This is the author's version of a paper that was later published as:

Worthington, Andrew (2004) Frontier Efficiency Measurement in Healthcare: A Review of Empirical Techniques and Selected Applications. *Medical Care Research and Review* 61(2):pp. 1-36.

Frontier Efficiency Measurement in Healthcare: A Review of Empirical Techniques and Selected Applications

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Acknowledgements: The author would like to thank two anonymous referees for helpful comments on an earlier version of this paper. The financial assistance of an Australian Technology Network (ATN) Research Grant is also gratefully acknowledged.

ABSTRACT

Healthcare institutions worldwide are increasingly the subject of analyses aimed at defining, measuring and improving organizational efficiency. However, despite the importance of efficiency measurement in healthcare services, it is only relatively recently that the more advanced econometric and mathematical programming frontier techniques have been applied to hospitals, nursing homes, health management organisations and physician practices, amongst others. This paper provides a synoptic survey of the comparatively few empirical analyses of frontier efficiency measurement in healthcare services. Both the measurement of efficiency in a range of healthcare services and the posited determinants of healthcare efficiency are examined.

Healthcare costs in most developed economies have grown dramatically over the last few decades and it is widely believed that the inefficiency of healthcare institutions, at least in part, has contributed. In response to this belief, an extensive body of literature has addressed the empirical measurement of efficiency in healthcare institutions around the world. And while hospitals have been the subject of most of these efficiency studies to date, the efficiency of other healthcare institutions has also been addressed. These include nursing homes, health maintenance organisations, physician practices, district health authorities, and even the costs associated with individual patients. Nevertheless, these studies share a common focus; namely, the growing volume of healthcare costs, the effect of these costs on public expenditure and private industry, and the impact of increased competition in the healthcare market.

Economists have developed three main measures of efficiency to meet the needs of researchers, healthcare managers and policy makers in this regard. Firstly, <u>technical efficiency</u> refers to the use of productive resources in the most technologically efficient manner. Put differently, technical efficiency implies the maximum possible output from a given set of inputs. Within the context of healthcare services, technical efficiency may then refer to the physical relationship between the resources used (say, capital, labor and equipment) and some health outcome. These health outcomes may either be defined in terms of intermediate outputs (number of patients treated, patient-days, waiting time, etc.) or a final health outcome (lower mortality rates, longer life expectancy, etc.) (Palmer and Torgenson 1999). Secondly, <u>allocative efficiency</u> reflects the ability of an organisation to use these inputs in optimal proportions, given their respective prices and the available production technology. In other words, allocative efficiency is concerned with choosing between the different technically efficient combinations of inputs used to produce the maximum possible outputs. Palmer and Torgenson (1999, 1136) illustrate healthcare-related allocative efficiency as follows:

> Consider, for example, a policy of changing from maternal age screening to biochemical screening for Down's syndrome. Biochemical screening uses fewer amniocenteses but it requires the use of another resource – biochemical testing. Since different combinations of inputs are being used, the choice between interventions is based on the relative costs of these different inputs.

Finally, when taken together allocative efficiency and technical efficiency determine the degree of productive efficiency (also known as total economic efficiency). Thus, if a healthcare organisation uses its resources completely allocatively and technically efficiently, then it can be said to have achieved total economic efficiency. Alternatively, to the extent that either allocative or technical inefficiency is present, then the organisation will be operating at less than total economic efficiency.

The empirical measurement of economic efficiency centers on determining the extent of either allocative efficiency or technical efficiency or both in a given organisation or a given industry. Most recently, economists have employed frontier efficiency measurement techniques to measure the productive performance of healthcare services. Frontier efficiency measurement techniques use a production possibility frontier to map a locus of potentially technically efficient output combinations an organisation is capable of producing at a point in time. To the extent an organisation fails to achieve an output combination on its production possibility frontier, and falls beneath this frontier, it can be said to be technically inefficient. Similarly, to the extent to which it uses some combination of inputs to place it on its production frontier, but which do not coincide with the relative prices of these inputs, it can be said to be allocatively inefficient. Equivalently, cost functions transform the quantitative physical information in production frontiers into monetary values such that cost efficiency entails producing technically efficient combinations of outputs and inputs at least cost. More detailed theoretical introductions to frontier efficiency measurement techniques may be found in Fried et al. (1993), Charnes et al. (1995) and Coelli et al. (1998).

Accordingly, if we can determine production frontiers that represent total economic efficiency using the best currently known production techniques, then we can use this idealized yardstick to evaluate the economic performance of actual organisations and industries. By comparing the actual behavior of organisations against the idealized benchmark of economic efficiency we can determine the degree of efficiency exhibited by some real-world agency. This review concentrates on selected efficiency studies using frontier efficiency measurement techniques published since the mid-1980s. EconLit, the Journal of Economic Literature electronic database, was searched to identify articles that were representative of the contexts and techniques associated with frontier efficiency measurement in healthcare services. References were also used from these studies to identify other relevant articles.

Of the thirty-eight studies presented in Table 1, fifty-four percent are based on healthcare organizations in the United States; sixty-eight percent are in hospitals, ten percent in nursing homes, five percent each in health management organizations (HMOs) or local area health authorities and the remainder in other settings; while sixty-eight percent employ nonparametric techniques with the remainder using parametric techniques. However, despite their dissimilar contexts and techniques these studies share a common step-by-step empirical procedure that determines first the choice of frontier efficiency measurement approach, second the specification of inputs and outputs to be used in the selected approach, and finally, the method used to explain efficiency differences and the factors thought to be associated with these differences. This common process, as depicted in Figure 1, forms a convenient framework for the following review.

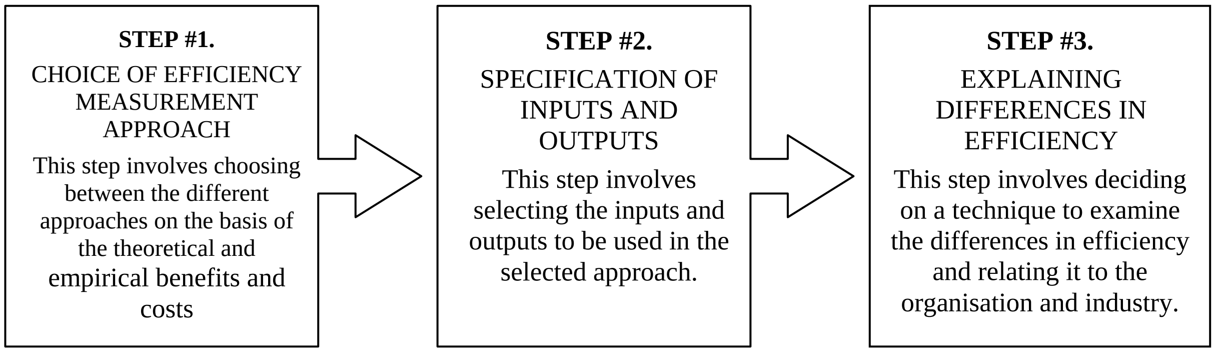

FIGURE 1 Empirical Steps in Measuring and Analysing Healthcare Efficiency

NEW CONTRIBUTION

At least one study, Hollingsworth et al. (1999), has surveyed frontier efficiency measurement techniques as they apply to healthcare services. However, Hollingsworth et al. (1999) only reviews non-parametric methods and applications and focuses on the efficiency measures obtained, not the steps used to obtain these measures. The current article is the first attempt to examine each of the main frontier efficiency measurement approaches as they apply to healthcare services. Moreover, apart from discussing the strengths and weaknesses of the different approaches, this article also examines the steps faced by researchers as they move from a selected approach, to the specification of inputs and outputs, to the means of explaining efficiency differences. This highlights the empirical problems that have received attention in the literature, and the efforts by researchers to overcome these problems. It therefore provides guidance to those conducting empirical research in healthcare efficiency and also an aid for policymakers, managers and practitioners interpreting the outcomes of frontier efficiency studies.

CHOICE OF EFFICIENCY MEASUREMENT APPROACH

All efficiency measures assume the production frontier of the fully efficient organisation is known. As this is usually not the case, the production frontier must be estimated using sample data. Two approaches are possible. These are: (i) a nonparametric piecewise-linear convex frontier constructed such that no observed point should lie outside it (known as the mathematical programming approach to the construction of frontiers); or (ii) a parametric function fitted to the data, again such that no observed point should lie outside it (known as the econometric approach). These approaches use different techniques to envelop the observed data, and therefore make different accommodations for random noise and for flexibility in the structure of the production technology.

First, the econometric approach specifies a production function and normally recognizes that deviation away from this given technology (as measured by the error term) is composed of two parts, one representing randomness (or statistical noise) and the other inefficiency. The usual assumption with the two-component error structure is that the inefficiencies follow an asymmetric half-normal distribution and the random errors are normally distributed. The random error term is generally thought to encompass all events outside the control of the organisation, including both uncontrollable factors directly concerned with the ‘actual’ production function (such as differences in operating environments) and econometric errors (such as misspecification of the production function and measurement error). This type of reasoning has primarily led to the development of the ‘stochastic frontier approach’ (SFA) which seeks to take these external factors into account when estimating the efficiency of real-world organisations, and the earlier ‘deterministic frontier approach’ (DFA) which assumes that all deviations from the estimated frontier represent inefficiency. A number of studies have used these approaches to estimate the efficiency of healthcare institutions. These include Wagstaff (1989), Hofler and Rungeling (1994), Zuckerman et al. (1994), Defelice and Bradford (1997), Chirikos (1998), Gerdtham et al. (1999) and Street and Jacobs (2002).

Second, and in contrast to the econometric approaches which attempt to determine the absolute economic efficiency of organisations against some imposed benchmark, the mathematical programming approach seeks to evaluate the efficiency of an organisation relative to other organisations in the same industry. The most commonly employed version of this approach is a linear programming tool referred to as ‘data envelopment analysis’ (DEA). DEA essentially calculates the economic efficiency of a given organisation relative to the performance of other organisations producing the same good or service, rather than against an idealised standard of performance. A less-constrained alternative to DEA sometimes employed in the analysis of efficiency (though presently unapplied to healthcare) is known as ‘free-disposal hull’ (FDH). Both DEA and FDH are nonstochastic methods in that they assume all deviations from the frontier are the result of inefficiency. Banker et al. (1986), Fizel and Nunnikhoven (1992), Kooreman (1994), Parkin and Hollingsworth (1997), Burgess and Wilson (1998) and Rollins et al. (2001) have applied these approaches to healthcare institutions. Applications that use Malmquist productivity indexes (MI) (as derived from DEA-like linear programs) to measure changes in efficiency and productivity over time are also found in the healthcare literature. These include Fare et al. (1993), Linna (1998) and Maniadakis and Thanassoulis (2000).

A simple representation of these differences are shown in the single-input (x), single-output (y) scatter diagram in Figure 2. In the mathematical programming approach the frontier (solid black line) is constructed using the observations themselves, upon which at least some will always lie (black-filled points). Organizations within the frontier (hollow points) are then compared to this observed standard of performance. In the econometric approach a parametric function is fitted to the data (curved dotted line) but there is no requirement that any organization will necessarily lie on this line (though one does here). Once again, all organizations within this frontier are assayed against the frontier measure of performance by measuring their deviation from it. Importantly, in both the mathematical programming and econometric approaches the distance to either frontier for a representative ‘inefficient’ organization (double-arrowed dashed line) could be the result of inefficiency and/or misspecification of the production function or measurement error. The main differences between the mathematical programming and econometric approaches then revolve around the method of constructing the frontier in the first instance and then the differing assumptions regarding the distances to this frontier from the organizations within.

The discussion thus far has addressed three separate, though conceptually similar, theoretical approaches to the assessment of productive efficiency. These are the deterministic frontier approach (DFA), the stochastic frontier approach (SFA), and the mathematical programming approach (including DEA, FDH and MI). Details of the approach (or approaches) taken by selected healthcare studies are detailed in Table 1. Whilst the selection of any particular approach is likely to be subject to both theoretical and empirical considerations, it may be useful to summarize the strengths and weaknesses of each technique. The emphasis here is not on selecting a superior theoretical approach, as it should be emphasized that the mathematical programming and econometric approaches address different questions, serve different purposes and have different informational requirements.

The first approach examined was the construct of the deterministic statistical frontier [see, for example, Wagstaff (1989)]. Using statistical techniques a deterministic frontier is derived, such that all deviations from this frontier are assumed to be the result of inefficiency. That is, no allowance is made for noise or measurement error. In the primal (production) form the ability to incorporate multiple outputs is difficult, whilst using the dual cost frontier such extensions are possible. However, if the cost frontier approach is employed, it is not possible to decompose inefficiency into allocative or technical components, and therefore all deviations are attributed to overall cost inefficiency.

In terms of computational procedure, the deterministic frontier approach necessitates a large sample size for statistical reasons. In addition, it is generally regarded as a disadvantage that the distribution of the technical inefficiency has to be specified, i.e. half-normal, normal, exponential, log-normal, etc. Ideally this would be based on knowledge of the economic forces that generate such inefficiency, though in practice this may not be feasible. If there are no strong a priori arguments for a particular distribution, a choice is normally made on the basis of analytical tractability. Similarly, the choice of a particular technology is imposed on the sample, and once again this may be a matter of empirical convenience (i.e. Cobb-Douglas, translog, etc). Moreover, the choice of a particular production function may place severe restrictions on the types of analysis possible, and therefore the content of policy prescriptions, using this particular approach.

The second approach discussed, namely the stochastic frontier, removes some of the limitations of the deterministic frontier [see, for example, Zuckerman et al. (1994), Gonzalez Lopez-Valcarcel and Barber and Perez (1996) and Linna (1998)]. Its biggest advantage lies in the fact that it introduces a disturbance term representing noise, measurement error, and exogenous shocks beyond the control of the production unit. This in turn permits the decomposition of deviations from the efficient frontier into two components, inefficiency and noise. However, in common with the deterministic approach, an assumption regarding the distribution (usually normal) of this noise must be made along with those required for the inefficiency term and the production technology. The main effect here is that under both approaches, especially the stochastic frontier, considerable structure is imposed upon the data from stringent parametric form and distributional assumptions. In addition, stochastic frontier estimation usually uses information on prices and costs, in addition to quantities, which may introduce additional measurement errors.

The final programming approach differs from both statistical frontier approaches in that is fundamentally nonparametric, and from the stochastic frontier approach in that is nonstochastic [see, for example, Grosskopf and Valdmanis (1987), Byrnes and Valdmanis (1993), Kooreman (1994a), Thanassoulis et al. (1996) and Puig-Jonoy (1998)]. Thus, no (direct) accommodation is made for the types of bias resulting from environmental heterogeneity, external shocks, measurement error and omitted variables. Consequently, the entire deviation from the frontier is assessed as being the result of inefficiency [stochastic DEA has been recently developed, though there are no known applications in healthcare (Hollingsworth et al. (1999)]. This may lead to either an under or over-statement of the level of inefficiency, and as a nonstochastic technique there is no possible way in which probability statements of the shape and placement of this frontier can be made. In view of erroneous or misleading data, some critics of DEA have questioned the validity and stability of measures of DEA efficiency.

However, there a number of benefits implicit in the mathematical programming approach that makes it attractive on a theoretical level. Given its nonparametric basis, substantial freedom is given on the specification of inputs and outputs, the formulation of the production correspondence relating inputs to outputs, and so on. Thus, in cases where the usual axioms of production activity breakdown (i.e. profit maximization) then the programming approach may offer useful insights into the efficiency of these types of industries [some assumptions regarding the production technology are still made regardless, such as that relating to convexity]. Similarly, it is entirely possible that the types of data necessary for the statistical approaches are neither available nor desirable, and therefore the imposition of as few as possible restrictions on the data is likely to be most attractive. Simulation studies [see, for instance, Banker et al. (1988)] have also indicated that the piecewise linear production frontier formulated by DEA is generally more flexible in approximating the true production frontier than even the most flexible parametric functional form.

These theoretical and empirical considerations explain part of the dominance of DEA in healthcare efficiency measurement studies. The obvious desirability of quantifying multiple inputs and outputs in different units of measurement is one consideration. For example, many healthcare studies define inputs as the number of physicians, nursing and ancillary staff along with non-labor inputs in dollar terms, especially plant and equipment assets [see, for instance, Grosskopf and Valdmanis (1987), Valdmanis (1992) and Parkin and Hollingsworth (1997)]. Alternatively, outputs are often defined as the number of patient days, surgeries or discharges, along with indexes of case mix categories and the percentage of cases using certain equipment [examples include Wagstaff (1989) and Gonzalez Lopez-Valcarcel and Barber Perez (1996)]. Likewise the difficulty in defining input costs in many public sector contexts may account for the emphasis of healthcare efficiency studies on measuring technical efficiency alone [see, for example, Chattopadhyay and Ray (1996), Puig-Jonoy (1998) and Burgess and Wilson (1998)]. Finally, and once again in a public sector context where the usual axioms of production activity breakdown, there is the ability to define inputs and outputs depending on the conceptualization of healthcare performance thought most appropriate.

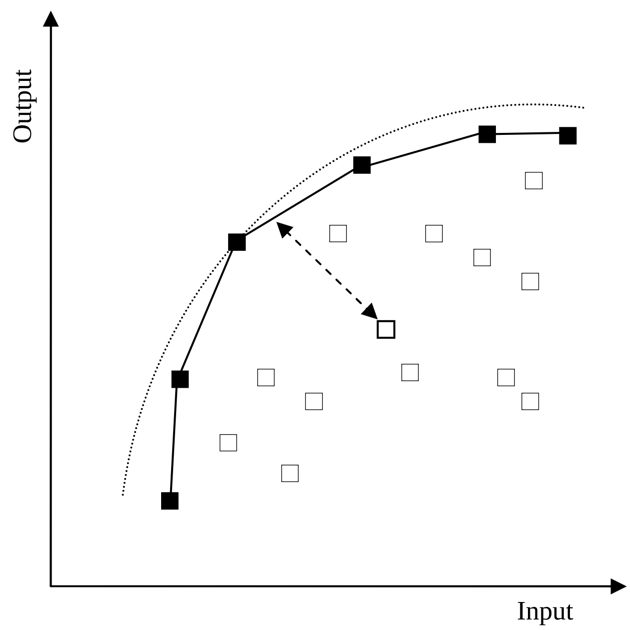

FIGURE 2 Comparison of mathematical programming and econometric approach to frontiers

SPECIFICATION OF INPUTS AND OUTPUTS

Within the broad scope of healthcare services, frontier efficiency measurement techniques have been applied to many different types of institutions. As shown in Table 1, these include hospitals (Banker et al. 1986; Ley 1991; Färe et al. 1993; Chirikos 1998; Giuffrida and Gravelle 2001; Street and Jacobs 2002), physician practices (Chillingerian 1993; Defelice and Bradford 1997), nursing homes (Nyman and Bricker 1989; Gertler 1989; Gertler and Waldman 1992; Hofler and Rungeling 1994; Chattopadhyay and Ray 1996), health management organizations (HMOs) (Rosenman et al. 1997; Rollins et al. 2001) and substance abuse treatment organizations (Alexander and Wheeler 1998). And while the literature has been predominantly concerned with the efficiency of North American institutions, applications in Spain (Wagstaff 1989; Ley 1991), Scandinavia (Fare et al. 1993; Magnussen 1996; Luoma et al. 1996; Mobley and Magnussen 1998), Taiwan (Lo et al. 1996) and the United Kingdom (Thanassoulis et al. 1996; Parkin and Hollingsworth 1997) have also been made. As indicated, the primary frontier technique employed in assaying the efficiency of healthcare services has been the data envelopment analysis or DEA approach (Fizel and Nunnikhoven 1992; Valdmanis 1992; Kooreman 1994; Thanassoulis et al. 1996; Parkin and Hollingsworth 1997; Chirikos and Sear 2000; Rollins et al. 2001).

The measures of efficiency obtained by these studies have varied widely. Parkin and Hollingsworth's (1997) analysis of Scottish hospitals found DEA mean efficiencies (depending on the model used) between 79 and 96 percent, while Linnna et al. (1998) used both parametric and nonparametric techniques in a study of Finnish hospitals and found mean efficiencies of 91 to 93 percent for DEA and 92 to 93 for SFA. In the US, Chirikos and Sear (2000) calculated mean efficiencies of 80 to 97 percent and 82 to 84 percent for DEA and SFA respectively, while Rosko (2001) found mean SFA efficiencies of 85 percent. In non-hospital studies, Rollins et al. (2001) measured inefficiencies of between 19 and 42 percent in health maintenance organizations (HMOs) and Bradford et al. (2001) estimated inefficiencies of between 9 and 27 percent in the treatment of cardiac revascularization patients. This divergence in results has, of course, awakened interest in the consistency of frontier-based measures of efficiency, both with alternative frontier approaches and with the earlier least squares production and cost functions.

As early as Banker et al. (1986), an attempt was made to compare the results of the conventional translog cost function and DEA. Of especial interest in this particular study was the level of similarities or differences between the two approaches in ascertaining increasing, constant or decreasing returns-to-scale, and estimating marginal rates of output transformation and technical inefficiencies of individual hospitals. Measuring inputs in terms of nursing, ancillary, administrative and general services, and outputs in terms of patient days, Banker et al. (1986, 38) using a sample of North Carolina hospitals found that DEA was "able to examine the possibility of increasing or decreasing returns to scale prevailing in specific segments of the production possibility set". More particularly, whereas the translog cost function indicated cost returns-to-scale across the sample, DEA found that the most productive scale size varied dramatically with different output mixes and capacity. Nonetheless, when it came to comparing the efficiency ratings, Banker et al. (1986) concluded inter alia that the two techniques were in broad agreement.

Comparisons between frontier efficiency measurement techniques have also been made. For example, Gonzalez Lopez-Valcarcel and Barber Perez (1996) compared DEA-based technical efficiency measures with stochastic frontier cost efficiency indexes in a sample of Spanish general hospitals, and Linna (1998) examined DEA measures and stochastic frontier estimates of cost efficiency in Finnish acute care hospitals. Both studies concluded that the choice of approach did not significantly influence the results. Chirikos and Sear (2000) and Giuffrida and Gravelle (2001) have also made comparisons of the different approaches to frontier efficiency measurement. Further, efforts have also been made in healthcare services to compare frontier techniques and ratio analysis as alternative tools for assessing performance. For example, Thanassoulis et al. (1996) compared U.K. National Health Service (NHS) performance indicators (PI) for perinatal care units with DEA measures of productive performance. They concluded that not only was there no reason why PI values could be routinely accompanied by DEA measures of performance, but that the multiple-input, multiple-output nature of the latter could be used in a straightforward manner to set performance targets. Nunamaker (1983) also compared univariate ratios and DEA, though this time in the form of cost per patient day.

In so far as subsequent empirical research is concerned, the Banker et al. (1986) study is important, not so much because it compares alternative techniques for efficiency measurement [an issue similarly developed in Wagstaff (1989)], but that it sets an important precedent for the specification of healthcare inputs and outputs. Thus, most subsequent studies [see, for example, Byrnes and Valdmanis (1993), Kooreman (1994a) and Parkin and Hollingsworth (1997)] conceptualize healthcare as combining the inputs of labour (normally the number of staff) and capital (often proxied by bed capacity) in order to produce some easily-observed unit of output, such as discharges or inpatient days. For example, Valdmanis (1992) conceptualized Michigan hospitals as managing the inputs of house staff, physicians and nurses in order to maximize adult, pediatric and intensive care inpatient days and emergency and ambulatory visits. Alternatively, Thanassoulis et al. (1996) in a study of U.K. district health authorities focused on the obstetrical/gynecological function and measured output as the number of deliveries, legally induced abortions and the length of patient stay.

Nevertheless, placing emphasis on the production of inpatient care because it normally comprises the largest component of hospital costs and can be readily measured, can be called into question on at least three counts. First, as noted by Kooreman (1994a, 305) one of the problems of efficiency analysis of healthcare institutions is that the conceptual output – improved health status, or even more generally, improved quality of life – is difficult, if not impossible, to measure. Recognizing these data problems, Chillingerian (1993) argued that defining healthcare output by patient days, or discharges, or even cases, is acceptable so long as adjustment is made first for the mix, or complexity of cases, and second for the intradiagnostic severity of cases. Using a sample of U.S. physicians, Chillingerian (1993) incorporated these concepts by classifying discharges on the basis of either a satisfactory (i.e. a healthier state) or unsatisfactory outcome (i.e. the presence of morbidity or mortality).

However, the more usual case is to engage in some form of aggregation in order to ensure homogeneous outcomes. For example, Banker et al. (1986) categorized outputs in terms of patient's age: that is, Medicare patients, pediatric patients and adult patients. Alternatively Grosskopf and Valdmanis (1987) disaggregated outputs by type of treatment: that is, acute in-patient days, intensive care inpatients days and the number of surgeries. Notwithstanding these attempts, Newhouse (1994) argued that case-mix controls by hospital (ordinarily diagnosis-related groups) usually encompass non-random variation, and therefore even outputs that are case mix-adjusted are misspecified. The problem of defining healthcare output is further highlighted when it is realized that even diagnosis-related group outputs, which in turn are aggregated measures, are likely to involve several hundred separate categories. Citing earlier studies, Newhouse (1994) gives the example where patients may be disproportionately admitted to hospitals that are equipped to undertake specific treatments, and accordingly is not the result of variation in efficiency, rather variation in a healthcare institution's patients. This has obvious implications for the validity of efficiency measures.

Skinner (1994, 324), for example, argues that "Vitaliano and Toren (1994a; 1994b) and Zuckerman et al. (1994) are among the best applications of the stochastic frontier approach in that both carefully specify the underlying cost variables, and (more importantly) controlling to the extent possible for both the quality of care provided and the case-mix of patients".

The second problem found with this conceptualization of healthcare behavior is that several inputs, most often capital, are typically not measured. For example, Fizel and Nunnikhoven (1992) and Kooreman (1994a) measured the efficiency of Michigan and Dutch nursing homes on the basis of labor inputs only. Kooreman (1994a, 306) justified this selective input approach on the basis that management typically has control over labor inputs, "…but the use of capital inputs is largely beyond their ability to determine". While omitted inputs may certainly lead to functional misspecification a defense is that the omitted variable (mostly capital) is used in fixed proportions to other inputs. Regardless, even where attempts are made to incorporate non-labor inputs, more commonplace measurement problems may arise. In these instances, capital has been proxied by the number of hospital beds (Byrnes and Valdmanis 1993; Hofler and Rungeling 1994), depreciation and interest expenses per bed (Zuckerman et al. 1994), net plant assets (Valdmanis 1992) and the United Kingdom's National Health Service (NHS) capital charge on assets and investments (Parkin and Hollingsworth 1997). Even recent studies such as Burgess and Wilson (1998) and Maniadakis and Thannassoulis (2000) have opened themselves to misspecification bias by including capital in this manner. But most importantly, the theoretically appropriate capital input measure is the flow of capital services, not capital stock. On this basis, nearly all studies in healthcare overestimate the use of capital and then (incorrectly) suggest that reducing the level of capital could increase efficiency.

However, variation within the sample may also arise in unmeasured inputs that are likely to have an even greater influence on hypothesized inefficiency. For example, the presence of hospital teaching and research programs further complicates the issue, and has only been addressed by a small, but steadily increasing, number of studies [see, for instance, Wagstaff (1989), Zuckerman et al. (1994), Burgess and Wilson (1998), Gerdtham et al. (1999) and Chirikos and Sear (2000)]. Lastly, the degree of central planning and control found in most national healthcare systems, and regulation governing input prices, also implies that input prices may be more easily discerned than in equivalent contexts, particularly in the case of public hospitals (Fare et al. 1993; Vitaliano and Toren 1996).

The final problem with most healthcare studies, namely the difference between 'public' and 'not-for-profit' or 'voluntary' health organisations, and more broadly, the issue of ownership form and efficiency, has generally received more attention in the literature (Grosskopf and Valdmanis 1987; Fizel and Nunnikhoven 1992; Valdmanis 1992; Hofler and Rungeling 1994; Kooreman 1994; Rollins et al. 2001). In general, it is argued that in the case of not-for-profit entities, the act of ploughing back excess revenues into recurrent expenditure makes them attractive to meeting physician demands for high quality and advanced medical technology, and other hospital substitutes for physician input. Nonetheless, these incentives to behave inefficiently may be off-set by the need to ensure financial viability in order to expand services, especially those that "lose money (i.e. research and charity care)" (Valdmanis 1992, 187). Conversely, while public hospitals may be relatively inefficient due to the administrative goals of Niskanen-type budget-maximizing bureaucrats, and hiring excess labour inputs under public hospital employment policy, the governmental budgetary constraints may also serve to constrain cost inefficiencies.

A number of studies have addressed these and related issues empirically. Using a sample of U.S. hospitals, both public and not-for-profit, Valdmanis (1992) concluded that DEA rather than cost or profit functions added valuable insights into the production practices of these two ownership forms. Valdmanis (1992, 197) justified ten different model specifications using a selection of nine outputs and inputs on a number of counts:

> Given the various possibilities of specifying inputs and outputs, several iterations of the DEA could be applied to answer a policy or management question. However, what needs to be determined is whether minor changes in the specification would fundamentally alter the results.

With reference to the latter, Valdmanis (1992) found that slight alteration in the input and output variables resulted in only small changes to the results, and public hospitals were consistently found to be more efficient than not-for-profit hospitals on the basis of technical efficiency. Conversely, Fizel and Nunnikhoven (1992) using a DEA approach, and later Hofler and Rungeling (1994) and Kooreman (1994a) employing an econometric and mathematical programming approach respectively, found that for-profit nursing homes had higher mean levels of efficiency than non-profit homes. Using a property rights framework, Fizel and Nunnikhoven (1992) theorised that since for-profit homes have exclusive rights to income generated, with the resulting incentive to meter input productivity and rewards conscientiously, and given the threat of take-overs, an incentive existed to produce efficiently. On the other hand, in a non-profit home the owner’s rights to income are attenuated (and ultimately non-transferrable) and non-pecuniary goods are consumed at the expense of efficiency and wealth. Using DEA frontiers for non-profit and for-profit homes, both separately and pooled, Fizel and Nunnikhoven (1992, 437) concluded that the for-profit isoquant was statistically lower than the non-profit isoquant. Hofler and Rungeling (1994) and Kooreman (1994a) observed similar results in studies of U.S and Dutch nursing homes respectively, though in the context of second-stage regressions.

EXPLAINING DIFFERENCES IN EFFICIENCY

An increasing number of empirical studies have made inroads into examining the determinants of the efficiency of healthcare institutions, particularly nursing homes and hospitals. Apart from the issue of ownership type, factors that are hypothesized to exert an influence on outcomes may be broadly grouped into (i) size and capacity, (ii) output quality and degree of specialization, (iii) market structure and funding issues, and (iv) geographic location. Most often frontier-based efficiency scores are grouped and simple analytical techniques are used to compare the distribution of efficiency [see, for instance, Ley (1991), Byrnes and Valdmanis (1993), Chattopadhyay and Ray (1996), Bradford et al. (2001), Street and Jacobs (2002)]. However, one of the most pervasive analytical tools in data envelopment analysis in particular, and the efficiency literature in general, is the use of a two-step or stage procedure to analyze efficiency scores (see Table 1 for details). The basic idea is that the efficiency scores, whether obtained from an econometric frontier or data envelopment analysis, are treated as the dependent variable in an auxiliary regression. For example, a number of healthcare studies have regressed the predicted inefficiencies on a set of organizational-specific factors, such as the percentage of doctors on staff, the extent of local competition, and dummy variables for teaching, non-profit and for-profit hospitals. This approach is likely to provide valuable insights into the causes of efficiency differentials. However, three problems typically arise.

To start with, depending on the type of inefficiency score computed, efficiency scores are typically censored. For example, DEA measures of inefficiency are bound by zero and unity, with a large number of observations, depending upon the model specification, found at the upper limit. SFA and DFA also have limited distributions, though in practice almost no organizations will have efficiency scores at unity (perfectly efficient). As a consequence, ordinary least squares estimation is not appropriate and the results from second-stage least squares regressions studies such as Vitaliano and Toren (1996) and Burgess and Wilson (1998) are then likely to be called into question. Accordingly, limited dependent variable models are usually called for (such as probit or logit) and studies by Alexander et al. (1998), Chirikos and Sear (2000) and Rollins et al. (2001) are good examples.

The two remaining problems are largely conceptual and closely related. The first is that if the variables employed in the second stage are thought to affect performance, why were they not included in the original model? The reasons for this can often be ascribed either to limitations in the underlying model, such as the inability to incorporate categorical or exogenous variables (such as in DFA and SFA), or more prosaically, to empirical convenience. However, perhaps the more intractable problem resides in the issue of the distribution of the errors in both steps. That is, if the variables used in specifying the original efficient model are correlated with the explanatory variables used in the second stage, then the second-stage estimates will be inconsistent and biased. Recent theoretical papers (Battese and Coelli 1995) have noted this inconsistency and have specified stochastic frontier models in which the inefficiency effects are made an explicit function of firm-specific factors, and all parameters are estimated in a single-stage maximum likelihood procedure. Rosko (2001) and Brown’s (2003) studies of U.S. hospitals have both employed this single-stage technique.

Returning to the empirical literature, a number of healthcare studies have incorporated a measure of size in the second-stage analysis (Fizel and Nunnikhoven 1992; Kooreman 1994a; Zimmerman et al. 1994). For example, Kooreman (1994a) employed both a measure of size (proxied by the number of beds) and the occupancy rate of these beds. In the first instance, Kooreman (1994) argued that since the efficient frontier in his study of Dutch nursing homes exhibited constant returns-to-scale, the size variable would probably be an important explanatory variable. A positive relationship between size and efficiency would be expected to hold. Kooreman (1994a, 310) argued that a higher occupancy rate would generally impinge upon the ability of management to attain efficient outcomes, since they were not generally “able to smoothly and quickly adapt the size of the staff to fluctuations in the number of patients”. Zuckerman et al. (1994) also employed occupancy rate in their analysis of U.S. hospitals. However, they theorized and found that occupancy rates are inversely related to inefficiency. Finally, in a third approach to the question of capacity, Fizel and Nunnikhoven (1992) argued that the use of different categories of beds would highlight substantial cost structure differences between, say, ‘skilled nursing’ and ‘intermediate nursing’ care. In common with Kooreman (1994), they observed a negative relationship between size and efficiency.

Secondly, a number of studies have attempted to incorporate a measure of ‘quality’ or ‘specialization’ as an explanatory factor in healthcare efficiency (Fizel and Nunnikhoven 1992; Chillingerian 1993). For example, Fizel and Nunnikhoven (1992) argued that an increase in the quality of healthcare is likely to require additional input units per unit of output, thereby implying lower relative efficiency for higher quality providers. In a related approach, Chillingerian (1993, 170) linked ‘quality’ in healthcare with ‘specialization’ and presented evidence that health providers that are more specialized have been associated with a less efficient use of input resources. However, this evidence was not conclusive, since there was no significant relationship between the level of specialization and the level of technical efficiency. Interestingly, Grosskopf and Valdmanis (1987, 93) argued that:

> [P]ublic hospitals may actually ‘minimize’ quality because it is difficult to quantify when appealing for budget increases to the legislature ... or to city or county government. ‘Visible’ outputs and inputs are emphasized in this budgetary process, which may result in less costly, relatively low ‘quality’ health care.

Thirdly, some studies have attempted to incorporate issues of market structure and funding into the determinants of inefficiency. For example, the primary aim of Chillingerian's (1993) analysis of U.S. physicians was to determine if prepaid group practices provided an incentive to use resources more efficiently, compared with more traditional types of practice settings (i.e. fee-for-service). The evidence indicated that this was the case. By contrast, Fizel and Nunnikhoven (1992) and later Rosenman et al. (1997) and Burgess and Wilson (1998) incorporated Herfindahl indexes of market concentration to evaluate the impact of increased competition on industry efficiency. Support for the hypothesized positive relationship in these studies was not forthcoming. Finally, a number of studies have employed the second-stage regression approach in order to proxy the effect of nondiscretionary inputs on healthcare efficiency, in particular geographic location. Zuckerman, Hadley and Iezzoni (1994) and Hofler and Rungeling (1994) established efficiency differences between urban and rural hospitals. In sum, the evidence found generally supports the proposition that imposed environmental factors affect the ability of healthcare organisations to attain efficient outcomes, be they hospitals, nursing homes, or even physician's practices.

CONCLUDING REMARKS

In contrast to the widespread acceptance of econometric and mathematical frontier estimation techniques in many other service-based industries, the adoption of these same methods in healthcare is still in its infancy. Some critics hold that the generic problems of omitted outputs, unmeasured inputs, and the imposition of strong and non-testable assumptions means that is "doubtful that the regulator can recover 'true' or efficient cost or production parameters from observed data with any degree of precision [moreover] even if one could recover them, they probably would have changed a few years later given the pace of change in this industry" (Newhouse 1994, 321). Still others argue that there has been substantial misuse of frontier techniques in healthcare. For example, one of the reasons for the rather icy reception for frontier efficiency techniques, particularly in public hospitals, may be that many studies have employed them to make direct policy recommendations regarding budget controls and cuts [see, for example, Zuckerman et al. (1994) and Hadley and Zuckerman (1994)]. Policy recommendations such as these are, however, not universally held. Kooreman (1994a), for instance, argues that it is conceivable that the appropriate action may not to be to cut the budget, rather to replace management. This particularly would be the case where cutting budgets may "result in a situation which is in conflict with government standards for the minimum capacity and quality of healthcare in a particular region" (Kooreman 1994, 346). Other policy recommendations made on the basis of efficiency measures have also included using them as a marketing tool to attract contracts and factors to incorporate into pricing models.

Notwithstanding these policy-related arguments, a number of empirical uncertainties are also found in the literature. For instance, despite the fact that early studies emphasized that the arguments in the first stage of a two-stage regression analysis must be completely distinguishable from those in the second, and that the second-stage should be treated as a truncated regression, lapses in thoughtful modeling are common in healthcare applications (Dor 1994, 331). Thus, while factors affecting inefficiency are now the focus of empirical research in other services, it is argued that healthcare research in the future should place more emphasis on carefully specifying the frontier. Moreover there is merit in the suggestion that technical problems such as zero inputs and outputs at certain hospitals and whether outputs are homogeneous and exogenous, do complicate this matter. However, it is unlikely that the health industry forms a sufficiently different case to isolate it from the substantial advances made in equally complex empirical contexts such as financial services and education.

Nevertheless, and in spite of the sensitivity of the results to seemingly minor changes in assumptions and model specification, frontier efficiency measures have added much to our understanding of technical, allocative and economic efficiency in healthcare. First, it is an important finding that for-profit organizations are generally more efficient than their public sector counterparts. Efficiency also seems to be positively related to organizational size and, in the case of hospitals, whether it is a teaching and/or research institution, whereas remoteness, a narrow range of services and high levels of unionization and market concentration appear to be associated with inefficiency. Second, the funding of healthcare organizations also has a role to play. Generally, output-based reimbursement improves efficiency over the budget-based allocation of funds and as a result reforms in health system funding have mostly improved allocative, rather than technical, efficiency. Finally, it is also the case that the efficiency of healthcare organizations and industries has improved over time. This bears palpable relation to the ever-increasing focus of policymakers and practitioners at all levels in the United States and elsewhere on efficient outcomes in healthcare provision.

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TABLE 1. Selected Frontier Efficiency Measurement Applications in Healthcare

Author(s)	Approach[a]	Sample[b]	Inputs, outputs and explanatory variables (if applicable)[c]	Analytical technique[d]	Main findings
Banker, Conrad & Strauss (1986)	DEA	114 North Carolina hospitals, 1978.	Nursing, ancillary, administrative and general services expenditure, capital expenditure. Patient days for inpatients less than 14 years, patient days for inpatients between 14 and 65 years, patient days for inpatients aged above 65 years.	Comparison of returns-to-scale, marginal rates of transformation and technical efficiency.	DEA identifies a richer and more diverse set of behavior than non-frontier techniques.
Grosskopf & Valdmanis (1987)	DEA	66 Californian hospitals, 1982.	Number of physicians, full-time equivalent non-physician labour, admissions, plant and equipment assets. Acute and intensive care inpatient days, number of inpatient and outpatient surgeries, number of ambulatory and emergency care visits.	Descriptive analysis across public and not-for-profit hospitals.	Public hospitals have lower costs than not-for-profit hospitals.
Wagstaff (1989)	DFA and SFA	49 Spanish hospitals, 1977-1981.	Total costs (excluding capital expenditure), Six case mix categories (internal medicine, general surgery, gynecology, pediatrics, intensive care, and other) as indexes, stock of beds, case flow, dummy variable for teaching status.	Interpretation of parameter estimates.	Mean level of efficiency highly dependent upon approach employed.
Ley (1991)	DEA	139 Spanish hospitals, 1984.	Number of doctors, technical degree and other personnel, purchases of sanitary supplies and number of beds. Patient days, discharges because of recovery (medicine, surgery, obstetrics, pediatrics and intensive care), patient days in other wards (psychiatry, tuberculosis, long-term), number of emergency cases, operations and new-borns.	Descriptive analysis.	Private hospitals more efficient than public, no difference in efficiency between teaching and non-teaching hospitals.
Fizel & Nunnikhoven (1992)	DEA	167 Michigan nursing homes, 1987.	Registered nurse hours, licensed practical nurse hours, aides and orderlies hours. Skilled and intermediate-care. Percentage of skilled beds, number of empty beds, assessed penalty points, Medicare patients and beds, Herfindahl index of market concentration, dummy variables for urban and profit and not-for-profit homes.	Descriptive statistics across disaggregated sample. Second-stage least squares regression.	Second-stage regression analysis purges efficiency indices of ‘confounding’ factors. For-profit homes are more efficient than not-for-profit ones.
Valdmanis (1992)	DEA	41 Michigan hospitals, 1982.	Number of attendances, house staff, physicians, nurses, other full-time equivalent staff, admissions, beds, net plant assets. Adult, pediatric, elderly, acute, intensive care inpatient days, number of surgeries, number of emergency care and ambulatory visits, total house staff.	Descriptive analysis across public and private not-for-profit hospitals.	Public hospitals more efficient than non-profit hospitals. Alterations in input-output model bring differences in efficiency levels and ranks.
Byrnes & Valdmanis (1993)	DEA	123 Californian hospitals, 1983.	Number of registered nurses, management and administrative personnel, number of technical services personnel, aides and orderlies, licensed practicing nurses, price of labor (reported wage rate), capital (average staffed beds), price of capital (depreciation divided by number of beds). Medical-surgical acute, medical-surgical intensive, and maternity discharges.	Descriptive analysis.	Advance on previous studies by incorporating price measures as well as physical unit measures.

Author(s)	Approach[a]	Sample[b]	Inputs, outputs and explanatory variables (if applicable)[c]	Analytical technique[d]	Main findings
Chillingerian (1993)	DEA	36 U.S. physicians, 1987.	Average length of stay, total ancillary services. Number of low-severity and high-severity cases. Average age of patients, area of specialization, average severity, relative weight of caseload, physician's age, fraction of caseload with satisfactory outcomes, local or pre-paid practice membership.	Comparison of DEA with ratio analysis, slack analysis, Mann-Whitney tests, second-stage logit regression.	Key factors that influence physician efficiency include pre-paid group practices vs. fee-for-service payment structure.
Fare, Grosskopf, Lindgren & Roos (1993)	MI	17 Swedish hospitals, 1970-1985.	Real labor input (average labor expenditure per hour), real non-labor input (food, drugs, medical supplies and laundry excluding capital costs). Short-term inpatient care (proxied by discharges), long-term chronic care (proxied by bed days), ambulatory care (proxied by doctor visits).	Descriptive analysis of relative efficiency over time.	Advantages of approach over Tornqvist, Paasche and Laspeyres index-type productivity measures.
Hofler & Rungeling (1994)	SFA	1,079 U.S. nursing homes, 1985.	Total variable costs, nursing staff hourly wages, hourly wage for physicians and other professional staff, hourly wage for all other staff, capital (as proxied by number of beds). Skilled inpatient days, intermediate care inpatient days, other inpatient days. Type of home certification, physician availability, nursing staff characteristics, geographic region, chain membership, ownership type and hospital affiliation.	Second-stage OLS regression. Interpretation of parameter estimates.	Nursing homes appear to be cost efficient.
Kooreman (1994)	DEA	320 Dutch nursing homes, 1989.	Number of medical doctors, nurses, nurse trainees, therapists, general and other staff. Number of full and day-care, physical disability, and psycho-disability patients. Number of beds, occupancy rate, proportion of patients older than 85 years, length of stay, hospital affiliation, regional dummies, religious affiliation, dummy variable for patients' council.	Descriptive statistics, second-stage probit and tobit regressions.	A number of quality indicators have a negative effect on efficiency. Practical usefulness of DEA limited by the availability of data.
Zuckerman, Hadley & Iezzoni (1994)	SFA	4,149 U.S. hospitals, 1986/87.	Total costs, average annual salary per full-time equivalent employee, depreciation and interest expenses per bed. Post-admission inpatient days, post-admission inpatients days, outpatient visits. Percentage of beds in intensive care, non-surgery outpatient visits, long-term admissions, ratio of births to admissions, average case mix, inpatient surgical operations per admission, index of high technology services, ratio of residents to beds, accreditation indicator, individual Medicare-specific variables.	Correlation coefficients between alternative model specifications, inefficiency estimates from pooled and partitioned hospital groups.	Inefficiency measures generated insensitive to functional form. Large number of hospital outputs may not be treated exogenously nor homogeneously.
Chattopad-hyay & Ray (1996)	DEA	140 U.S. nursing homes, 1982/93	Labor hours for dietary, housekeeping, laundry, director, registered nurse, licensed practical nurse and nurses aides staff, total expenditure on non-labor inputs. Medicare, Medicaid, private and other patient days.	Descriptive analysis.	For-profit home more efficient than not-for-profit homes.

Author(s)	Approach[a]	Sample[b]	Inputs, outputs and explanatory variables (if applicable)[c]	Analytical technique[d]	Main findings
Lo, Shih & Chen (1996)	DEA	82 Taiwanese hospitals, 1982.	Number of doctors, nurses, other staff and beds. Number of visits, operations and patient days, and average patient days. Dummy variables for public, military, corporate, religious and university hospitals, hospital size, percentage of patients over 65 years, percentage of beds in city, dummy variable for scanning equipment.	Descriptive analysis, second-stage tobit regression.	Public hospitals less efficient than private hospitals.
Luoma, Järviö, Suoniemi & Hjerppe (1996)	DEA	220 Finnish health centers, 1991.	Total operating costs (excluding rehabilitation), cost of purchased services, cost adjustment for remote areas. Health care and medical visits to a physician, health care or medical care visits to other personnel, supervised domiciliary care visits, dental care visits, special examinations, short-term inpatients days, long-term inpatient days for heavy and non-heavy dependence categories. Percentage of state subsidy, local government taxation per patients, distance to nearest hospital, proportion of population over 65 years, number of personnel posts, dummy variable for single-municipality heath centre.	Descriptive analysis, second-stage Tobit regression.	Inefficiency linked to larger state subsidies and higher per capita taxable income, remote centers more inefficiency. Efficiency also linked to increases in proportion of elderly in area.
Gonzalez Lopez-Valcarcel & Barber Perez (1996)	DEA and SFA	75 Spanish hospitals 1991-1993.	Number of doctors, other staff and beds, total costs for cost frontier. Medical, surgical, intensive care, obstetric and new-born inpatient days, number of ambulatory surgical procedures, operations with hospitalization and total admissions, index of ambulatory/emergency visit and high-tech activity. Percentage of doctors on staff, percentage of sub-contracted work, rate of hospital admission per 1000 population, dummy variables for regions.	Descriptive analysis, second-stage Tobit regression.	Differences in efficiency associated with size, the extent of sub-contracting and the rate of capacity utilization.
Vitaliano & Toren (1996)	SFA	219 New York state hospitals, 1991.	Total costs, wages of registered nurses and radiologists. Number of patient days, case-mix index, technology index, occupancy rate, emergency room and outpatient clinic visits, teaching hospital identifier. Unionization, small and large number of beds, malpractice payments, for-profit and government hospitals, Medicare, Medicaid and Blue Cross discharges.	Descriptive analysis, second-stage least squares regression.	Facilities with larger Medicare populations and number of beds are more efficient, unionization and excess bed capacity adds significantly to hospital costs.
Magnussen (1996)	DEA	46 Norwegian hospitals, 1989-1991.	Number of physicians and other personnel, number of beds. Medical, surgical, simple and complex patient days, number of medical and surgical patients, number of long-term care days and outpatient visits.	Descriptive analysis.	Difficulty in identifying high, medium and low performers using DEA.
Thanassoulis, Boussofiane & Dyson (1996)	DEA	189 U.K district health authorities, 1985/86.	Numbers of obstetrics/gynecology staff, pediatricians, midwives and nurses, general practitioner's fees. Number of deliveries, deliveries to resident mothers, babies less than 1500g birthright and legally induced abortions, length of stay.	Descriptive analysis, correlation between efficiency indexes and performance indicators.	DEA and performance indicators weakly agree on unit performance. DEA as a tool for target setting.

Author(s)	Approach[a]	Sample[b]	Inputs, outputs and explanatory variables (if applicable)[c]	Analytical technique[d]	Main findings
Defelice & Bradford (1997)	SFA	924 U.S. physicians, 1984/95.	Number of physician visits. Weekly hours of medicine practice by physician, nursing and clerical time per physician, percentage of visits using lab tests or x-rays. Years of physician experience, percentage of physicians earning in excess of $10,000 exogenous income, percentage of physicians in general or family practice, percentage of physicians working in internal medicine, pediatrics or partnerships, number of physicians in practice, percentage of physicians sharing net revenue equally and multi-specialty groups. Number of board-certified physicians in specialty in county, number of HMOs and hospitals in country, number of physicians per 1000 county population, percentage of patients insured by Medicaid, percentage of visits provided by hospital, number of offices with lab or x-ray equipment, level of malpractice premiums.	Descriptive analysis, single-stage least squares regression.	No difference in efficiency between group and solo practices.
Parkin & Hollings-worth (1997)	DEA	75 Scottish hospitals, 1991-94.	Number of staffed beds, total number of trained and learning nurses, total professional, technical, administrative and clerical staff, total non-nursing medical and dental staff, cost of drug supply, NHS capital charge on capital assets and investments. Medical and surgical discharges, accident and emergency attendance, outpatient attendance, obstetrics and gynecological discharges, other specialty discharges.	Efficiency scores across different combinations of inputs-outputs and time.	Large amount of difference in efficiency results depending upon specification.
Rosenman, Siddharthan & Ahern (1997)	DEA	28 Florida health maintenance organisations (HMOs), 1994.	Total administrative expenses, total assets, total medical expenses. All enrollees, Medicare enrollees, Medicaid enrollees. Plan size (total enrolment), Herfindahl index of enrolment concentration (Commercial, Medicare and Medicaid enrollees).	Descriptive analysis, second-stage OLS regressions.	Efficiency is equal across organizational and ownership. HMOs that accept Medicaid patients are more efficiency.
Chirikos (1998)	SFA	186 U.S. hospitals, 1982–1993.	Total operating expenses. Number of post-admission patient days with Medicare, Medicaid or other as primary payer, case weighted admission index, case-equivalent outpatient index (ratio of gross outpatient revenue to gross inpatient revenue) emergency room outpatient index (ratio of gross ambulatory revenue to gross emergency services revenue). Wage rates of three categories of personnel (inpatient and ambulatory, ancillary, and administrative), ratio of depreciation to book value of plant and equipment, ratio of interest charges to current assets. Cost per case, annual cases, control of ownership status (government, proprietary or voluntary), licensed beds, teaching status, market share, population density, and physicians per 100,000 persons.	Descriptive analysis across explanatory variables.	Empirical results sensitive to specification of outputs, factor prices or other covariate models. Government-controlled hospitals more efficient, less-efficient hospitals in highly competitive, population- and physician-dense areas.

Author(s)	Approach[a]	Sample[b]	Inputs, outputs and explanatory variables (if applicable)[c]	Analytical technique[d]	Main findings
Linna (1998)	SFA, MI, DEA.	43 Finnish acute care hospitals, 1988-94.	Net operating costs, total number of beds, average hourly wage rate, annual price index for local government health care expenditure. Total number of emergency visits, total scheduled and follow-up visits, weighted number of total admissions, total bed days, number of residents receiving training, number of on-the-job nurse training weeks, impact weighted scientific publications. Dummy variables for teaching status, readmission rate for admissions, year dummies.	Descriptive analysis, rank correlation between efficiency scores, single-stage SFA incorporating efficiency effects.	Choice of modeling approach does not affect results. SFA and DEA models revealed productivity growth over period to be the result of exogenous technical change.
Puig-Junoy (1998)	DEA	993 Spanish patients in 16 intensive care units (ICU), 1991/92.	Patient survival probability at admission, mortality risk level, weighted ICU days, non-ICU days, available nurse and physician days per patient, technological availability Number of surviving days in hospital, surviving discharge status. Dummy variable for for-profit hospitals, Herfindahl competition index, number of beds in ICU, proportion of patients in same risk group, number of inpatient days for ICUs using clinical guidelines and nurse/physician evaluation program, number of daily visits, dummy variable for teaching hospital, mortality risk score, age, dummy variables for respiratory failure, cardiovascular disease, trauma, urgent admission, postoperative patients with programmed admission,	Descriptive analysis, second-stage log-linear regression.	Higher risk patients managed less efficiently than lower risk patients, higher technical efficiency in for-profit teaching hospitals, and those with nurse and physician program evaluation. Diagnostic variable generally unrelated.
Burgess & Wilson (1998)	DEA	1,545 U.S. hospitals, 1985-88.	Number of acute-care beds, long-term hospital beds, registered nurses, practical nurses, other clinical and non-clinical labor, Acute care inpatient days, case-mix adjusted acute care inpatient discharges, long-term care inpatient days, outpatient visits, ambulatory surgical procedures, inpatient surgical procedures. Dummy variables for state/local government, non-profit, for-profit, Veterans Affairs and teaching hospitals, Herfindahl index of county competition, average length of stay, percentage of registered nurses, ratio of clinical to non-clinical staff, administration cost per bed day.	Descriptive analysis, second-stage least squares regression.	No difference in efficiency across different ownership structures or in teaching hospitals. Greater expenditures on administration and nursing staff associated with higher efficiency.
Linna, Häkkinen & Linakko (1998)	SFA	48 Finnish acute care hospitals, 1994.	Net operating costs and number of beds. Factor prices from average hourly rate of doctors and other employees. Number of emergency visits, scheduled and follow-up visits, DRG-weighted admissions, bed-days exceeding cut-off points, residents receiving training, on-the-job training weeks of nurses, clinical training weeks of medical students, impact-weighted scientific publications.	Descriptive analysis.	University hospitals produce teaching and research output at lower marginal and average cost than other hospitals.

Author(s)	Approach[a]	Sample[b]	Inputs, outputs and explanatory variables (if applicable)[c]	Analytical technique[d]	Main findings
Alexander, Wheeler, Nahra and Lemack (1998)	DEA	442 U.S. outpatient substance abuse treatment (OSAT) organizations, 1995.	Number of full and part-time staff hours, consultant hours and normalized expenditures. Number of individual, group and family therapy hours. Number of clients, percentage of clients for whom managed care oversight activities (MSA) specify treatment plans, require written utilization review, require correspondence with treatment team, impose visit limits, impose sanctions, identifiers if affiliated with a hospital, mental health center, provides methadone treatment, private for-profit and not-for-profit ownership, accreditation, percentage of clients Afro-American, dual diagnoses, abuse multiple drugs and some insurance, lump sum revenues, level of non-price competition, number of substance abuse providers in county, identifier for urban location.	Descriptive analysis and second-stage probit and least squares regressions.	Few significant associations between managed care dimensions and technical efficiency in outpatient treatment organizations. Efficiency associated with hospital and mental health center affiliation, accreditation, receipt of lump sum revenues, methadone treatment modality, and unemployed and multiple drug abuse clients.
Gerdtham, Löthgren, Tambour & Rehnberg (1999)	SFA	26 Swedish hospitals, 1989-1995.	Cost of production, number of beds, type of government (conservative or liberal), time variable, proportion of population older than 70 years, proportion of private visits to total visits, university hospital identifier. Number of operations, discharges and physician visits.	Descriptive analysis.	Output-based reimbursement improves technical efficiency over budget-based allocation.
Chirikos & Sear (2000)	SFA and DEA	186 Florida hospitals, 1982-93.	Costs of wage and salary payments to personnel in patient care activities, nonpatient care activities, other expenses in patient care cost centers, capital costs for plant assets, adjusted depreciation, other administrative expenses. Factor prices using mean wages for each personnel category, rate of depreciation for capital inputs and interest rate on debt financing. Number of case mix-weighted admissions for Medicare, Medicaid and Blue Cross and other private patients, composite index of outpatient activity for special tests and procedures and emergency room. Number of beds, occupancy rate, length of stay, type of control (religious, proprietary, government), teaching facility, above and below local average in inputs and outputs.	Descriptive analysis and second-stage probit regression.	DEA and SFA yield convergent evidence about hospital efficiency at the individual level but convergent at the industry level.
Maniadakis & Thanassoulis (2000)	MI	75 Scottish hospitals, 1991/92-1995/96.	Number of doctors, nurses and other personnel, number of beds and area of hospital in cubic meters. Factor prices of doctor, nurse and other personnel salaries and capital charge per bed and cubic meter. Number of accident and emergency attendances, adjusted inpatients, day cases and outpatients.	Descriptive analysis.	Productivity improvements associated with reforms in NHS, mainly associated with improvements in allocative efficiency.

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Giuffrida & Gravelle (2001)	DEA and SFA	90 U.K. Family Health Service Authorities (FHSA), 1993/94-1994/95.	Gross expenditure, cost of GPs and practice nurses, number of nurses. Number of GPs, deaths, practices employing practice nurse, GPs with less than 2,500 patients in their list, GPs not practicing single-handed, GPs with highest rate of payment for childhood immunization, GPs meeting target for cervical cytology, GPs with higher rate of payment for pre-school boosters, general practices, GPs on minor surgery list.	Descriptive analysis and correlation among alternative models and techniques.	Efficiency scores are highly correlated within variants of DEA and regression techniques and across years.
Rosko (2001)	SFA	1,631 U.S. hospitals, 1990-96.	Total expenses less physician expenses, average wage rate and price of capital (depreciation and interest expenses per bed). Binary variable for teaching hospital, number of emergency department visits and outpatient surgeries as a proportion of total outpatient visits. HMO enrollment as a percentage of population, share of Medicare and Medicaid discharges as a percentage of total discharges, identifier for investor-owned hospitals, Hirschman-Herfindahl index for concentration of hospital admissions.	Descriptive analysis and single-stage regression analysis.	Mean estimated efficiency decreased during the study period. Inefficiency negatively associated with HMO penetration and industry concentration and positively associated with Medicare share and for-profit status.
Bradford, Kleit, Krousel-Wood & Re (2001)	SFA	645 U.S. cardiac revascularization patients, 1994.	Accounting cost of treatment. Identifiers for comorbidities, gender, smoking, age, myocardial infarction, use of established or new technology, ejection fraction, number of vessels, time, and doctor. Separate estimations for balloon angioplasty and cardiac bypass surgery.	Descriptive analysis.	Potential cost savings associated with making angioplasty a more perfect substitute for bypass surgery.
Rollins, Lee, Xu & Ozcan (2001)	DEA	36 U.S. health maintenance organizations (HMOs), 1993-97.	Administrative costs, inpatient, physician and other professional expenses. Number of inpatient days, physician and non-physician ambulatory encounters. Federal qualification, age and type (group, staff, network) of HMO, size and profit status (for profit, not-for-profit).	Descriptive analysis and second-stage logistic regression.	HMO type, profit status, federal eligibility and age are predictive variables for efficiency. Improvements in HMO efficiency over time.
Street & Jacobs (2002)	SFA	217 U.K. acute care hospitals, 1999.	Case mix cost index. Number of transfers into and out of hospital, emergency sessions, finished consultant episode inter-specialty transfers, non-primary outpatient attendances, index of unexpected emergency admission episodes per spell, HRG weight, proportion of patients under 15 years of age and 60 years or older, proportion of female patients, student whole time teaching equivalents, percentage of revenue spent on research, weighted average of staff, land, building and London weighting to reflect market forces.	Descriptive analysis.	Use of least squares residuals as against stochastic frontier overestimates inefficiency.

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Brown (2003)	SFA	1,907 U.S. hospitals, 1992-96.	Number of patient cases and level of diagnosis related group (DRG) cases. Number of beds, capital expenses, full-time employees. Mean DRG weight, number of residents, membership of Council of Teaching Hospitals, public or for-profit, firm concentration, dummy variables for years, identifiers for HMO and preferred provider organization (PPO) hospitals,	Single-stage regression analysis.	Increase in efficiency of estimates associated with single-stage regression method over second-stage. Managed care insurance associated with improved technical efficiency.
Street (2003)	SFA	226 U.K. acute care hospitals, 1999.	Total cost. Number of case mix adjusted inpatients, specialty weighted outpatient attendances, accident and emergency attendances, transfers in and out of hospital per spell, emergency admissions per spell, finished consultant episodes per spell, non-primary outpatient attendances per spell, index of unexpected emergency admissions, episodes per spell, proportion of patients under 15 years and over 60 years, proportion of female patients, number of student whole time teaching equivalents per spell, percentage of revenue spent on research , market forces factor obtained by weighted average of staff, land, building and London weighting factors.	Descriptive analysis.	Estimates of hospital efficiency are sensitive to method of estimation and the use of these techniques to set performance targets should be avoided.

Notes: (a) DEA – Data Envelopment Analysis, SFA – Stochastic Frontier Analysis, DFA – Deterministic Frontier Analysis, MI – Malmquist Indices; (b) Singular dates represent calendar or financial year cross-sections, intervals represent time-series; (c) In order by paragraph, for SFA and DFA paragraphs are ordered by dependent, independent and explanatory variables; (d) All DFA and SFA studies usually discuss the estimated coefficients, significance and sometimes elasticities for the production and cost parameters as well as the measures of efficiency obtained. Analytical technique of descriptive analysis includes analysis of distributions (mean, standard deviations) and/or analysis of efficiency by groups within sample and correlation between efficiency scores obtained by different techniques. Second-stage regression involved regressing efficiency scores from DEA, MI, SFA or DFA on additional explanatory variables in a separate regression (usually probit or logit), single-stage regression refers to Battese and Coelli's (1995) stochastic frontier model where efficiency estimates are estimated simultaneously with the coefficients on the explanatory variables.