 94. T-Statistics in parenthesis. CE = Cost efficiency; AE = Allocative efficiency; TE = Technical efficiency; PTE = Pure technical efficiency; SE = Scale efficiency; C = Congestion efficiency. Z3 = Herfindhal–Hirschman index of market concentration. Z5 = Proportion of service revenues from NHS.

Table 7
Correlation coefficients of DEA scores with partial indicators of performance[a]

Indicator	CE	AE	TE	PTE	SE	C
Length of stay	0.1732	0.1570	0.1147	0.0745	0.0493	0.0708
Occupancy rate	0.5488[c]	0.1904	0.6394[c]	0.3012[c]	0.4576[c]	0.2688[b]
Labour intensity per case	−0.5647[c]	−0.6130[c]	−0.2924[b]	0.0242	−0.2597[b]	−0.2178
Average discharge cost	−0.3032[b]	−0.5716[c]	0.0516	0.1585	−0.0096	−0.0474
Average cost per patient day	−0.3388[c]	−0.6235[c]	0.0263	0.1308	0.0165	−0.1045
Percentage of cost covered by grants	−0.4273[c]	−0.2775[b]	−0.3770[c]	−0.4407[c]	−0.2169	0.0170

[a] Note: CE = Cost efficiency; AE = Allocative efficiency; TE = Technical efficiency; PTE = Pure technical efficiency; SE = Scale efficiency; C = Congestion efficiency.
[b] $P < 0.01$;.
[c] $P < 0.001$.

consonance with observed potential input savings from cost efficiency scores, that labor is used in excess relative to other inputs.

The cost per unit (discharge or patient-day) is not correlated with technical efficiency. Nevertheless, this indicator is negatively related to cost and allocative scores, where both include consideration of input prices. And, finally, grants partially financing functioning costs are negatively correlated with scores for pure technical efficiency and allocative efficiency.

6. Summary and conclusions

Leibenstein and Maital [37] argued that DEA merits consideration as a primary method for measuring and partitioning X-inefficiency. In this paper, cost efficiency of acute care hospitals in Catalonia (Spain) has been analyzed by means of an extended version of Data Envelopment Analysis. The paper has proposed a method to obtain a global measure of cost efficiency decomposed into its allocative, pure technical, scale and congestion components. In doing so, we used a DEA assurance approach to consider the fact that exact knowledge of input prices is generally difficult.

The main findings of this study may be summarized as follows:

1. Average cost inefficiency in hospital production was 24.5%. Hospital cost was, on average, 24.5% higher than needed if all hospitals were operating on the cost efficiency frontier. Under the latter conditions, then, cost might be reduced more than one fourth. This inefficiency level is the result of a 12.2% level of allocative inefficiency, 3.0% of pure technical inefficiency, 4.8% of scale inefficiency, and 2.9% of congestion inefficiency. Allocative inefficiency thus appears more relevant than does technical efficiency.
2. The degree of market competition (and the number of competitors in the local market) contributed positively to increased technical efficiency levels. That is, effective or potential competition apparently matters even in a highly regulated hospital market. This conclusion is more important when many local markets have very few competitors [9].

3. Allocative efficiency was independent of technical efficiency. Thus, privately financed hospitals (hospitals with a low proportion of service revenues from NHS) may realize higher allocative efficiency scores in comparison to public and nonprofit institutions (where the latter have higher proportions of financial resources obtained from public funding).

Problems of DEA frontier estimation are related to the existence of omitted outputs or inputs, as well as to the assumption of no measurement error or random fluctuations in output. Although these problems have been managed in this paper through a two-stage approach, this research might be extended in several ways. Input and output variables might be improved by taking into account the quality dimension of health. It is essential that the relationship between quality and input volume be accounted for in the measurement of inefficiency. The method employed in this paper might be used when estimating allocative and cost efficiencies rather than limiting attention to technical efficiency. Although we focused on hospital efficiency here, we did not determine if patients received an appropriate amount of care.

Additional work on DEA measurement of hospital efficiency should address two main problems. First, DEA generally ignores the fact that observations in any data set may be subject to random fluctuations. Deterministic scores should thus be converted into stochastic ones, which may be obtained through complete panel data and chance-constrained DEA models. And, second, DEA scores may be biased by measurement problems in the input–output set, which may be tempered by accurately measuring changes in the severity of illness from admission to discharge. This would allow for the use of homogeneous patient groups, outcome predictive models computed at the patient level, e.g. Mortality Probability Model for Intensive Care Units [38], and the measurement of quantity and quality of life for discharged patients. In these ways, we might improve the measurement of patient characteristics in the input/output set of variables.

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