Efficiency measurement of health care: a review of non-parametric methods and applications *

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There has been increasing interest in measuring the productive performance of health care services, since the mid-1980s. This paper reviews this literature and, in particular, the concept and measurement of efficiency and productivity. Concerning measurement, we focus on the use of Data Envelopment Analysis (DEA), a technique particularly appropriate when multiple outputs are produced from multiple inputs. Applications to hospitals and to the wider context of general health care are reviewed and the empirical evidence from both the USA and Europe (EU) is that public rather than private provision is more efficient.

1. Introduction

Health care institutions are not always expected to be efficient. Similarly, there is no obvious reason why a doctor should choose to be efficient, at least in terms recognisable to an economist. In contrast to assumed behaviour in the economic theory of the firm where efficiency is a corollary of profit maximisation, hospitals do not adhere to traditional neo-classical optimising behaviour, in part due to uncertainty caused by a lack of information on prices and costs [27]. Thus, there is a commonly-held view, based on the length of waiting lists, the number of hospital closures, media reports of patients being refused treatment, reports of cost cutting and so on, that the delivery of health care is inefficient. This view is being debated at Government level both in the EU and the USA with health care expenditure rising throughout the developed world [60]. While health care reform is being undertaken at a local level in the USA, and at a national level in other developed countries, especially the UK, the efficiency of health care delivery units – in particular hospitals which use most resources – is increasingly being examined.

Since the mid-1980s, Data Envelopment Analysis (DEA) has been used increasingly to measure the productive performance of health care services. The rationale for using DEA is its applicability to the multiple input–output nature of health care provision and the simplicity of the assumptions underlying the method. Other techniques that measure efficiency and productivity, such as simple ratio analysis or (least-squares or frontier) regression analysis, are not examined since their use is limited in the context discussed here.

In this review, we examine the economic theory of efficiency and productivity and their measurement in health care using DEA. We explain both the conceptual foundations of efficiency and productivity measurement and how DEA is used as the method of measurement. Our review is intended as a reference for academics, health care managers and policymakers. We review applications in the area of health care, and highlight the potential benefits and problems of measuring efficiency.

2. Theoretical foundations of efficiency measurement

The term "efficiency" is widely used in economics and refers to the best use of resources in production [78]. In particular and following the seminal work of Farrell [34], "technical efficiency" (the main focus of our review) is producing the maximum amount of output from a given amount of input, or alternatively producing a given output with minimum quantities of inputs. Thus, when a firm (in our case, a hospital) is technically efficient, it operates on its production frontier. Allocative efficiency occurs when the input mix is that which minimises cost given input prices, or alternatively, when the output mix is that which maximises revenue given output prices. Technical and allocative efficiency comprise "overall efficiency". When a firm is efficient overall it operates on its cost or revenue frontier.

We can illustrate these efficiency concepts by considering the simple case of a single output (y) being produced from two inputs, X_1 and X_2. The production function (or frontier) shows the maximum output produced from all input combinations and, in general, is: $y = f(X_1, X_2)$. For simplicity assume that the production function is linearly homogeneous. (Farrell assumed constant returns to scale

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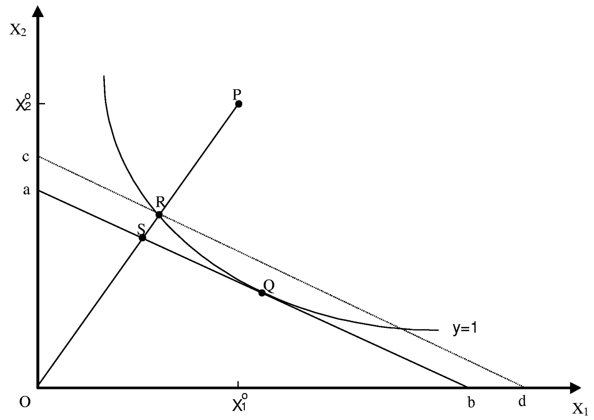

Figure 1. Farrell's measures of efficiency.

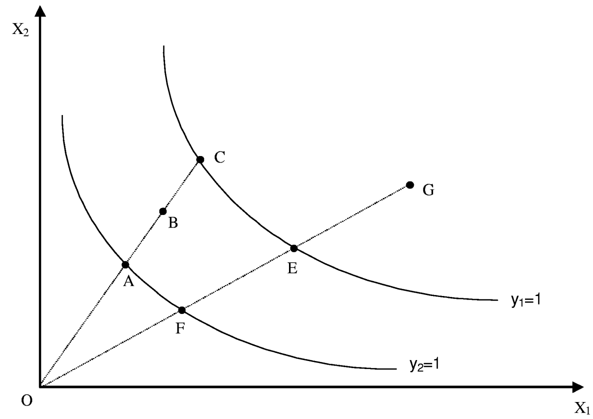

Figure 2. Efficiency and productivity and the Malmquist index.

but increasing or decreasing returns are also possible.) The efficient unit isoquant, $y = 1$ in figure 1, shows the technically efficient input combinations used to produce a unit of output. Suppose that the actual observed input–output combination is at P, with input-mix (X_1^0, X_2^0) and unit output $y = 1$. Production at P is technically inefficient since the firm could produce output $y = 1$ employing the same input mix but using the input quantities at point R on the isoquant. Therefore, technical efficiency, TE, at P is: $TE = OR/OP$ $(0 < TE \leqslant 1)$. If $TE = 1$, the firm is technically efficient and operates on the efficient isoquant; and when $TE < 1$, the firm is technically inefficient and the more inefficient the unit, the smaller is TE. It should be noted that a firm may also be cost-minimising. With given relative factor prices, shown in figure 1 by the isocost line ab, the optimal (cost minimising) input-mix to produce $y = 1$ is at Q. If the unit at P is technically efficient, that is, operating at R, its cost is represented by the isocost line cd, which is above minimum cost (ab). Thus, at its observed input mix, unit P needs to use input quantities that correspond to point S to deliver a unit of output at minimum cost. Therefore, allocative (or price) efficiency, AE, is: $AE = OS/OR$ $(0 < AE \leqslant 1)$. The overall cost of producing at Q relative to P is the measure of overall (economic or productive) efficiency, OE, which is the product of technical and allocative efficiency, that is: $OE = OS/OP = OR/OP \times OS/OR$ $(0 < OE \leqslant 1)$.

Farrell's analysis is static but it is possible to analyse efficiency over time when the frontier may move. This is done within the framework of productivity measurement. Productivity is defined as the ratio of an index of output to an index of input use. The change over time of this measure is termed "productivity change". Initially economists attributed productivity changes to technological changes, i.e., shifts of the production or cost frontier. However, following Nishimizu and Page [56] it became increasingly accepted that productivity change can also be caused by efficiency change, that is, by shifts over time of firms relative to their frontier, and recently productivity measurement has incorporated efficiency measurement (see [40]).

To illustrate, consider production in two time periods (1 and 2, respectively). In figure 2 the unit isoquant in period 1 is represented by $y_1 = 1$ and similarly in period 2 by $y_2 = 1$. Due to technological change, the isoquant moves closer to the origin in period 2, indicating that lower input quantities are used to produce a unit of output; thus, technological progress takes place. Consider the firm which operates at G in period 1 and B in period 2. Thus, it is not only the production frontier that moves but also the firm relative to it. Technical efficiency in each period is: $TE_{11} = OE/OG$, $TE_{22} = OA/OB$, where the first subscript relates to the time period of the reference production frontier and the second to the time period of the firm evaluated. Similarly, technological change is: $TC_{21} = OF/OE$, $TC_{22} = OA/OC$, where the reference technology is that of period 2 and the shift is measured first at period 1 input mix and then at period 2 input mix. Clearly, if the reference technology is that of period 1 the ratios are the reciprocals.

Various approaches have been taken to measure and decompose productivity in this context (see [40,48]), but that used most often is the Malmquist [52] index, first proposed in the context of consumer theory and later adapted to productivity measurement by Caves et al. [13], and extended further by Färe et al. [29] to measure hospital productivity. The Malmquist productivity index is defined in terms of distance functions [76] but, as the distance function is the reciprocal of the technical efficiency measures presented earlier, the index is often presented in terms of the latter [31] and this is the approach we follow here. The input oriented Malmquist productivity index (IMPI) in terms of efficiency measures and the corresponding distances in figure 2 is

$$\mathrm{IMPI} = \left[\frac{OE/OG}{OC/OB} \times \frac{OF/OG}{OA/OB}\right]^{0.5}. \tag{1}$$

The index is the geometric mean of two indices. The first takes the production frontier of period 1 as given and measures the distance of the two production points (representing the firm in the two different time periods) from it. The second index is similar except the reference frontier is that of period 2. A score less than unity indicates productivity progress in the sense that the firm delivers a unit of output in period 2 using less inputs. In other words, the firm in period 2 is more efficient relative to itself in period 1. Similarly, a score greater than unity implies productivity regress and constant productivity is signalled by a unit score. The index can then be decomposed:

$$\mathrm{IMPI} = \frac{OE/OG}{OA/OB}\left[\frac{OA}{OC} \times \frac{OF}{OE}\right]^{0.5}. \tag{2}$$

The component outside the brackets is the ratio of technical efficiency in each period and measures efficiency change when moving from period 1 to period 2. It indicates whether the unit "catches up" its production frontier. The second component of the Malmquist index in (2) captures technological change evaluated from both time periods. Thus, productivity change is decomposed into technical efficiency change and technological change. The components of the index have similar interpretations to the index.

3. Data envelopment analysis

To measure efficiency and productivity, we require knowledge of the production or the cost frontier. In practice, the frontier is formed by the most efficient among a sample of firms, that is, it is defined in terms of the firms which use the least input to produce a certain output or alternatively produce the most output for a given input. The efficiency of other firms in the sample is defined relative to these best performers. Furthermore, the efficiency of these best performers in one period relative to the best performers in another period is used to define movements of the frontier, that is, the technological change.

There are two major features that distinguish alternative empirical approaches for forming the frontier and measuring efficiency and productivity methods: whether they are parametric or not, and whether they are deterministic or stochastic. Parametric methods assume a specific functional form for the frontier whereas non-parametric methods do not; and deterministic methods assume that the distance of a unit from its frontier is a result of inefficiency whereas stochastic methods assume that some of it is due to random error. The methods are summarised in table 1.

Parametric programming is based on the application of linear (or quadratic) programming to construct a smooth parametric frontier and has the usual drawback of imposing a possibly inappropriate structure on the technology. Also, since it is deterministic, the results are sensitive to outliers. The parametric, statistical approach uses econometric techniques to estimate either a deterministic or a stochastic frontier function. The former has the disadvantages of both parametric and deterministic approaches: the latter has the advantage that it accounts for stochastic error, which is not included as part of the measure of (in)efficiency but its disadvantage is the imposition of a parametric structure on the production function and on the distribution of efficiency [3,28,38,79,88]. There are few parametric health care applications. Indeed, to our knowledge there are no published applications of parametric programming in health care and there are few applications of stochastic frontier analysis, the most prominent of which have been included in a special issue of the *Journal of Health Economics* 13(3) (1994).

By contrast, DEA is a non-parametric technique which uses linear programming to construct a piece-wise linear-segmented efficiency frontier based on best practice. It is deterministic and thus is sensitive to outliers. However, it has important advantages. The method is based on simple assumptions made in activity analysis. First, and especially for the analysis of health care services, it is able to deal with multiple outputs and multiple inputs easily. Second, no assumptions are needed about the form underlying the technology of production or the distribution of errors. It is computationally simple to use.

Stochastic DEA is a recently developed and developing technique which combines the best features of all methods. However, there are no applications in health care and few in general. Deterministic DEA has dominated the literature of health services performance measurement, it is the focus of this review.

The basis of DEA to measure technical efficiency uses Farrell's radial concept within a single dimension [14] and it has been used in many studies (see [73] for a survey). In the simple case of a single input–output firm and within a single time period, technical efficiency – and productivity, as in this context they are synonymous – is defined as: $TE = y/x$. The more output (y) is produced from a given amount of the input (x) the greater is TE. For a multiple-output, multiple-input hospital which treats different types of cases using heterogeneous staff with different expertise, various equipment and so on, technical efficiency is

$$TE = \frac{\sum_{r=1}^{p} y_r}{\sum_{i=1}^{m} x_i}, \tag{3}$$

where i indexes inputs and r indexes outputs. The problem in (3) is that inputs and outputs cannot be simply summed.

Table 1
Analytical methods to efficiency and productivity measurement.

	Parametric	Non-parametric
Deterministic	• Parametric mathematical programming • Deterministic (econometric) frontier analysis	• Data envelopment analysis (DEA)
Stochastic	• Stochastic (econometric) frontier analysis	• Stochastic data envelopment analysis

Rather, weights are assigned to each input and output so that (3) becomes:

$$TE = \frac{\sum_{r=1}^{p} u_r \cdot y_r}{\sum_{i=1}^{m} v_i \cdot x_i}, \quad 0 < TE \leqslant 1, \tag{4}$$

where y_r is output r, u_r is the weight attached to output r, x_i is input i, v_i is the weight attached to input i, where the weights are specific to each unit. For a sample of hospitals, a measure of technical efficiency can be calculated for each hospital, defined as the ratio of a weighted sum of the outputs relative to a weighted sum of its inputs, if u and v are fully flexible. The objective of each hospital is to maximise this ratio subject to its technological constraints. When this maximum is attained, $TE = 1$ and when not $TE < 1$.

For $j = 1, \ldots, n$ hospitals in the sample, this framework can be expressed as a programming model:

$$\begin{aligned} \text{maximise:} \quad & h_0 = \frac{\sum_{r=1}^{p} u_r y_{r0}}{\sum_{i=1}^{m} \nu_i x_{i0}} \\ \text{subject to:} \quad & \frac{\sum_{r=1}^{p} u_r y_{rj}}{\sum_{i=1}^{m} \nu_i x_{ij}} \leqslant 1, \quad j = 1, \ldots, n, \\ & u_r > 0, \quad r = 1, \ldots, p, \\ & v_i > 0, \quad i = 1, \ldots, m, \end{aligned} \tag{5}$$

where h_0 denotes the efficiency of hospital zero, under evaluation in the sample of n hospitals. The interpretation of (5) is straightforward: the objective is to maximise weighted output over weighted input subject to the constraint that the maximum that this ratio can be for all hospitals in the sample is unity. As such the weights are positive.

Problems such as the above are difficult to solve, but they can be reformulated into a straightforward linear programming (LP) problem by constraining the numerator or denominator of the efficiency ratio in (5) to equal unity. Thus, it is the relative values of the numerator and denominator that are important, not their absolute values. The problem then becomes one of either maximising the weighted output with the weighted input set equal to unity, or minimising the weighted input with the weighted output set equal to unity as a primal LP which computes weights and of all the possible sets of weights which satisfy all constraints, it chooses that which gives the most favourable view of the hospital under evaluation and maximises its efficiency score. The dual of the primal problem is simpler to solve and has a useful interpretation. For hospital zero, the dual problem is:

$$\begin{aligned} \text{minimise:} \quad & h_0 = Z \\ \text{subject to:} \quad & \sum_{j=1}^{n} x_{ij} \lambda_j \leqslant x_{i0} Z, \quad j = 1, \ldots, n, \\ & \sum_{j=1}^{n} \lambda_j y_{rj} \geqslant y_{r0}, \quad j = 1, \ldots, n, \\ & \lambda_j \geqslant 0, \quad j = 1, \ldots, n, \end{aligned} \tag{6}$$

where λ_j are the weights on hospitals sought to form a composite hospital to out-perform the hospital under evaluation. The model in (6) computes the factor Z needed to reduce the input of hospital zero to a frontier formed by its peers – or convex combinations of them – which produce no less output than hospital zero and use no more input than hospital zero. It is solved for each hospital in the sample and if $Z = 1$, the hospital is efficient and there is no other hospital or combination of hospitals which outperform it. If $Z < 1$, the hospital is technically inefficient.

DEA models assume that the production frontier exhibits constant returns to scale, but it is possible to impose other returns to scale, such as variable returns by adding the following constraint: $\sum_{j=1}^{n} \lambda_j = 1$ to (6). Applications which measure productivity and the Malmquist index can also use (6). The two cross-period efficiency measures can be computed with similar models but in this case the data forming the technology and the data referring to the hospital under evaluation are from different time periods (see [29]).

DEA models have seen many extensions over the last two decades. These include non-radial measures of technical efficiency, models that take into account slacks in inputs and outputs, allowances for categorical and non-discretionary variables, models where convex combinations of inputs and outputs are not feasible, incorporation of *a priori* knowledge and judgement to restrict the weights (see [15] for a summary). Finally, the aim of the analysis may not to measure efficiency and productivity per se but to analyse their determinants. This can be undertaken by regressing efficiency scores against various explanatory variables which are thought to influence performance; where TOBIT analysis is the most appropriate technique, with DEA scores being maximum likelihood estimators [1].

4. Applications of DEA to health care performance measurement

We now review the applications of DEA to measure the efficiency and productivity of health services. The literature focuses on technical rather than allocative efficiency, because of problems in valuing the inputs and outputs in health care provision (only two studies report allocative efficiency [11,35]). First we present some summary statistics.

The total number of studies identified up to and including 1997 is 91, of which the earliest is Nunamaker [57] reflecting the contemporary nature of the applications. Several patterns emerge. First, there is a recent rapid increase in the number of studies, with over 50% occurring since 1991 (see figure 3).

Second, over 60% of studies use DEA alone (see figure 4). This is not unexpected given that most methodological developments, such as using the efficiency score as the dependent variable in secondary regression analysis and applications of the Malmquist index, have occurred only recently. Further, more than 20% of studies use regression

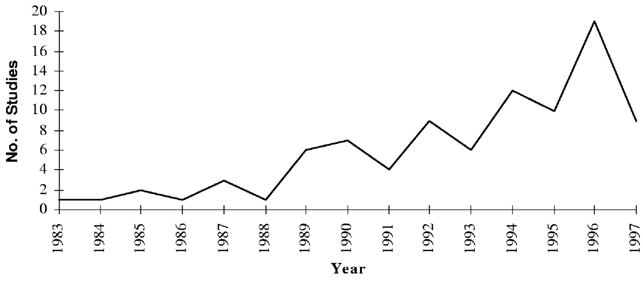

Figure 3. Number of efficiency studies 1983–1997.

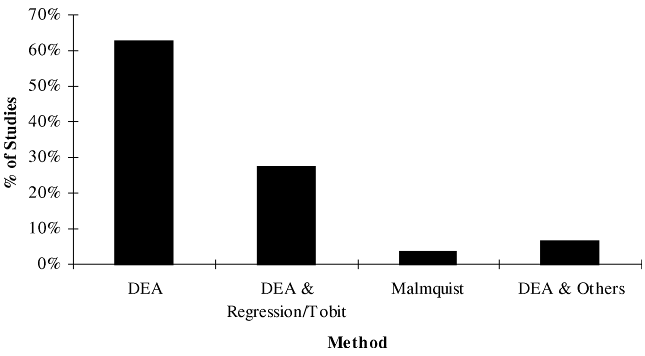

Figure 4. Methods used in reported studies.

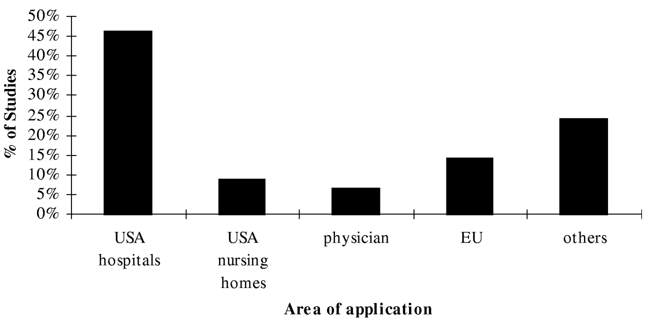

Figure 5. Areas of application.

analysis, typically to regress factors on the efficiency scores in an attempt to identify the determinants of efficiency.

Third, almost 60% of applications are in hospitals or nursing homes in the USA (see figure 5). Applications are increasing elsewhere, but are still mainly in secondary care.

Fourth, the output variables used are almost all measures of physical performance, such as patient days or discharges. There is little use (in only five studies) of outcome measures which examine changes in health status of individuals treated. Input variables are mainly measures of staff and capital employed. Most results are in the form of simple measures of technical efficiency.

Finally, although most studies are straightforward applications, a small number have tested methods such as weight restricted models and analysis of returns to scale. Similarly, a small number of studies have used statistical or sensitivity analysis of results. Here, we categorise studies that have published results and undertake a meta-type analysis of these results by application area. Overall, 70% of studies publish results we can use: the rest either do not publish the efficiency scores, or are duplicates of results in other studies. (A full list of all studies is available from the authors.)

4.1. Applications of DEA to hospitals

Details of hospital studies are in table 4 in the appendix which shows the type of hospital, country, number of hospitals in the sample studied, author(s) and efficiency scores. Summary statistics are shown in table 2, and a boxplot of the efficiency scores by hospital category, in figure 6, shows the 25th and 75th percentiles (Tukey's hinges), the median, and the values that are far removed from the rest [81]. The mean efficiency across the whole sample excluding the within hospital studies is 0.84 and the median is 0.87.

Comparing efficiency across the hospital sector[1], public hospitals have the highest mean efficiency (0.96) and the highest median (0.96), compared with not-for-profit (generally private) hospitals which have a lower mean efficiency (0.80) and a lower median (0.84). Defence and Veterans' Administration (VA) hospitals (which are public) also have a higher mean (0.87) and a higher median (0.87) than not-for-profit hospitals. Not-for-profit firms care for 70% of all in-patient cases in acute hospitals in the USA and account for over 30% of health care spending [37]; these results correlate with comparisons made in individual studies where public and private provision are compared [41,54,86,87], Examination of the standard deviations (S.D.) and minima demonstrate the gap between actual efficiency and best practice. For not-for-profit hospitals, the S.D. is 0.11 and the minimum is 0.60 which represents a large spread compared with the mean of 0.80; hence potential efficiency gains are substantial. Those for public hospitals are less obvious (S.D.: 0.02, minimum: 0.96, and mean: 0.96) and defence/VA hospitals (S.D.: 0.08; minimum: 0.77; and mean: 0.87). There are also potential gains for acute/general hospitals (S.D.: 0.12; minimum: 0.65; and mean: 0.84).

A comparison of efficiency of hospitals across countries indicates the efficiency of different means of health care delivery. Most results are from the USA where the average efficiency is 0.83, with a median of 0.85 and a range of 0.60–0.98. Here, the system is predominantly one of private provision of health care insurance, with a safety net of public insurance (Medicaid and Medicare) to cover the poor and elderly, respectively. In contrast, health care in Europe is characterised by public provision or social insurance where the mean efficiency is 0.91, with a median of 0.93 and a range of 0.88–0.93, higher than for USA hospitals. Accordingly, there is greater potential for efficiency gain in the USA, which has a S.D. of 0.11 and a

[1] Ownership definitions used here are: public – state owned/run firms; for profit – privately run; not-for profit – in some cases are voluntary/charity run firms which serve the poor. However, health care not-for-profit firms obtain 90% of revenue from sales and receipts, are privately run, are entitled to many tax exemptions and advantages, make a residual surplus and compete with for-profit hospital firms. For a discussion of the roles of not-for-profit, for-profit and public delivery of health care, see [37].

Table 2
Summary statistics for hospital efficiency scores.

	No. of studies	Mean	Median	S.D.	Minimum	Maximum
For profit	2	0.72	0.72	0.16	0.61	0.83
Not-for-profit	9	0.80	0.84	0.11	0.60	0.91
Public	4	0.96	0.96	0.02	0.94	0.98
Defence/VA	5	0.87	0.87	0.08	0.77	0.95
Non-teaching	1	0.77	–	–	0.77	0.77
Teaching	2	0.85	0.85	0.12	0.77	0.94
Acute/general	8	0.84	0.88	0.12	0.65	0.97
Non specified	7	0.84	0.79	0.10	0.70	0.95
All hospitals	*35*	*0.84*	*0.87*	*0.11*	*0.60*	*0.98*
USA hospitals	32	0.83	0.85	0.11	0.60	0.98
European hospitals	3	0.91	0.93	0.03	0.88	0.93
Within hos. (physicians)	6	0.79	0.79	0.12	0.61	0.92

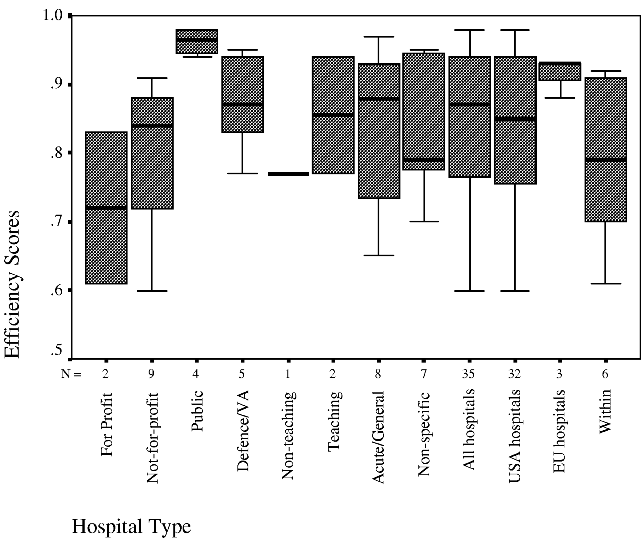

Figure 6. Boxplot of distribution of efficiency scores by category of hospital.

minimum of 0.60 compared with 0.03 and 0.88 for Europe. Finally, there are several studies which examine the efficiency of clinicians within hospitals, and in particular their ability to treat different cases under different payment regimes.

4.2. Applications of DEA to general health care

There are several other general health care areas in which DEA has been applied and details are given in table 5 in the appendix. Summary statistics, shown in table 3, and a boxplot of the efficiency scores by category, shown in figure 7, demonstrate the potential for efficiency gains.

For Health Districts, the potential gains are evident, both in Europe and the USA (means of 0.84 and 0.79, and minima of 0.80 and 0.67, respectively). There are also scope for efficiency gains in primary care: in Europe where the mean is 0.78 compared with the USA of 0.64. That there appears more potential for gains in the USA, where primary care is a growth area, especially in terms of "gate-keeping" the route to secondary care in an effort to reduce the growth in health care expenditure, when compared with those in Europe, where primary care has a long established tradition, may reflect the diverse nature of primary care delivery. A more valid comparison is of nursing homes, a rapidly growing area in health care, which in the USA is more efficient, compared with those in Europe (means: 0.83 and 0.82, and medians: 0.86 and 0.82, respectively), whereas both have potential for improvement, with the minimum of 0.66 and 0.77 and similar relatively small S.D. (0.09 and 0.07), suggesting there is no great variation across the samples. This result is reflected in the nursing home literature where for-profit firms, which in the USA account for 75% of care [37], are in general found to be more efficient than not-for-profit firms [36,37,58,59]. However, this may simply reflect differences in markets [39].

4.3. Applications of DEA productivity analysis in health care

Table 6 in the appendix summarises the six studies published in the area of productivity analysis in health care. No summary statistics are presented for these studies as they are difficult to compare, are few in number and may be unrepresentative. At the most general level, Färe et al. [33] examine changes in productivity between 19 countries between 1974–1989. Two models are used, one using intermediate outputs (days and discharges), which shows little evidence of productivity growth, and one using health outcomes (life expectancy and infant mortality), which demonstrates some evidence of growth. Tambour [83] examines 20 public ophthalmology units between 1988–1993. Changes in productivity are positive in all but one period. Two studies review hospital productivity, one for USA hospitals and one for EU hospitals. The USA study [9] finds Federal hospitals to demonstrate a significant amount of technical regress while there are small changes in non-Federal units. The EU study [31] examines 17 Swedish public hospitals and finds considerable variation in productivity across hospitals and time. Two studies [30,32] examine the productivity of Swedish pharmacies, the second with the novel inclusion of quality variables.

Table 3
Summary statistics for general health efficiency scores.

	No. of studies	Mean	Median	S.D.	Minimum	Maximum
Care programme	2	0.63	0.63	0.04	0.60	0.65
Health districts Euro.	3	0.84	0.86	0.04	0.80	0.87
Health districts USA	3	0.79	0.85	0.11	0.67	0.86
Nursing homes Euro.	2	0.82	0.82	0.07	0.77	0.87
Nursing homes USA	8	0.83	0.86	0.09	0.66	0.93
Primary care Euro.	3	0.78	0.79	0.10	0.67	0.88
Primary care USA	2	0.64	0.64	0.28	0.44	0.83
Pharmacies	1	0.71	–	–	0.71	0.71

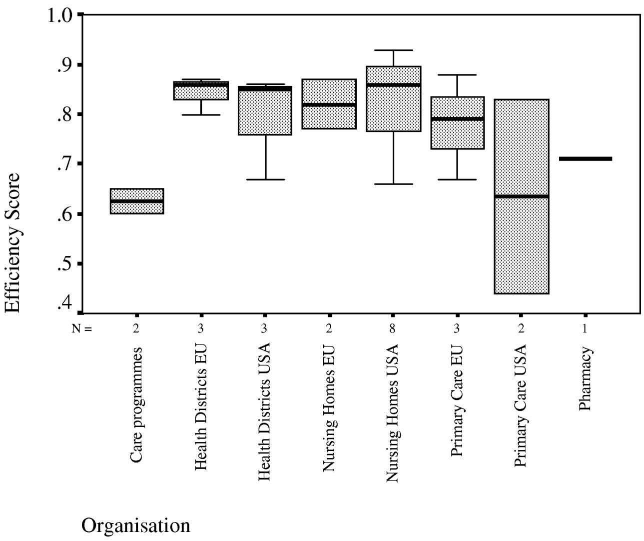

Figure 7. Boxplot of distribution of efficiency scores by general health category.

5. Summary and conclusions

Recently, the number of studies which seek to measure health service efficiency and productivity has increased dramatically and there is now an extensive literature that reflects this growing interest. However, because of the distinct features of the health care industry, this research should be interpreted cautiously. The inability to measure *real* outputs in the health care industry, changes in health status and the low quality of data are problem areas. As Newhouse [55] notes, these techniques work better when the product is homogeneous and uni-dimensional (for example, kilowatt/hour in the electricity industry) and not multiple and heterogeneous as in health care. Moreover, it is almost certain that health industry studies suffer from omitted variable bias. The techniques used to overcome these problems have been often criticised. To complicate matters, the estimated results may be sensitive to changes in the basic assumptions or specifications of the models used, the characteristics of the environment in which the units operate, and the results may only be valid for the specific units under investigation.

Our review of results should be treated with caution and we suggest it most useful in identifying trends. In the studies here, little sensitivity analysis (exceptions include [62,67]) or statistical testing has been undertaken. This may be in part because there are no accepted methods for proceeding (for example, formulating model specification) and no standard statistical tests, in contrast with econometrics. Progress with this is being made [2,80], especially with bootstrapping techniques [26]. Further, it may be more productive in measuring health services performance to use disaggregated data and concentrate on homogeneous and small segments of the health care system. In this case, the number of inputs and outputs decreases and both are better defined and more accurately measured, and the calculated efficiency measures are more accurate.

The accuracy of the estimated performance measures depends on the use of appropriate and well-specified models, the inclusion of relevant inputs and outputs, and the use of accurate data. The choice of an appropriate model is an important methodological issue. Different approaches have advantages and disadvantages and the choice of the most appropriate estimation method should depend on the type of organisations under investigation, the perspective taken, and the quality of available data. DEA is a non-parametric method and does not impose a functional form on the production frontier and hence can accommodate wide-ranging behaviour. However, measurement errors can bias results and DEA may be best employed in applications having relatively small potential measurement errors. A further line of enquiry is the impact on efficiency scores of sample size, and of more advanced DEA techniques which allow for the ranking of efficient, as well as in-efficient units.

Because of the special features of health services provision, DEA methods must be tested and developed further to provide reliable results that can be utilised in management and policy-making. At present, they are most useful in identifying general trends, investigating the association of performance with managerial and organisational characteristics, and in testing general hypotheses, rather than in providing assessments of individual organisational efficiency. This is the context in which we interpret the results here. Nevertheless, the results have policy implications and reflect the organisational structure of health care delivery in different countries. In the USA, it is an important finding that public hospitals in general out-perform private hospitals. Similarly, European hospitals out-perform USA hospitals. The implication of both these findings appears to be that public provision of health care is in general more efficient than private provision. Although there is a danger that the analysis of particular sectors may be undertaken without due attention to the problems we highlight, such as specification of the model and the sensitivity of results to changes in assumptions or sample size, we conclude that DEA is the most appropriate measure currently available for measuring efficiency in health services given the special nature of these markets. However, it should not be relied upon as the sole decision-making mechanism, but rather it is an indication of best performance. There is a need for further research to be undertaken both at methodological and applied levels. Too many studies simply report the efficiency scores of health care institutions, and there is a potential for research on market structure, concentration and the scope of production.

Appendix

Table 4
Summary of studies on hospital efficiency.

Hospital type	Country	No. of units	Author	Efficiency scores	
Federal/defence/veterans' administration	USA	284	Bannick and Ozcan (1995) [4]	Defence mean:	0.87
				VA mean:	0.78
	USA	89	Burgess and Wilson (1993) [8]	Range:	0.93–0.97
	USA	2246	Burgess and Wilson (1996) [10]	Efficiency scores, mean:	
				VA	0.87
				Non-Fed	0.82
				FP	0.83
				NFP	0.83
	USA	93	Hao and Pegels (1994) [43]	Range:	
				Teaching:	0.54–1
				Non-teaching:	0.55–1
	USA	3780	Ozcan and Bannick (1994) [63]	Means:	
				Army:	0.94
				Air Force:	0.96
				Navy:	0.91
				Dept. of Defence:	0.95
For profit/not-for-profit	USA	160	Bitran and Valor-Sabatier (1987) [5]	NFP mean:	0.60
	USA	123	Byrnes and Valdmanis (1994) [11]	AE:	0.73
				TE:	0.84
				SE:	0.94
	USA	82	Grosskopf and Valdmanis (1987) [41]	Pooled, means:	
				Public:	0.94
				NFP:	0.91
				Separate, means:	
				Public:	0.96
				NFP:	0.94
	USA	108	Grosskopf and Valdmanis (1993) [42]	Range:	
				Case-mix adjusted:	0.86–0.88
				Case-mix un-adjusted:	0.85–0.86
	USA	60	Morey et al. (1990) [54]	Public mean:	0.95
				NFP mean:	0.65
	USA	85	Ozcan et al. (1996a) [65]	Overall mean:	0.65
				FP:	0.61
				NFP:	0.72
	USA	41	Valdmanis (1990) [86]	Public:	0.98
				NFP:	0.88
	USA	41	Valdmanis (1992) [87]	Means, range:	
				Public:	0.97–1
				NFP:	0.83–0.94
				Scale efficiency:	
				Public:	0.79–1
				NFP:	0.92–0.97

Table 4
(continued.)

Hospital type	Country	No. of units	Author	Efficiency scores	
Acute	USA	52	Borden (1988) [7]	Mean scores range:	0.95–0.99
	USA	189	Chirikos and Sear (1994) [24]	Mean:	0.65
	USA	105	Dittman et al. (1991) [25]	Range:	0.49–1
	USA	40	Ozcan (1992) [62]	Mean range:	0.51–0.92
	UK	75	Hollingsworth and Parkin (1995) [44]	Range:	0.63–1
	Norway	46	Magnussen (1996) [51]	Mean range:	0.93–0.94
	UK	75	Parkin and Hollingsworth (1997) [67]	Mean range:	0.85–0.91
General	USA	1535	Ozcan and Lynch (1992) [61]	Mean:	0.88
	Spain	75	Lopez-Valcarcel and Perez (1996) [47]	Overall range: Overall scale:	0.92–0.95 0.96–0.98
Non-specific	USA	360	Ferrier and Valdmanis (1996) [35]	CE: TE: AE: SE:	0.68 0.79 0.87 0.89
	USA	7	Sherman (1984) [77]	Range:	0.88–1
	USA	55	Maindiratta (1990) [50]	Efficiency range: Scale efficiency range:	0.51–1 0.51–1
	USA	105	Morey and Dittman (1996) [53]	Mean:	0.95
	USA	16	Nunamaker (1983) [57]	Range:	0.91–1
	USA	170	White and Ozcan (1996) [89]	Church: Secular:	0.81 0.76
	USA	22	Young (1992) [91]	Range:	0.40–1
Within hospital	USA	36 physicians	Chilingerian (1989) [18]	Mean:	0.91
	USA	36 physicians	Chilingerian (1994) [20]	Surgeons: Interns:	0.72–1 0.63–1
	USA	36 physicians	Chilingerian (1995) [21]	Pure TE: TE/SE:	0.90–0.95 0.80–0.89
	USA	326 physicians	Chilingerian and Sherman (1997) [23]	Range:	0.21–1
	USA	15 physicians	Chilingerian and Sherman (1990) [19]	Range:	0.54–1
	USA	326 physicians	Chilingerian and Sherman (1996) [22]	Range:	0.4–1

Table definitions:
VA: Veterans administration.
LG: Local government.
FP: For profit.
NFP: Not-for-profit.
Non-Fed: Non federal.
CE: Cost efficiency.
TE: Technical efficiency.
AE: Allocative efficiency.
SE: Scale efficiency.

Table 5
Summary of studies on general health organisation efficiency.

Organisation type	Country	No. of units	Author	Efficiency scores	
Health districts	USA	319	Ozcan (1995) [64]	Range:	0.72–1
	USA	298	Ozcan et al. (1996b) [66]	Range	0.79–0.90
	USA	28	Rosenman et al. (1997) [69]	Mean FP:	0.68
				Mean NFP	0.66
	UK	15	Hollingsworth and Parkin (1995) [44]	Range:	0.76–1
	UK	15	Parkin and Hollingsworth (1997) [67]	Range:	0.72–1
	UK	189	Thanassoulis et al. (1996) [84]	Range:	0.60–1
	UK	85	Salinas-Jiménez and Smith (1996) [71]	Range:	0.73–1
Care programmes	USA	54	Schinnar et al. (1990) [72]	Range:	0.62–0.67
	USA	40	Yeh et al. (1997) [90]	Overall mean:	0.60
Primary care	USA	159	Sexton et al. (1989a) [74]	Range:	0.66–1
	USA	39	Tyler et al. (1995) [85]	Mean:	0.44
	Finland	202	Luoma et al. (1996) [49]	Mean:	0.88
	Spain	10	Pina and Torres (1992) [68]	Range:	0.58–1
	UK	52	Szczepura et al. (1993) [82]	Range:	0.35–1
Nursing homes	USA	140	Chattopadhyay and Heffley (1994) [17]	Mean:	0.90
	USA	140	Chattopadhyay and Ray (1996) [16]	Mean NFP:	0.81
				Mean FP:	0.94
	USA	22	Kleinsorge and Karney (1992) [45]	Range:	0.71–1
	USA	184	Nyman and Bricker (1989) [58]	Mean:	0.89
	USA	296	Nyman et al. (1990) [59]	Mean:	0.93
	USA	52	Sexton et al. (1989b) [75]	Means range:	0.76–0.78
	USA	104	Fizel and Nunnikhoven (1993) [36]	Means (all FP):	
				Overall:	0.66
				Chain:	0.71
				Independent:	0.62
	USA	461	Rosko et al. (1995) [70]	Means:	
				FP:	0.82
				NFP:	0.71
	Netherlands	232	Kooreman (1994) [46]	CRS Mean:	0.80
				COD Mean:	0.94
	Netherlands	–	Blank et al. (1996) [6]	Mean:	0.70
Pharmacies	USA	68	Capettini et al. (1985) [12]	Range:	0.44–0.98

Table definitions:
FP: For profit.
NFP: Not-for-profit.
CRS: Constant returns to scale.
COD: Constant or decreasing returns.

Table 6
Summary of studies on productivity analysis.

Organisation type	Country	No. of units	Author	Results
General health	International	19	Färe et al. (1997) [33]	Some evidence of productivity growth when using outcomes rather than outputs
Opthalmology	Sweden	20	Tambour (1997) [83]	Positive changes in productivity
Hospital	USA	1545	Burgess and Wilson (1995) [9]	Technical regress in Federal Units
	Sweden	17	Färe et al. (1994) [31]	Variation in productivity
Pharmacy	Sweden	42	Färe et al. (1992) [30]	Over nine time periods, there were seven periods of improvement and two of regress
	Sweden	257	Färe et al. (1995) [32]	Quality matters when measuring productivity change

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