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Measuring Hospital Efficiency through Data Envelopment Analysis when Policy-makers' Preferences Matter.

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An Application to a sample of Italian NHS hospitals

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Abstract

In this paper we show how both the choice of specific constraints on input and output weights (in accordance with health care policy-makers' preferences) and the consideration of exogenous variables outside the control of hospital management (and linked to past policy-makers' decisions) can affect the measurement of hospital technical efficiency using the *Data Envelopment Analysis* (DEA). Considering these issues, the DEA method is applied to measure the efficiency of 85 (public and private) hospitals in Veneto, a Northern region of Italy. The empirical analysis allows us to verify the role of weight restrictions and of demand in measuring the efficiency of hospitals operating within a National Health Service (NHS). We find that the imposition of a lower bound on the virtual weight of acute care discharges weighted by case-mix (in order to consider policy-maker objectives) reduces average hospital efficiency. Moreover, we show that, in many cases, low efficiency scores are attributable to external factors, which are not fully controlled by the hospital management; especially for public hospitals low total efficiency scores can be mainly explained by past policy-makers' decisions on the size of the hospitals or their role within the regional health care service. Finally, non-profit private hospitals exhibit a higher total inefficiency while both non-profit and for-profit hospitals are characterised by higher levels of scale inefficiency than public ones.

JEL Codes: D24, I12

Keywords: Hospital performance, Technical efficiency, Data envelopment analysis, National Health Service

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1. Introduction

In many countries, measuring the efficiency of health care services has become increasingly important since the early 1980s. In Italy, the complete devolution of the National Health Service (NHS) to regional governments, which started in 2001, and the definition of national basic levels of public health care to be provided by each regional health system has made it crucial to compare the relative performance of health care services both across different regions and across different Local Health Authorities (LHA) within each region.

In this paper, we will focus on measuring the technical efficiency of acute hospitals operating within NHS, which provide important services within the basic package of public health care.

The technical efficiency of hospitals can be measured by parametric and non-parametric evaluation methods that permit simultaneous comparison of the inputs and outputs of a hospital's production process and produce concise indicators of efficiency. Both methods allow to consider the heterogeneous character of the output produced by different decision-making units (DMUs) and are particularly well-suited for developing indicators to compare the efficiency of different hospitals. Since each method is based on different hypotheses with differing degrees of stringency, they will lead to different (sometimes contrasting) results regarding the efficiency levels of the hospitals examined. Parametric analyses require a prior definition of a production function of hospital services, whereas the non-parametric analyses determine the relative efficiency scores of similar DMUs by means of linear programming techniques, without detailed descriptions of their production processes.[1]

Given the multi-output nature of the hospital production process, we will focus on a particular non-parametric method, *Data Envelopment Analysis* (DEA), which is encountering growing consensus as a powerful tool to measure hospital productivity because it allows the heterogeneity of

[1] For a comparison between parametric and non-parametric methods, see: Banker, Conrad and Strauss (1986), Chirikos and Sear (2000), Jacobs (2001).

delivered outputs to be taken into account. As it uses a particular type of linear programming, DEA makes it possible to determine the relative efficiency levels of similar hospitals without the need for a detailed description of the production process (i.e. without determining beforehand a certain number of parameters in order to explain the structure of the whole production process)[2]. DEA is particularly useful when input prices are not available, thus making it impossible to estimate a hospital cost function. This is the case of most Italian NHS hospitals, whose costs are generally embedded in the Local Health Authorities' costs and for which it would be unpracticable to assign a price to each used input. Moreover, DEA does not require a single objective function to be defined for all DMUs. On the contrary, DEA defines efficiency as the ratio between a weighted sum of outputs and a weighted sum of inputs and it allows each DMU to choose the preferred weights to attach to inputs and outputs in order to maximise its efficiency ratio with respect to the other DMUs.

As Allen et al. (1997) pointed out, the flexibility of DEA may be brought into question when it is considered that the correct evaluation of the relative efficiency of hospitals may require the consideration of value judgements which can restrict the acceptable ranges of variation of the input and output weights. These ranges can vary according to the perspective of the analysis. At one extreme, a *hospital management perspective* (hospital management's maximum freedom when choosing the weights of inputs and outputs) can be adopted. At the other extreme, a *complete centralised perspective* can be adopted, in which individual input and output weights are not determined endogenously by the DEA method but defined univocally by a central policy maker; in this case, however, the DEA method loses its significance as the use of simple efficiency ratios would be sufficient. At an intermediate level, a *constrained DEA model* can be adopted in which a (national/regional) health authority sets the acceptable range of variations of

[2] An extensive review of DEA applications in the area of health care is given by Hollingsworth, Dawson and Maniadakis (1999). For some recent interesting applications of DEA to hospital efficiency evaluation, see: O'Neill (1998), Puig-Junoy (2000), Steinmann and Zweifel (2003), Ventura, Gonzalez and Carcaba (2004).

the weights that each DMU can choose. In fact, since the outputs provided by hospital services are usually included in the basic levels of public health care, the evaluation of the relative efficiency of hospitals should take into account the policy-maker’s preferences. This implies imposing particular constraints on input and output weights.

Another issue that has often been neglected is the influence of variables outside the direct control of hospital management on hospital performance. In particular, we will show that the level of technical inefficiency observable using DEA can be broken down into *internal* inefficiency (attributable to hospital managers) and *external* inefficiency due both to an excess of supply with respect to demand and to scale inefficiencies. If these external inefficiency factors arise from past choices of health care planners, they should be considered exogenous with respect to the decisions of the hospital management.

In this paper, we show how both the choice of specific constraints on input and output weights (in accordance with health care policy-makers’ preferences) and the consideration of exogenous variables outside the control of hospital management (exogenous demand, past policy-makers’ decisions) can affect the measurement of hospital technical efficiency with DEA.

Subsequently, we develop four DEA models to measure the levels of technical efficiency of 85 acute hospitals in Veneto, a region in Northern Italy. The empirical analysis allows us to evaluate the role of demand and weight restrictions and will provide some useful insights into the levels of efficiency of hospitals in the Veneto region (Northern Italy).

The plan of the paper is the following. Section 2 briefly describes the main characteristics of DEA as a technique for measuring hospital technical efficiency. In section 3 we argue that precise value judgements are necessary in order to apply this method to the efficiency evaluation of hospitals operating within a National Health Service (NHS). These value judgements concern particularly production technology and managers’ or policy-makers’ preferences for hospital output mix and imply the adoption of constraints on input and/or on output weights. In section 4 we analyse the importance of distinguishing between different components of the technical inefficiency of hospitals operating within an NHS: *internal* inefficiency attributable to the responsibility of hospital management and *external* inefficiency that could be due to past health care policy decisions and to exogenous demand. In section 5, the DEA method is applied to measure the levels of technical efficiency of the hospitals in Veneto. Finally, section 6 reports some conclusions.

2. Measuring hospital technical efficiency with DEA

Detailed descriptions of DEA can be found in several sources (Charnes, Cooper and Rhodes 1978; Charnes et al. 1994; Ganley and Cubbin 1992; Cooper, Seiford and Tone 2000). Therefore, we provide here only a brief description of the basic constant return to scale model (CCR model from Charnes, Cooper and Rhodes 1978).

Let's consider *J* homogeneous hospitals ($j = 1, \dots ,J$) to be evaluated, each using varying quantities, x_{ij}, of *I* different inputs ($I = 1, \dots,I$) to produce varying quantities, y_{kj}, of *K* different outputs ($k = 1, \dots ,K$). Defining u_{kj} and v_{ij} the weights attached to the *k*th output and to the *i*th input, technical efficiency e_j of hospital *j* can be written as:

(1) $$e_j\left(y_j, x_j, u_j, v_j\right) = \frac{u_{1j}y_{1j} + u_{2j}y_{2j} + \ldots + u_{kj}y_{kj} + \ldots + u_{Kj}y_{Kj}}{v_{1j}x_{1j} + v_{2j}x_{2j} + \ldots + v_{ij}x_{ij} + \ldots + v_{Ij}x_{Ij}} = \frac{\sum_{k=1}^{K} u_{kj}y_{kj}}{\sum_{i=1}^{I} v_{ij}x_{ij}}$$

Since the model can provide only relative efficiency scores, the hospital *j's* efficiency ratio e_j is defined as a percentage of the highest level of absolute technical efficiency attainable, where all the hospitals are assigned the weights chosen by hospital *j* in order to maximise its absolute efficiency. This is equivalent to attaching to outputs and inputs of hospital *j* those weights that cast its activity in the best light.

The relative efficiency of hospital *j* is calculated by solving the following mathematical linear programming problem:

(2) $$\max_{u_j, v_j} e_j\left(y_j, x_j, u_j, v_j\right)$$

subject to constraints

$$\frac{\sum_{k=1}^{K} u_{kj} y_{kl}}{\sum_{i=1}^{I} v_{ij} x_{il}} \leq 1 \qquad l = 1,\ldots, J \tag{3}$$

$$u_{kj}, v_{ij} \geq 0 \quad k = 1,\ldots, K;\ i = 1,\ldots, I. \tag{4}$$

Constraints (3) set an upper limit equal to 1 for the efficiency indicators of all the hospitals calculated with the weights of hospital *j*. Constraints (4) impose the non-negativity of weights. Problem (2) can be solved in two ways: by minimising the quantities of inputs to obtain preset output levels (*input-oriented model*), or by maximising the quantities of outputs produced by given levels of inputs (*output-oriented model*).

The maximisation problem for hospital *j* is solved by finding the vectors of weights u_j and v_j that maximise the efficiency score e_j. These are the best possible weights for the hospital as any other weight vector would lead to a lower efficiency indicator. If a combination of weights for which $e_j = 1$ can be found, then hospital *j* will be efficient. On the other hand, if a value of $e_j < 1$ were found, then hospital *j* would be inefficient. In the latter case, we can say that there are no weights u_j and v_j that could put hospital *j* at the top of the efficiency league of the hospitals examined.

This process is repeated to obtain the level of relative technical efficiency (efficiency score) and the "optimal" weights required to attain that level for each of the *J* hospitals. The optimal weights obviously differ from hospital to hospital.

The DEA weights provide particularly important information about the implicit choices made by each hospital in order to appear as efficient as possible in relation to the others. Making the weight attachment process endogenous can thus lead to different input and output weights depending on which hospital is considered. This is one of the strengths of DEA but, at the same time, it is also one of its weaknesses. It is a strength because if a given hospital is found to be inefficient even when the most favourable weights are applied for measuring its efficiency, then there are reasonable grounds to classify it as inefficient. In fact, despite the best weights being selected to maximise its efficiency, a score $e_j < 1$ indicates that a more efficient linear combination of other hospitals exists. It is a weakness because each hospital can obtain a high level of efficiency by choosing the most suitable weights. Hence the efficiency scores calculated for the various DMUs are not properly comparable as they derive from different weighting processes. In this way, however, outliers that focus on just one output (input) while neglecting the rest may appear to be fully efficient (O'Neill, 1998).

3. The need for value judgements and DEA weight restrictions

The great flexibility in selecting optimal weights is a particular feature of DEA and is often wrongly confused with absolute lack of *a priori* hypotheses on the form of the production function of DMUs but we should not ignore the fact that the acceptable range of weights can vary according to the perspective of analysis that is adopted. At one extreme, a *hospital management perspective* can be adopted, that is, maximum freedom when choosing weights[3]. At the other extreme, a *complete centralised perspective* can be adopted in which input and output weights are determined univocally. In this case, however, the DEA loses its significance as it is reduced to the traditional type of analysis where each hospital's efficiency is measured as the ratio between weighted aggregations of selected outputs and inputs. At an intermediate level the relevant authority (e.g. a national or regional health care authority within an NHS) can set maximum and minimum boundaries for some or for all the weights. In this case, a *constrained DEA model* is applied according to the targets of the policy-maker.[4] Since many hospital services are considered of great social value, it is inevitable that to some extent the evaluations of relative efficiency of hospitals will be conditioned by value judgements.

[3] However, a value judgement is implicitly formulated as the implicit weights chosen by each hospital are considered acceptable.

[4] Allen et al. (1997) calls the single hospital perspective a "bottom up" approach and the policy-maker perspective a "top down" approach.

Following Allen et al. (1997), value judgements concerning the relative importance of inputs and outputs can be incorporated in the CCR model, via weight restrictions, according to three broad approaches having different implications on the assessed relative efficiency of hospitals:

1) imposing direct restrictions on the weights of some or all inputs and outputs. This approach can be applied in two ways:

   i) *absolute weight restrictions*, by imposing lower and upper bounds to weights;

   ii) *assurance region methods*, which impose constraints on the marginal rates of substitution between inputs or outputs (defined by the ratio between input or output weights);

2) adjusting the observed input-output levels (cone-ratio approaches);

3) restricting the virtual weights of inputs and/or outputs. For example, the virtual weight for output *k* of hospital *j* - which defines the proportion of the total virtual output of DMU *j* devoted to output *k*, and is expressed as $\left(u_{kj} y_{kj}\right) / \left(\sum_{k=1}^{K} u_{kj} y_{kj}\right)$ - could be restricted within a given range.[5]

The bounds used in weight restrictions can be either exogenously set according to policy-maker (or top management) objectives, expert opinion and price/cost information (where available) or endogenously derived from the data. In the latter case, running an unbounded DEA at the first stage could provide useful information for definition of the weight restrictions to use in the constrained DEA at the second stage.[6]

In the empirical analysis of section 5, we will use a restriction on output virtual weights. This choice allows us to take into account the contribution of output levels to hospital technical efficiency.

It is useful to explore the effect of restriction on output virtual weights by using a simple example in which two outputs y_1 (acute care admissions) and

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5 See Pedraja-Chaparro, Salinas-Jimenez and Smith (1997), Charnes et al. (1994) and Cooper, Seiford and Tone (2000) for further reading on the role and implications of weight restrictions in DEA.

6 For example, Chilingerian and Sherman (1997) obtained optimal weights for inputs and outputs of primary care physicians with an unbounded DEA, at the first stage, and then used these weights to define a cone-ratio in a subsequent bounded DEA model based on HMO management's objectives.

y_2 (day hospital treatments) are considered. The marginal rate of technical transformation between the two outputs, for a given level of efficiency, is the ratio $-u_{1j}/u_{2j}$, which is the slope of the indifference curves in the output space (see fig. 1).

Let's consider a constraint on virtual weights represented by a lower bound α imposed on the relative value judgement assigned to output y_1:

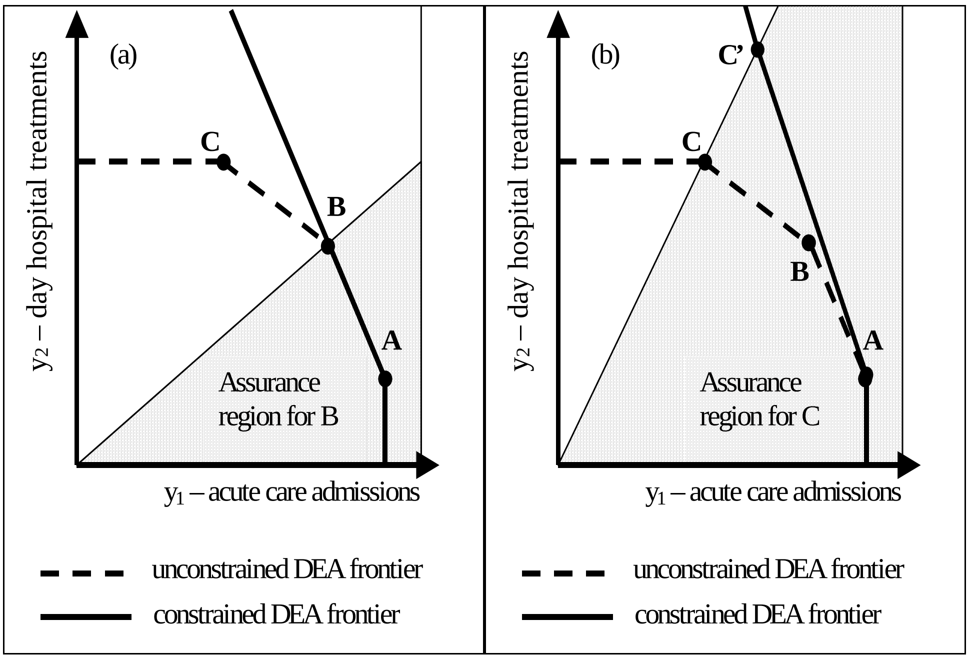
(5) $$\frac{u_{1j}y_{1j}}{u_{1j}y_{1j}+u_{2j}y_{2j}} \geq \alpha$$

with $0 \leq \alpha \leq 1$. Solving this constraint for y_{2j} yields the associated assurance region:

(6) $$y_{2j} \leq \frac{1-\alpha}{\alpha}\frac{u_{1j}}{u_{2j}}y_{1j}$$

where $\frac{1-\alpha}{\alpha}\frac{u_{1j}}{u_{2j}}$ represents the slope of the line defining the boundary of the assurance region in the output space (fig. 1).

Fig. 1 - Constraint on virtual weights: the effect of an increase in the marginal rate of technical transformation on the assurance region



It is well known (Wong and Beasley 1990, Pedraja-Chaparro, Salinas-Jimenez and Smith 1997, Allen et al. 1997) that, when a constraint is applied to virtual weights, both the marginal rate of transformation and the assurance region are DMU-specific because they depend upon the DMU’s choice of the absolute weights.

As is shown in fig. 1(a), for a given value of α, the DMU B is efficient also with the constrained DEA because its virtual weights satisfy condition (6) even in the unconstrained DEA model. Fig. 1(a) shows the assurance region chosen by B, which is compatible with the ratio between its best absolute weights u_{1B} / u_{2B}. On the contrary, the DMU represented by point C in Fig. 1(b), which would be efficient according to the unconstrained DEA, is now inefficient and its inefficiency is measured by CC'. The DMU C chooses its absolute weights by increasing the ratio u_{1C} / u_{2C} in order to belong to a larger assurance region (with respect to B). As a consequence, the slope of the indifference curve also increases and this determines the inefficiency score measured by CC’.

To summarise, constraints on virtual weights seem to be less binding than constraints on absolute weights. In fact, the latter determine a unique assurance region for all DMUs, while the former allow DMUs to choose the absolute weights that guarantee their best assurance region.

4. The role of demand and of scale efficiency in the performance of NHS hospitals

If the set of hospitals under examination includes units with excess supply with respect to demand, then the analysis of efficiency should capture this effect. In an NHS, an excess supply of hospital services could be due to past decisions of health care policy-makers, determining over-sizing of capacity with respect to actual demand with a negative influence on DEA efficiency scores. This particular source of inefficiency can be defined as *demand inefficiency*. Moreover, if we consider the hospitals operating within an NHS (which make their decisions according to national and regional health care authorities’ guidelines), health care policy-makers could also be responsible, at least partly, for another source of inefficiency, i.e. *scale inefficiency*, arising from over- or under-sizing of hospitals with respect to their actual activity levels.

Both these sources of inefficiency can exist in the short term and can be considered, somehow, "external" to NHS hospitals' management responsibility, being determined in most cases by the decisions of health care planners. In fact, within an NHS, a hospital could be kept active for reasons regarding broader health care policy, even if it exhibits a non-optimal bed capacity, high levels of potential production and insufficient demand.[7] In this case, an NHS hospital could operate efficiently given the actual demand for its services (internal technical efficiency), but at the same time it could show external technical inefficiency (both scale and demand inefficiency), as its size is non-optimal and its input endowments are excessive in relation to actual demand. While the external inefficiency of public NHS hospitals can be due to decisions taken by national and regional policy-makers at a higher level than hospital management, private hospitals (for-profit and non-profit) operating within an NHS could be publicly subsidized in order to operate with a given (non-optimal) capacity and in a given (low demand) area. In both cases, scale inefficiency and demand inefficiency can be attributed to the responsibility of policy-makers and are therefore external to the hospital management.

The point can be further explained with the help of fig. 2, where we consider a very simple production process (one output y, acute care admissions, obtained via the utilization of one input x, the number of beds). In fig. 2 we show the frontier production function (FPF) for a given set of hospitals, describing the higher level of output y attainable via an efficient utilization of input x, and the observed production function (OPF^j) of a given hospital j.[8] In the example of fig. 2, we consider the existence of an expressed admissions demand y^L which is always lower than the number of

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7 For example, consider hospitals in poorly-served areas - such as islands, mountainous districts and other peripheral and low population density areas - which, if closed, would force people to travel long distances or face long waiting lists.

admissions that can be satisfied by the hospital, considering its OPF^j. We can distinguish between two cases: a) the hospital's bed capacity is optimal (x^j=x*; fig. 2(a)); b) the hospital's bed capacity is above its optimal size (x^j>x*; fig. 2(b))[9].

In case a), *total inefficiency* can be split into two components: *internal inefficiency* (the distance between FPF and OPF^j, i.e. $y^*(x^*)$- $y^j(x^*)$), and *demand inefficiency* (the distance between OPF^j and the line y^L, i.e. $y^j(x^*)$- y^L). In this case, by definition, there is no *scale inefficiency* (as x^j=x*) and the hospital is inefficient because its output is lower than the maximum level attainable with the quantity of input x* (i.e., $y^j(x^*)< y^*(x^*)$ - internal inefficiency), and also because its supply of in-patient care is higher than the expressed demand ($y^j(x^*)>y^L$).[10]

In case b), *total inefficiency* can be split into three components:

- *scale inefficiency* (the distance between the dotted line OM, linking the origin to point M that defines the optimal output with respect to actual capacity x^j, and the FPF, i.e. $y^M(x^j)$- $y^F(x^j)$);
- *internal inefficiency* (the distance between FPF and OPF^j, i.e. $y^F(x^j)$- $y^j(x^j)$);
- and *demand inefficiency* (the distance between OPF^j and the line y^L, i.e. $y^j(x^j)$-y^L).

Therefore, unless hospital size is optimally chosen, it is always possible to identify three different components of inefficiency: *internal inefficiency*; *scale inefficiency*; and *demand inefficiency*. As previously said, if we consider hospitals operating within an NHS, the latter two components of inefficiency can be considered as *external* source of inefficiency because they are, at least in the short run, outside the control of hospital management.

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8 Fig. 2 is used here just for explanatory purposes, while in the DEA the production frontier would be represented by a piecewise line.

9 We do not consider a third case in which the hospital's bed capacity is under its optimal level.

10 If the level of expressed demand of in-patient care were higher than $y^j(x^*)$ (e.g. the dotted straight line y^{LL} in fig. 2(a)), hospital *j* would exhibit only internal inefficiency MN, while we could not observe the gap between expressed demand and satisfied demand LN.

Fig. 2a Components of hospital total inefficiency with optimal bed capacity

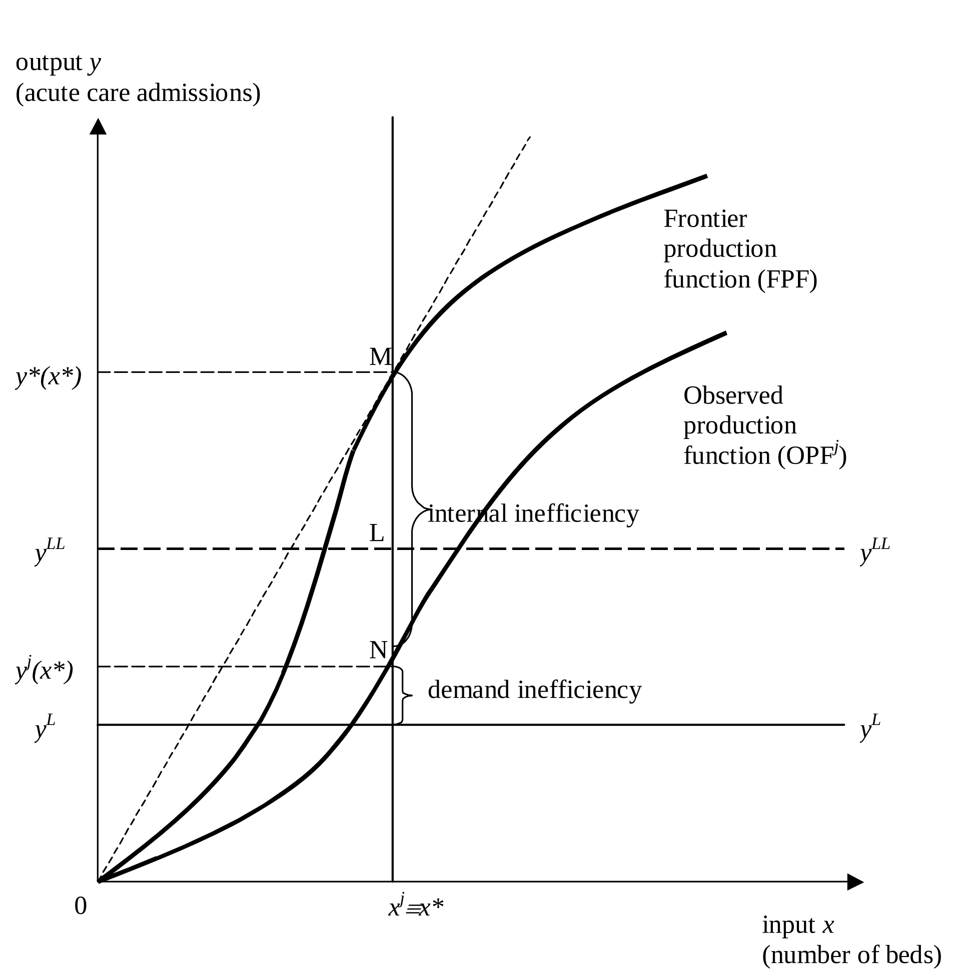
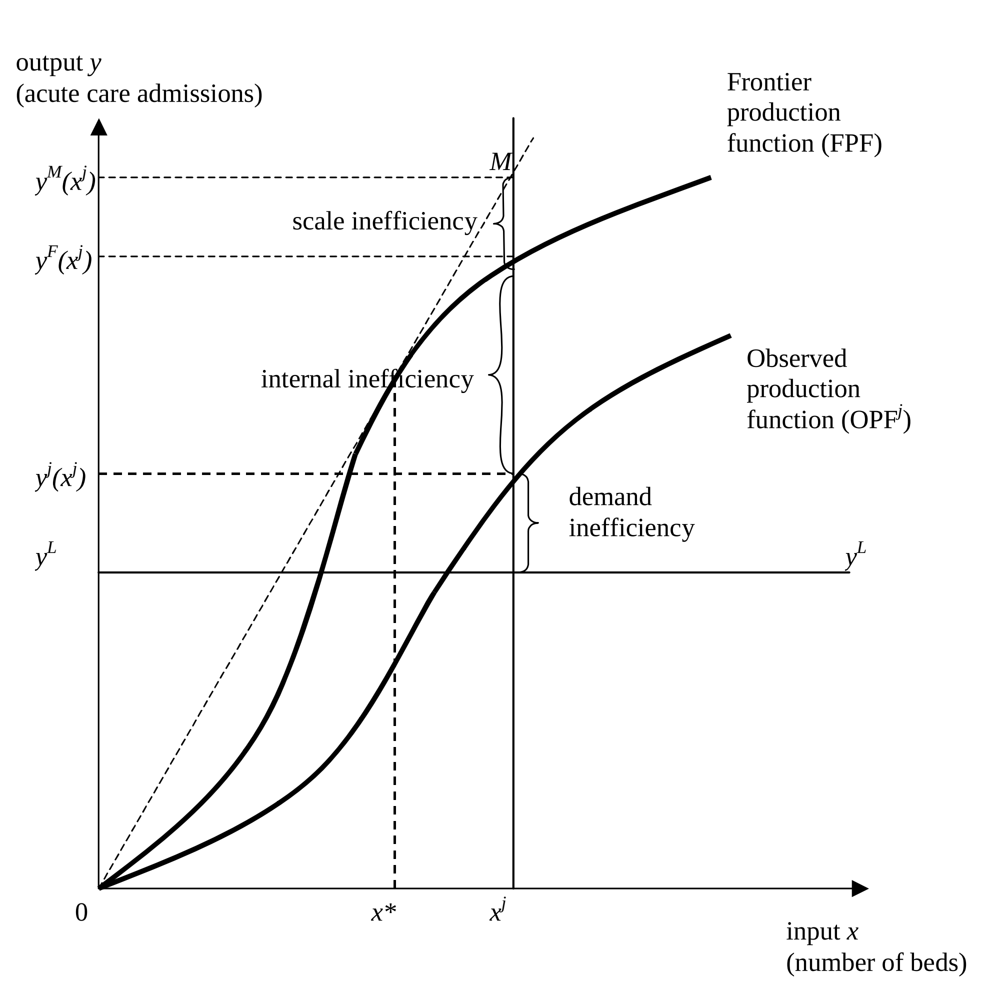


Fig. 2b Components of hospital total inefficiency with capacity above the optimal level



Using DEA, it is possible to provide evidence of both sources of *external inefficiency*. *External scale inefficiency* (due to a non-optimal hospital size) can be measured by introducing the assumption of variable returns to scale (VRS), as in the BCC model (Banker, Charnes and Cooper 1984). On the other hand, measuring *external demand inefficiency* (due to a shortage of actual demand with respect to supply) should take account of the existence of an additional constraint on the demand side. This can be done by adding to the BCC-DEA model a non-discretionary demand variable (that proxies the actual demand level) among inputs, i.e. an exogenous demand variable that cannot be modified at the discretion of individual hospital managers, such as y^L in fig. 2. The consideration of an additional exogenous demand input in BCC-DEA can be made following Cooper-Seiford-Tone's approach to the treatment of a non-controllable (NCN) variable (Cooper, Seiford and Tone, 2000, chapter 7). Obviously, considering an additional input will tend to increase the number of efficient hospitals. This happens because low efficiency scores are now attributable to external variables beyond the control of hospital managers.

In order to measure demand inefficiency, we should consider a demand variable completely exogenous with respect to hospital management decisions. A good example of such a variable seems to be the potential demand of admissions for each hospital measured either by past hospitalisation rates or by a good estimation of the number of in-patients within the hospital's catchment area. Unfortunately these data are very often not available (as in our case) so the non-discretionary demand variable could be proxied either by the hospitalisation rate or by the number of residents in the Local Health Authority area where the hospital is located. However, the choice of these non-discretionary variables does not appear appropriate for several reasons. Firstly, hospitals are "point-services" whose demand cannot be easily circumscribed to a specific area (even though the higher percentage of admissions refers to residents within a particular LHA boundary). Secondly, since more than one hospital operates within the territory of a given LHA, it is difficult to share residential LHA demand between each hospital.

To overcome these problems, a possible choice (that we adopt in the next section) could be to approximate the non-discretionary level of demand y^L by considering the actual number of hospital admissions. This is clearly an unsatisfactory choice, since the satisfied admissions demand is undoubtedly influenced by the hospital's production process. In any case, it should be noted that the number of admissions (satisfied demand) cannot be larger than the expressed demand and that both are lower than the actual (latent) admissions demand. Therefore, if - after including in the BCC-DEA model the number of admissions among the inputs (as a non- discretionary variable) - we do not find any demand inefficiency, this can be surely considered a robust result.

Summing up, by using the assumption of VRS (with a BCC-DEA) and then including an NCN demand variable, it is possible to distinguish between:

- *total technical efficiency with VRS*: e_j^S;
- *internal technical efficiency with VRS*, e_j^I, which signals the ability of the hospital management to apply the most efficient production technique.

  Therefore, the total inefficiency of a hospital j ($1-e_j$) can be considered as the result of three components[11]:

- *internal inefficiency* due only to hospital management, computed as ($1-e_j^I$);
- *external scale inefficiency*, computed as the difference between total efficiency with VRS and total efficiency with CRS: ($e_j^S - e_j$);
- *external demand inefficiency*, computed as the difference between internal efficiency with VRS and total efficiency with VRS: ($e_j^I - e_j^S$).

5. A case study: the hospitals of the Veneto Region - Italy

5.1. The model

Let's examine the effect of what we have discussed so far using data concerning the acute hospitals in Veneto, a region in Northern Italy. The hospital technology is described by a simplified model with three outputs: an index of in-patient output calculated by weighting the number of acute care discharges with DRG weights (y_1); the number of days of treatment in day hospital (y_2); the number of treatments provided by emergency services (y_3), and five inputs: the number of physicians (x_1); the number of nurses

[11] The three different components of inefficiency can be measured by comparing the scores obtained with three different DEA models: the CCR model; the BCC model; the Non-Controllable Variable BCC model. See Cooper et al. (2000). In section 5, we will adopt this methodology.

(x_2); the number of other employees (x_3); the number of hospital beds (x_4); the total number of acute care admissions as an additional input used as a proxy for hospital demand (x_5).

Output y_1 is built as a weighted sum of medical and surgical discharges differentiated by DRG (excluding day hospital cases). As aggregation weights, we use the relative standard costs (DRG tariffs) attached to each DRG, considered as proxies of the intensity of care embodied in each discharge classified in that DRG.[12] Output y_2 is given by the number of days of treatment provided by medical and surgical day-hospital services. Output y_3 is the number of treatments provided by accident and emergency services.

The staff numbers (x_1, x_2, and x_3) are measured as the average number of full-time equivalent staff for the year, while the number of beds (x_4) is a proxy of the capital used in the hospital production process. Finally, the additional input x_5 represents a non-controllable demand variable introduced in order to separate total technical efficiency into its internal (managerial) and external components, according to the analysis in section 4.

We consider four different DEA models reported in Table 1[13].

[12] The DRG classification includes 492 categories, as in the 10th version of HCFA-DRG in the U.S.

[13] In model 2, the restriction on the virtual weights of output y_1 (acute care discharges adjusted with DRG) implies that each hospital cannot attribute a virtual weight lower than 70% to output y_1. The particular choice of the lower bound of 70% can be justified by two different arguments. Firstly, the output virtual weights that can be chosen by each hospital should not be too far from the virtual weight chosen by a DMU built as the aggregate of the Veneto hospitals under evaluation (“Veneto” DMU) that can be interpreted as an implicit expression of the Veneto Region’s preferences concerning the relative importance of different outputs. The average virtual weight of output y_1, calculated for Veneto DMU in model 1, is 86%. Secondly, it should be noted that the more recent health care policy of the Veneto Region gives incentives to shift hospital production from traditional forms of in-patient care towards day hospital and emergency treatment. Consequently, the virtual weights of y_1 should be lower than 86% in order to guarantee that each hospital does not overlook other outputs.

Table 1 – The analysed DEA models

Model	*Orien-tation*	*Return to scale*	*Technical efficiency*	*Constraints*	*Responsibility for technical inefficiency*
1 (CCR)	Input Output(*)	Constant (CRS)	Total	None	Hospital management and Policy-maker
2 (CCR)	Output	Constant (CRS)	Total	Virtual weight of output $y_1 \geq$ 70%	Hospital management and Policy-maker
3 (BCC)	Input	Variable (VRS)	Total	None	Hospital management and Policy-maker
4 (BCC -NCN)	Input	Variable (VRS)	Internal (addition of input x_5)	None	Hospital management

(*) Results obtained either with input-oriented or output-oriented CCR model are equivalent.

Key:

1. *CCR model: Charnes, Cooper and Rhodes, 1978*
2. *BCC model: Banker, Charnes and Cooper, 1984*
3. *BCC-NCN model: BCC model modified with a non-controllable (NCN) variable (Cooper, Seiford and Tone, 2000, chapter 7)*

5.2 The data

The data used for the analysis refer to the year 1997 and come from the hospital discharge records of the Ministry of Health and the Veneto Region databases (Regione Veneto, 1999). Due to the lack of some information, the sample does not include all the Region's public and private hospitals. Only 85 structures are considered out of the 95 that actually existed. The sample consists of 59 LHA-public hospitals (i.e. hospitals directly run by Local Health Authorities), 2 public hospital trusts (the teaching hospitals of Padua and Verona) and 24 private hospitals affiliated to LHAs (seven of which are non-profit). As far as outputs y_1 and y_2 are concerned, the revenues of hospital trusts and private hospitals are based upon DRG tariffs, while LHA-public hospitals are financed partly on a capitation basis (considering the needs of the population residing within each Local Health Authority's territory) and partly by DRG tariffs (in order to compensate the services provided to patients residing outside the LHA). For all hospitals, on the other hand, emergency services y_3 are compensated by special funds on a retrospective basis.

5.3 Results and discussion

In model 1 (CRS total efficiency without constraints) most hospitals exhibit a very high virtual weight for output y_1 “discharges adjusted with DRG”. In any case, as no constraints are imposed, it is possible to retrace some hospitals which exhibit a very low (or nil) virtual weight for y_1, while assigning a very high virtual weight to the number of days in day hospital y_2 or to emergency services y_3. This is plainly unsatisfactory, as discharges are an important component of total hospital output. Therefore, in model 2 (CRS total efficiency with a constraint on y_1 virtual weights) we try to overcome this shortcoming by imposing a constraint on the virtual weights of hospital output y_1.

Table 2 shows that, after the introduction of the constraint on y_1 virtual weight, on average, total efficiency decreases from 74.5% (model 1) to 71.3% (model 2). The restriction penalises the DMUs that in model 1 assigned a virtual weight of less than 70% to acute care discharges. Table 2 shows this effect: 25 hospitals that in the unbounded DEA (model 1) exhibited high performances have very low efficiency scores in model 2. Two cases that stand out are the LHA-public hospitals U07 and U21, which give absolute priority to day-hospital care (with weights close to 100% in model 1), and which drop from total efficiency scores of 100% to 48.4% and 71.2% respectively.

Table 2 – The effect of a constraint on $y_1$virtual weights *(subset of hospitals affected by the constraint on virtual weights; scores in % ranked by total efficiency level)*

Hospital	*Total efficiency with CRS (model 1)*	*Constrained total efficiency with CRS (model 2)*	*Reduction of efficiency due to restrictions on y_1 weight (mod. 2 - mod.1)*
U68	44.6	23.7	-21.0
U25	50.6	49.4	-1.3
U54	53.2	51.8	-1.4
U20	57.2	35.0	-22.2
U29	58.6	40.0	-18.6
U75	59.6	47.7	-11.9
U40	69.8	60.9	-8.8
U41	71.3	71.2	-0.2
U44	76.0	69.9	-6.1
U10	81.3	68.3	-13.0
U27	83.8	71.1	-12.7
U31	86.9	85.6	-1.3
U51	87.3	86.7	-0.5
U32	89.9	88.5	-1.4
U26	93.6	90.9	-2.6
U50	94.5	90.0	-4.5
U06	95.6	71.9	-23.7
U78	95.6	81.0	-14.7
U66	95.8	86.2	-9.6
U24	97.3	96.5	-0.8
U76	98.6	98.4	-0.3
U90	99.2	92.4	-6.8
U67	99.7	98.2	-1.5
U07	100.0	48.4	-51.6
U21	100.0	71.2	-28.8
number of full efficient DMUs	13	11	-2
Average	74.5	71.3	-3.1
Minimum	15.6	15.6	-51.6
Maximum	100.0	100.0	-
Range	84.4	84.4	51.6
Standard deviation	22.8	23.1	8.0

Table 3 compares the main results from model 1, model 3 (VRS total efficiency without constraints) and model 4 (VRS internal efficiency without constraints). The table shows the data for the 72 hospitals that change (increase) their efficiency scores moving from model 1 to model 3 (among these DMUs, 51 increase their scores moving from model 3 to model 4). The total efficiency scores of model 3 are obtained running a BCC-DEA. Internal efficiency scores of model 4 are obtained by including among the inputs in the BCC-DEA a non-controllable demand variable, the total number of admissions x_5.[14]

Table 3 – Scale and demand effects on hospital efficiency scores

(a selection of hospitals changing their efficiency scores moving from model 1 to models 3 and 4, ranked by total efficiency level; efficiency scores in %)

DMU	*Total efficiency with CRS* e_j *(model 1)*	*Total efficiency with VRS* e^S_j *(model 3)*	*Internal efficiency with VRS* e^I_j *(model 4)*	*Scale inefficiency* $(e^S_j - e_j)$ *(I)*	*Demand inefficiency* $(e^I_j - e^S_j)$ *(II)*	*External inefficiency* $(e^I_j - e_j)$ *(III=I+II)*	*Internal inefficiency* $(1 - e^I_j)$ *(IV)*	*Total inefficiency* $(1 - e_j)$ *(V=III+IV)*
U83	15.6	100.0	100.0	84.4	0.0	84.4	0.0	84.4
U70	19.9	54.9	55.1	35.0	0.1	35.2	44.9	80.1
U62	24.5	67.2	80.2	42.8	12.9	55.7	19.8	75.5
U13	26.8	80.3	84.6	53.5	4.2	57.7	15.4	73.2
U69	31.7	47.7	49.0	16.0	1.3	17.3	51.0	68.3
U61	34.6	37.5	37.8	2.9	0.3	3.2	62.2	65.4
U85	35.4	70.1	70.7	34.6	0.6	35.3	29.3	64.6
U38	37.3	75.0	100.0	37.7	25.0	62.7	0.0	62.7
U72	40.2	43.1	49.3	2.9	6.2	9.1	50.7	59.8
U42	41.9	100.0	100.0	58.1	0.0	58.1	0.0	58.1
U68	44.6	45.5	100.0	0.9	54.5	55.4	0.0	55.4
…	…	…	…	…	…	…	…	…
U06	95.6	100.0	100.0	4.4	0.0	4.4	0.0	4.4
U78	95.6	96.1	100.0	0.4	3.9	4.4	0.0	4.4
U66	95.8	100.0	100.0	4.2	0.0	4.2	0.0	4.2
U24	97.3	100.0	100.0	2.7	0.0	2.7	0.0	2.7
U56	98.1	100.0	100.0	1.9	0.0	1.9	0.0	1.9
U80	98.5	100.0	100.0	1.5	0.0	1.5	0.0	1.5
U76	98.6	100.0	100.0	1.4	0.0	1.4	0.0	1.4
U90	99.2	100.0	100.0	0.8	0.0	0.8	0.0	0.8
U74	99.6	100.0	100.0	0.4	0.0	0.4	0.0	0.4
U67	99.7	99.9	100.0	0.2	0.1	0.3	0.0	0.3
Number of efficient DMUs								
	13	33	47					
Average								
	74.5	86.3	90.8	11.8	4.5	16.3	9.2	25.5
Minimum								
	15.6	37.5	37.8	0.0	0.0	0.0	0.0	0.0
Maximum								
	100.0	100.0	100.0	84.4	54.5	84.4	62.2	84.4
Range								
	84.4	62.5	62.2	84.4	54.5	84.4	62.2	84.4
Standard deviation								
	22.8	16.6	14.8	16.6	9.0	18.7	14.8	22.8

[14] Assuming VRS and being able to use an extra non-controllable variable obviously leads to efficiency scores that are higher than (or equal to) those obtained for total efficiency. In model 1, only 13 hospitals (15.29% of the total) are efficient, while 14 have an efficiency score lower than 50%. In model 3, 33 hospitals (38.82% of the total) are efficient and four exhibit a score below 50%. In model 4, 47 hospitals (55.29% of the total) are efficient and three exhibit a score below 50%.

Under the assumption of VRS (model 3), we find increasing returns to scale (IRS) for 42 hospitals and decreasing returns to scale (DRS) for 23, while 20 hospitals demonstrate constant returns to scale (CRS) (seven of these hospitals increase their efficiency). Generally, IRS are linked to lower (sometimes very low) total efficiency scores, while DRS are linked to higher total efficiency scores. The existence of DRS is demonstrated only for public hospitals (21 LHA-hospitals and the two hospital trusts).

In general, we can conclude that most of the hospitals in Veneto are too small in relation to their output levels (i.e. IRS). This problem of scale inefficiency, which is the first cause of the low total efficiency scores, characterises mainly the private hospitals (about 80% of the total of private DMUs: 14 for profit and five non-profit)[15], while only 39% of the LHA-public hospitals (23 DMUs) exhibit a sub-optimal size. This result indicates the particular role of private hospitals within the Veneto health care system: these hospitals are considered important within regional health care planning, as providers of supplementary services integrating public supply, even though they operate at a sub-optimal scale[16].

Table 3 also reports internal efficiency scores obtained with model 4 and demand inefficiency levels, that is, the second component of external inefficiency determined by an excess supply with respect to expressed demand. Including an exogenous demand variable among the inputs has a noticeably positive impact on the efficiency scores, especially for many LHA-public hospitals (37 DMUs) and for some accredited private hospitals (nine for-profit and five non-profit) which can be considered as

15 For one non-profit and six for-profit hospitals, inefficiency depends only on an inefficient scale.

16 The previous conclusion is confirmed by considering the relationships between the level of scale inefficiency and hospital size, measured in terms of number of beds: the higher scale inefficiency is linked to IRS and to a small capacity. Out of the 28 hospitals with scale inefficiency above the average (i.e. above 11.8%), 25 show IRS and 20 have less than 200 beds. In contrast, only three units with scale inefficiency above the average have more than 200 beds and show DRS.

complementary to public services and which operate under the strict control of regional and local health authorities.[17]

External inefficiency (measured by e^I_j- e_j), due to non-optimal scale and/or to exogenous demand, is the only component of total inefficiency for 34 hospitals (22 public). Therefore, we can conclude that, for these DMUs, low total efficiency scores can be better explained by past decisions made by policy-makers concerning the size of the hospital or its role within the regional health care service.

Table 4 reports the results of OLS regression analysis for six different measures of hospital inefficiency: 1) increased inefficiency due to the introduction of a restriction on the virtual weights of y_1; 2) scale inefficiency; 3) demand inefficiency; 4) external inefficiency (given by the sum of scale and demand inefficiency); 5) internal inefficiency; 6) total inefficiency (given by the sum of internal and external inefficiency). The explanatory variables used in each regression are:

- four dummy variables representing the type of any single hospital (LHA-public, hospital trust, non-profit private, for-profit private). The first dummy - LHA-public hospitals - is considered a constant. Therefore, the estimated coefficients for the others should be interpreted as shifts from the average efficiency level of LHA-public hospitals observed for each of the other three types of hospital;
- the number of beds;
- the case-mix index, to account for the complexity of discharges;
- the rotation index (number of patients that use one bed in a year, calculated as the ratio between the total number of discharges and the number of beds), to account for the rate of utilisation of hospital capacity.

[17] 14 hospitals become fully efficient moving from model 3 (scale efficiency) to model 4 (internal efficiency). Among these hospitals, eight units exhibit a demand inefficiency index (e^I_j- e^S_j) higher than 10%: five LHA-public hospitals; two non-profit private hospitals and one for-profit hospital. As might be expected, all these DMUs are located in mountainous and/or low population density areas.

Table 4 – Parametric evaluation of different components of DEA inefficiency (*)

Dependent Variable / *Regressors*	*(1) Increased inefficiency due to restrictions on y_1*	*(2) Scale inefficiency*	*(3) Demand inefficiency*	*(4) External inefficiency*	*(5) Internal inefficiency*	*(6) Total inefficiency*
Constant – LHA public hospitals	4.51722 *0.480131*	84.3339 *5.46459*	4.04702 *0.378639*	88.381 *5.2102*	48.4443 *2.67096*	136.825 *7.23857*
Dummy-Hospital Trusts	11.4828 *1.23608*	13.0752 *1.42074*	-5.15282 *-0.80844*	7.92233 *0.783178*	-3.555 *-0.32868*	4.36734 *0.387449*
Dummy-Non-Profit Private hospitals	-4.65297 *-1.52156*	8.62623 *1.71443*	2.92939 *0.840641*	11.5556 *2.08945*	0.349079 *0.059033*	11.9047 *1.93174*
Dummy-For-profit Private Hospitals	-6.92871 *-3.12676*	10.867 *2.97552*	-3.11643 *-1.2321*	7.75055 *1.93075*	-7.99911 *-1.86366*	-0.24857 *-0.05557*
Number of beds	-0.006.51 *-1.62938*	-	-	-	-	-
Case-mix index	9.47797 *1.10406*	-54.4037 *-3.9579*	8.38364 *0.880649*	-46.0201 *-3.04595*	-24.2709 *-1.50242*	-70.2910 *-4.1751*
Rotation index	-0.2774 *-3.3897*	-0.79737 *-6.00593*	-0.2786 *-3.02994*	-1.07596 *-7.37327*	-0.49686 *-3.18436*	-1.57282 *-9.67235*
Adjusted R squared	0.191423	0.467729	0.125271	0.495009	0.077162	0.578027
F statistic (zero)	4.31437	15.7629	3.40595	17.4679	2.4047	24.013

(*) *T-statistic in italics*

The estimation results in Table 4 show that:

- the number of beds is significant only to explain the increased inefficiency due to the imposition of a restriction on the virtual weights of y_1;
- the growth of inefficiency due to the introduction of the weight restriction is lower when hospitals are private, with a large number of beds and a high rotation index; the high significance of the dummy for–profit private hospitals is not surprising, since outputs y_2 and y_3 are less important in the production process of these hospitals;
- a high rotation index is associated with a significant reduction in all the types of inefficiency; in any case, the growth of the rotation index produces a relatively lower impact on limiting the inefficiency determined by weight restrictions, since the DMUs with the virtual weight of y_1 over 70% are characterised by a higher bed rotation;

- *coeteris paribus*, increasing the intensity of care, as measured by the case-mix index, significantly reduces the levels both of total technical inefficiency and of external scale inefficiency;
- compared to LHA-public hospitals, non-profit private hospitals exhibit a higher total inefficiency; moreover, both non-profit and, especially, for-profit hospitals are characterised by higher levels of scale inefficiency.

These results partially confirm the findings of many DEA models showing that public provision of hospital services exhibits in general less inefficiency than private provision (for a survey of these empirical studies, see Hollingsworth et al., 1999).[18] In the case of hospitals in Veneto the relatively lower inefficiency exhibited by LHA-public hospitals depends mainly on the greater complexity of their case-mix (accounted for by output y_1), while accredited private hospitals, whose role in Veneto is often complementary to public services, deal especially with long-term and low complexity in-patient care which is characterised by DRG tariffs above actual costs.

6. Conclusions

The paper examines two possible directions of refinement of the DEA as a method for evaluating the relative technical efficiency of acute hospitals: 1) the adoption of a constrained DEA, with restrictions on output (and/or input) weights, which tightens the unbounded hospital production possibility set according to the value judgements of health care policy-makers; 2) the consideration of VRS and of a supplementary "demand" input in DEA in order to distinguish between internal (managerial) and external (political) responsibility for technical inefficiency.

First of all, since hospital services operating within an NHS are generally given high social value, hospital technical efficiency should be evaluated in relation to the preferences expressed by local and/or national communities through their elected representatives. For DEA, this means imposing constraints on input and output weights that are consistent with the preferences of the relevant policy-maker. Weight restrictions are based on modifications of the basic unbounded DEA model, in order to incorporate value judgements in the assessment of efficiency without eliminating a certain flexibility (freedom) vis-à-vis the value attached by hospitals to input and output variables.

Secondly, we have shown how the assumption of VRS and the inclusion of a demand variable among the inputs of the DEA model permit identification of how much inefficiency is due to factors outside the control of hospital management, such as past political decisions determining excess production capacity in relation to actual demand.

Based on these theoretical considerations, we have analysed the relative technical efficiency of hospitals in Veneto by using four models of DEA. Firstly, we find that the imposition of a lower bound of 70% on the virtual weight of acute care discharges weighted by case-mix (in order to encapsulate regional government objectives) reduces average efficiency from 74.5% to 71.3%; in fact, 25 hospitals worsen their efficiency levels because they attach too much importance to other outputs, such as day hospital care and emergency treatment.

Then, by assuming VRS and considering the impact of non-controllable demand on hospital efficiency, we show that, in many cases, low efficiency scores are attributable to external factors, which are not fully controlled by the hospital management. The problem of scale inefficiency characterises mainly the private hospitals (about 80% of the total of private hospitals exhibits increasing returns to scale), while only 39% of the LHA-public hospitals (23 DMUs) exhibits a sub-optimal size. The second source of

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[18] A recent work by Steinmann and Zweifel (2003) on the level of inefficiency of Swiss hospitals finds that private hospitals do not seem to be significantly less inefficient than public ones. The two authors remark that this result may be caused by the over-use of inputs (valued as amenities by patients) by private hospitals and they point out that this represents an important limitation in applying the purely quantitative criteria of DEA to hospitals.

external inefficiency (the shortage of demand) is important for many LHA-public hospitals (37 DMUs) and for some accredited private hospitals (nine for-profit and five non-profit). In general, for 34 hospitals (22 public) external inefficiency is the only component of total inefficiency. For these DMUs, low total efficiency scores can be mainly explained by past policy-makers' decisions on the size of the hospitals or their role within the regional health care service.

Finally, non-profit private hospitals exhibit a level of total inefficiency higher than LHA-public hospitals; moreover, both non-profit and for-profit hospitals are characterised by higher levels of scale inefficiency than public ones.

Despite some limitations of the empirical analysis (due to the lack of information on out-patient services and on quality of hospital care), this paper represents a preliminary attempt to adapt the DEA method to the particular features of the hospital sector. It analyses the implications of modifying the basic DEA model in order to consider the impact on the measurement of hospital performance of both demand variables and policy-maker objectives to be pursued via specific restrictions on weights. Both these changes have noteworthy policy implications. Firstly, since measurement of hospital relative efficiency with DEA should be based on particular value judgements, the evaluation process of productive performance should be transparent, with an explicit definition of restrictions on input and output weights according to policy-makers' choices. These restrictions are crucial for specification of the DEA model in which the policy-makers should be involved, directly or indirectly. Secondly, the adoption of corrective actions aimed at increasing efficiency requires a distinction to be made between internal and external inefficiency. In fact, reducing the two types of inefficiency calls for different interventions: at hospital management level (for internal efficiency) or at health care planning authority level (for external efficiency).

Since there is no all-purpose method for considering the influence of demand and for translating policy-maker objectives into restrictions on weights, these could be fruitful areas of development for future research.

References

Allen R., Athanassoupoulos A., Dyson R.G., Thanassoulis E. (1997), 'Weight Restrictions and Value Judgements in Data Envelopment Analysis: Evolution, Development and Future Directions', *Annals of Operations Research*, 73, pp. 13-34.

Banker R.D., Charnes A., Cooper W.W. (1984), 'Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis', *Management Science*, 30, pp. 1078-1092.

Banker R.D., Conrad R.F., Strauss R.P. (1986), 'A Comparative Application of Data Envelopment Analysis and Translog Methods: An Illustrative Study of Hospital Production', *Management Science*, 30(9), pp. 1078-1092.

Charnes A., Cooper W.W., Rhodes E. (1978), 'Measuring the Efficiency of Decision Making Units', *European Journal of Operational Research*, 2, pp. 429-444.

Charnes A., Cooper W.W., Lewin A.Y., Seiford L.M. (1994), *Data Envelopment Analysis. Theory, Methodology and Applications*, Kluwer, The Netherlands.

Chilingerian J.A., Sherman H.D. (1997), 'DEA and Primary Care Physician Report Cards: Deriving Preferred Practice Cones from Managed Care Service Concepts and Operating Strategies', *Annals of Operations Research*, 73, pp. 35-66.

Chirikos T.N., Sear A.M. (2000), 'Measuring Hospital Efficiency: A Comparison of Two Approaches', *Health Services Research*, 34(6), pp. 1389-1408.

Cooper W.W., Seiford L.M., Tone K. (2000), *Data Envelopment Analysis. A Comprehensive Text with Models, Applications, References and DEA-Solver Software*, Kluwer Academic Publishers, Boston.

Hollingsworth B., Dawson P.J., Maniadakis N. (1999), 'Efficiency Measurement of Health Care: A Review of Non-Parametric Methods and Applications', *Health Care Management Science*, 2, pp. 161-172.

Ganley J.A., Cubbin J.S. (1992), *Public Sector Efficiency Measurement: Applications of Data Envelopment Analysis,* North Holland, Amsterdam.

Jacobs R. (2001), 'Alternative Methods to Examine Hospital Efficiency: Data Envelopment Analysis and Stochastic Frontier Analysis', *Health Care Management* Science, 4, pp. 103-115.

O'Neill L. (1998), 'Multifactor Efficiency in Data Envelopment Analysis with an Application to Urban Hospitals', *Health Care Management Science*, 1, pp. 19-27.

Pedraja-Chaparro F., Salinas-Jimenez J., Smith P. (1997), 'On the Role of Weight Restrictions in Data Envelopment Analysis', *Journal of Productivity Analysis*, 8, pp. 215-230.

Puig-Junoy J. (2000), 'Partitioning Input Cost Efficiency into its Allocative and Technical Components: An Empirical DEA Application to Hospitals', *Socio-Economic Planning Sciences*, 34, pp. 199-218.

Regione Veneto (1999), *Relazione sanitaria della Regione Veneto. Anni 1996 e 1997*, Regione del Veneto, Giunta Regionale, Venezia.

Steinmann L., Zweifel P. (2003), 'On the (In)Efficiency of Swiss Hospitals', *Applied Economics*, Vol. 35, n. 3, pp. 361-370.

Ventura J., Gonzalez E., Carcaba A. (2004), 'Efficiency and Program-contract Bargaining in Spanish Public Hospitals', *Annals of Public and Cooperative Economics*, Vol. 75, n. 4, pp. 549-573.

Wong Y.H.B., Beasley J.E. (1990), 'Restricting Weight Flexibility in Data Envelopment Analysis', *Journal of Operational Research Society*, 41(9), pp. 829-835.