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A net benefit approach

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Including quality attributes in a model of health care efficiency: A net benefit approach

by

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Abstract

Quality attributes have been incorporated in analyses of efficiency in health care (e.g., hospitals) in various ways. For example, as a utility enhancing output, as a utility reducing "bad output" or as an exogenous factor. In this paper we argue that these approaches are inconsistent with the net benefit criterion that is commonly used in cost-effectiveness analysis in health. As a solution we propose a method that involves including quality variables (framed from a utility *reducing* perspective) as input variables in the efficiency model. We then show that an appropriate transformation of the standard net benefit measure allows one to obtain economic efficiency measures that are consistent with maximising net benefit, and that these economic efficiency measures can be subsequently decomposed into technical and allocative components. An additional advantage of the approach is that shadow prices can be derived for quality when output prices (e.g., of public hospital services) are unavailable. The method is illustrated using data on treatments for respiratory infections in 45 acute care hospitals in Australia.

Keywords: efficiency measurement; quality of services; maximizing net benefit.

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1. Introduction

Expenditure on health services has been increasing at a fast rate in recent decades in many countries. For example, the proportion of GDP devoted to health care services has been increasing in each country in the OECD, and overall has increased from 4% in 1960, when the OECD was founded, to more than 9% across OECD countries in 2005 (OECD 2007). The proportion of GDP varies considerably across health systems. In particular, it is significantly higher in the predominantly privately-provided health care system in the USA, where health expenditure was estimated as 15.3% of GDP in 2005. Higher health expenditure has however not necessarily been reflected in better health outcomes, with the USA again most notably lying 24th in life expectancy amongst the 30 OECD countries. Common to all health systems is an increasing concern over performance, efficiency and more generally the accountability and incentives of providers such as hospital. Such concerns have lead to various government and private agencies having a particular focus on analysis of efficiency of hospitals within and across health systems, where Hollingsworth (2003) has documented an increasing proliferation of efficiency studies.

However, one important drawback of many hospital efficiency measurement models is that they exclude quality measures and hence run the risk of producing incentives for managers to seek out reduction in resource use or cost per admission at the expense of quality of care, an issue highlighted by Newhouse (1994) and Eckermann (1994) in critiquing hospital efficiency measures. The desirability of taking into account the quality of services is reinforced when considering the impact of the quality of hospital services on expected outcomes beyond discharge. Health systems are characterised by incomplete integration across health services (Evans 1981) and hence the quality of hospital care within an admission can have significant impacts beyond hospital discharge on the wider health system. If hospitals are not held accountable for the expected effects of their care beyond discharge, perverse economic incentives are created for practices such as quicker-sicker care, cost-shifting and quality-skimping (Smith 2002). Such practices can reduce costs per admission, but beyond discharge have expected negative effects on health outcomes (outcome shifting) and consequently increase expected demands for, and use of, health care post-discharge (cost-shifting). Cost-shifting may manifest in increasing rates of readmission to hospitals, treatment in other institutional settings (general practice, specialist and aged care services), or informal care in non-institutional settings. In general, accounting for quality in hospital efficiency measurement would appear to be necessary to avoid perverse incentives for cost and outcome-shifting and to create incentives for appropriate quality of services.

Despite this, only a handful of studies have attempted to account for quality in models of hospital efficiency, as noted by Hollingsworth (2003). Studies such as Zuckermann et al. (1994) have attempted to model quality with exogenous variables, while Puig Junoy et al (1998) and Dawson et al (2005) have attempted to model quality with utility bearing output variables. More recently, Arocena and Garcia-Prado (2007) have specified quality as "bad output" variables, while Prior (2006), Eckermann (2004) and previously Morey et al. (1992) have specified quality as disutility bearing input variables.

In this paper we look at the relative merits of various alternative ways of including quality variables in efficiency models. We conclude that the specification of quality as input variables framed from a disutility perspective has a number of attractive properties. First and foremost, it allows one to measure performance in a manner which is consistent with net benefit maximisation, which many authors (e.g., Claxton and Posnett 1996; Stinnett and Mullahy 1998; Zehrhaus and Tambourne 1998; Willan and Lin 2001; Drummond et. al. 2005; Willan and Briggs 2006; Eckermann, Briggs and Willan 2008) argue is the most appropriate way to allow for costs and effects in health care. Second, it produces efficiency measures that are relatively easy to calculate. Third, it avoids the selection of optimal points that are clearly sub-optimal where quality variables are specified as weakly disposable bad outputs. Fourth, it allows one to obtain shadow price measures for the quality variables when prices of outputs are unobservable (as in public hospitals). Fifth, it allows one to calculate appropriate measures of allocative as well as economic efficiency, when an estimate of the "value" of a unit of quality is available.

The remainder of this paper is divided into sections. In section 2 we provide a brief summary and critique of the alternative ways in which quality variables can be incorporated into efficiency models. In section 3 we outline our modelling approach, which specifies quality as an input variable, and also indicate how this model can be applied to compare efficiency consistent with the net benefit criterion and be used to derive shadow prices for quality attributes. In section 4 we provide an empirical application of our method to acute care hospitals in the state of New South Wales in Australia. Concluding comments are then provided in the final section.

2. Alternative methods

Before we compare the merits of alternative ways in which quality could be incorporated into efficiency models we need to first explain what we mean by quality. There are many aspects to the quality of hospital services that one could consider, including technical aspects, timeliness, comfort, and so on. In the empirical part of this study we focus our attention on technical aspects measured by health effects (e.g. functional limitation, morbidity or mortality). However, various aspects of quality could feasibly be accommodated by the methods we discuss in this paper where cardinal measures are available.

i) Ignore quality

We consider a (hospital) production process where inputs (labour, equipment, etc.) are used to produce outputs (admissions). Initially we make the assumption that quality is uniform across all productive units and hence that quality can be ignored. We assume that a provider (hospital) produces a vector of m=1,2,...,M outputs, $\mathbf{y} \in \mathbf{R}_+^M$, using a vector of k=1,2,...,K inputs, $\mathbf{x} \in \mathbf{R}_+^K$. The feasible production set, T, is defined as:

$$T = \left\{ \left(\mathbf{y}, \mathbf{x} \right) \in \mathbf{R}_+^{M+K} \mid \mathbf{x} \text{ can produce } \mathbf{y} \right\}, \tag{1}$$

where the production technology is assumed to be convex and non-increasing in inputs, non-decreasing in outputs, and exhibits strong disposability in inputs and outputs.[1]

If the observed quantities $\left(\mathbf{y}, \mathbf{x} \right)$ for a particular provider lies on the outer boundary of the production set (i.e., not on the axes and not in the interior of the set) then the provider is said to be technically efficient (Farrell, 1957). If the observed quantity vector is not located on the efficient boundary of the technology set then the provider is said to be technically inefficient and the degree of technical inefficiency can be defined using a range of measures. The most commonly used measures are radial output oriented and input oriented measures. For example, an input oriented technical efficiency measure can be defined as:

$$TE_1(\mathbf{y}, \mathbf{x}) = \min_{\theta} \left\{ \theta \mid \left(\theta \mathbf{x}, \mathbf{y} \right) \in T \right\}, \tag{2}$$

where θ is a scalar that takes a value between zero and one. For example, a value of θ = 0.8 would indicate that the provider could produce the same output with 80% of the current input levels.

[1] See Coelli *et al.* (2005) for further discussion of these properties.

Alternatively, an output oriented technical efficiency measure can be defined as:

$$TE_2(\mathbf{y},\mathbf{x}) = \max_{\theta}\left\{\theta \mid \left(\mathbf{x},\theta\mathbf{y}\right) \in T\right\}, \tag{3}$$

where in this case θ is a scalar that takes a value greater than or equal to one. For example, a value of $\theta = 1.4$ indicates that the provider could produce 40% more output with the current level of inputs.

ii) Quality as a "bad output"

The above measures ignore quality issues. Let us now assume that quality can differ across providers (hospitals) and define a vector of s=1,2,...,S quality outcomes, $\mathbf{z} \in \mathbf{R}_{+}^{S}$, where higher values imply lower quality. That is, the quality variable is framed from a utility reducing (or disutility bearing) perspective. For example, quality could be represented by the number of patients who contract infections in hospital, do not regain function or who die. One then must decide how to include these quality variables into the production model.

Arocena and Garcia-Prado (2007) have attempted to model quality by including it as a weakly disposable "bad output" in the production model. The weak disposability assumption is used to ensure that one cannot dispose of the bad output without incurring some cost.[2] In this case the production technology in equation (1) becomes:

$$T = \left\{\left(\mathbf{y},\mathbf{x},\mathbf{z}\right) \in \mathbf{R}_{+}^{M+K} \mid \mathbf{x} \text{ can produce } \left(\mathbf{y},\mathbf{z}\right)\right\}, \tag{4}$$

where the production technology is assumed to be non-increasing and exhibits weak disposability in bad outputs.[3]

[2] Strong disposability in bad outputs implies that if the point $(\mathbf{x}_1,\mathbf{y}_1,\mathbf{z}_1)$ is feasible, then so too is any point $(\mathbf{x}_1,\mathbf{y}_2,\mathbf{z}_2) \le (\mathbf{x}_1,\mathbf{y}_1,\mathbf{z}_1)$. Alternatively, weak disposability in bad outputs implies that if the point $(\mathbf{x}_1,\mathbf{y}_1,\mathbf{z}_1)$ is feasible, then so too is any point $(\mathbf{x}_1,\alpha\mathbf{y}_2,\alpha\mathbf{z}_2)$, where $0 \le \alpha \le 1$. The former implies the latter but the converse need not apply.

[3] See Tyteca (1996) for further discussion of this type of technology in the context of including pollution measures in efficiency models.

This technology can be visualised by considering the diagram in Figure 1 where we consider a production technology involving one good output and one bad output. The production technology that has been drawn is piece-wise linear (for example constructed using data envelopment analysis) and the data points A, B, C and D represent the outputs of four firms, all of which are assumed to possess the same input vector (for the purpose of this illustration). The good output is assumed to possess the strong disposability property, which implies that one can freely dispose of unwanted amounts without penalty. Thus if the point C is feasible then so too is the point E, where one produces zero amounts of the good output. The bad output, on the other hand, is assumed to possess the weak disposability property, which implies that one cannot freely dispose of unwanted amounts without penalty. Thus if the point B is feasible then the point F (and points in between) are not feasible.

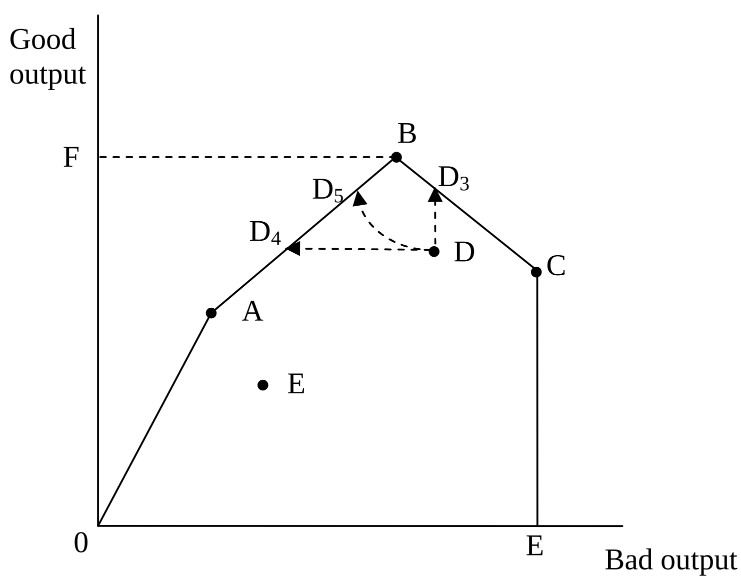

Figure 1: Technology with weak disposability in bad output

Thus the efficient boundary of the production technology is formed by 0ABCE, where the good output can be freely disposed but the bad output can only be disposed of if a proportional amount of the good output is also disposed of. Although widely used to deal with pollution in industrial and agricultural efficiency applications there are a number of drawbacks associated with this type of model. This becomes apparent when one attempts to define an efficiency measure.

One efficiency measurement option is to expand the good output to the frontier. Thus the TE measure in equation 3 becomes:

$$TE_3(\mathbf{y},\mathbf{x},\mathbf{z}) = \max_{\theta}\left\{\theta \mid \left(\mathbf{x},\theta\mathbf{y},\mathbf{z}\right) \in T\right\}. \tag{5}$$

Using this measure, the inefficient firm at point D in Figure 1 will be allocated an efficient target point of D_3. However, this point is clearly sub-optimal, because it is dominated by point B, which involves more good output and less bad output. Furthermore, the negative slope of the frontier at the point of projection implies a negative shadow price for quality, which is difficult to conceptualise.

Another option is to look at shrinking the bad output as much as possible. Thus the TE measure would be:

$$TE_4(\mathbf{y},\mathbf{x},\mathbf{z}) = \min_{\theta}\left\{\theta \mid \left(\mathbf{x},\mathbf{y},\theta\mathbf{z}\right) \in T\right\}. \tag{6}$$

Thus the efficient target point will now be D_4. This point is more sensible than point D_3 because it is not clearly dominated by other points. However, this assumes that all effort is put into quality improvement and not volume improvement. As a consequence some authors (e.g. Färe et al 1989) have suggested efficiency measures involving simultaneous reduction in good outputs and expansion of bad outputs. One such option is the hyperbolic efficiency measure used by Arocena and Garcia-Prado (2007):

$$TE_5(\mathbf{y},\mathbf{x},\mathbf{z}) = \max_{\theta}\left\{\theta \mid \left(\mathbf{x},\theta\mathbf{y},\mathbf{z}/\theta\right) \in T\right\}. \tag{7}$$

In this case the efficient target point becomes something like D_5. Although the choice of the direction of this efficiency measure seems rather arbitrary, it can avoid the selection of points such as D_3.[4] However, equi-proportional contraction of bad outputs and expansion of good outputs can still project onto segments of the frontier such as BC (for example with a firm at G) and in situations when the prices of outputs are unknown (as is generally the case in public health) one is unable to derive shadow price information from this model.

iii) Quality as an input variable

In this study we do not treat quality as a bad output. Instead we treat it as an input variable. This has been done in the past by Moorey (1992) for US hospitals and Prior (2006) in the Spanish hospital sector, and has also been used in a handful of industrial and agricultural pollution studies. For example, see Giannakis, Jamasb and Pollitt (2005) in electricity and Reinhard, Lovell and Thijssen (1999) in agriculture. The logic associated with treating quality as an input variable can be illustrated using Figure 2. Here we provide a diagram of a production frontier where one axis represents traditional inputs ($\mathbf{x}$) and the other a quality variable ($\mathbf{z}$, e.g., infection rate). For the purpose of the illustration we assume that there is only one input (e.g., staff) and all firms produce the same amount of output (e.g., admissions).

The boundary of the production technology is defined by the isoquant FABCE. Points on this isoquant (e.g., point B) are technically efficient while those to the north east (e.g., point D) are technically inefficient. The basic notion is that a hospital manager attempts to minimise the use of inputs ($\mathbf{x}$, e.g. nurses) and maximise quality (reduce $\mathbf{z}$, e.g. infection) for a given level of output ($\mathbf{y}$, e.g. admissions). If the manager faces no penalties for poor quality then one could argue that the "price" of quality he/she faces is zero and hence the optimal (cost minimising) point of operation is on the vertical portion of the isoquant. However, improving

[4] Another option could be to use directional distance functions. For example, see Färe and Grosskopf (2000). However, the selection of which direction to take is also arguably arbitrary in this case.

quality measured by reduction in **z** clearly has value (e.g. to the health system and society more generally) and hence we argue managers should face incentives, and be held accountable in performance measures, that reflect value of quality.[5]

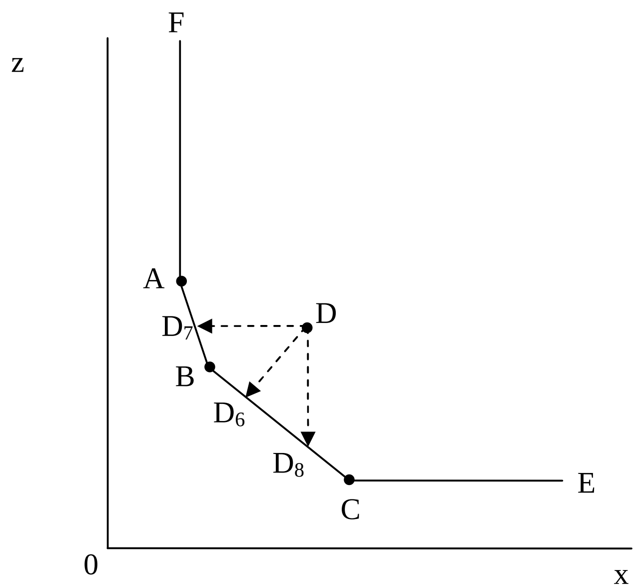

Figure 2: Technology where quality is an input variable

One can define a range of efficiency measures for this type of technology. For example, one could define a tradition radial input oriented TE score as:

$$TE_6(\mathbf{y},\mathbf{x},\mathbf{z}) = \min_{\theta}\left\{\theta \mid (\theta\mathbf{x},\mathbf{y},\theta\mathbf{z}) \in T\right\}, \tag{8}$$

where inputs (including quality) are proportionally reduced, producing the point D_6 in Figure 2. Alternatively, one could focus solely on the "standard inputs" and reduce it while holding quality and output constant. That is:

[5] Efficiency measures themselves can also be argued as creating appropriate incentives for quality. This is particularly the case for hospitals given the extent to which transaction conditions diverge from those of a perfect market (Williamson 1975). Providers are unlikely to be held accountable for quality of care by patients leading to the need for regulation of quality to create appropriate incentives which Donaldson and Gerard (1993) term 'the visible hand'. This is the case given hospital patients typically have bounded rationality (Simons 1957) from high complexity, uncertainty and information search costs leading to a-symmetry of information (Arrow 1963, Akerlof 1970) between patients and providers. Further, patient inability to distinguish quality ex-ante is not necessarily helped ex-post given outcomes are relative to counterfactual alternative treatment.

$$TE_7(\mathbf{y},\mathbf{x},\mathbf{z}) = \min_{\theta}\left\{\theta \mid \left(\theta\mathbf{x},\mathbf{y},\mathbf{z}\right) \in T\right\}, \tag{9}$$

producing D_7 in Figure 2.

One could also aim to derive a measure of potential quality improvement by reducing the quality variable while holding outputs and standard inputs constant:

$$TE_8(\mathbf{y},\mathbf{x},\mathbf{z}) = \min_{\theta}\left\{\theta \mid \left(\mathbf{x},\mathbf{y},\theta\mathbf{z}\right) \in T\right\}, \tag{10}$$

which provides a target point of D_8 in Figure 2.

These latter three measures have various advantages with respect to those based on the "bad outputs" model. First, they are technically easier to compute, with many standard DEA programs able to compute them easily. Second, unlike some of the "bad output" methods, they do not produce projected points which are sub-optimal. Third, they allow one to obtain shadow price measures for the quality variable, given that input price data is available – which is generally the case. Last, and by no means least, they allow one to define performance measures which are consistent with the net benefit criterion, including a measure of net benefit (economic) efficiency conditional on the "price of quality" (e.g., a threshold value per unit of effect).

iv) Quality as a "good output"

Historically, endogenous specification of quality variable in hospital efficiency measurement have been suggested under a 'quality-quantity trade-off' (Newhouse 1970), where quality and quantity are considered from a utility bearing perspective. In this case the production technology in equation (1) becomes: $T = \left\{\left(\mathbf{y},\mathbf{x},\mathbf{z}^u\right) \in \mathbf{R}_+^{M+K} \mid \mathbf{x} \text{ can produce } \left(\mathbf{y},\mathbf{z}^u\right)\right\}$, where $\mathbf{z}^u$ represents the vector of s=1,2,...,S quality outcomes, $\mathbf{z} \in \mathbf{R}_+^S$ framed from a utility bearing perspective. That is, where higher values imply higher quality. For example, quality could be represented by the number of patients who do not contract infections in hospital, regain function or who survive.

However, such a definition of technology while appropriate if $\mathbf{y}$ and $\mathbf{z}^u$ represented distinct output quantities of utility bearing goods becomes problematic in attempting to represent tradeoffs between quality and quantity of services, such as those in hospitals. For example, for a given input vector $\mathbf{x}$, increasing $\mathbf{y}$ (e.g., admissions) while $\mathbf{z}^u$ (e.g., number of survivors) remains constant, or more generally increasing $\mathbf{y}$ at a faster rate than $\mathbf{z}^u$, will not necessarily increase utility. In such cases a higher number of admissions implies a higher rate of disutility per service (e.g., higher mortality rate). Hence, such a representation of a technology, with quality and quantity specified as utility bearing outputs, in general, does not support Pareto improvement with increasing outputs for given inputs, with an inability to meaningfully represent utility in quality-quantity space.[6]

Activity *per se* is not necessarily utility bearing in hospitals, health care or service industries more generally where this implies lower quality (higher disutility) per service. In health economics this has lead to notion of a derived demand for health care services, with utility from health care services argued as derived from health outcomes alone (Culyer 1992). Consequently, health outcomes alone framed from a utility bearing perspective have been proposed as output measures. Examples include use of survival as a quality variable in Puig-Junoy (1998) and more generally effects framed from a utility bearing perspective (survival,

[6] The same problem does not exist in the case where quality is an input. This is because if one holds inputs and quality (e.g., morbidity) constant and increases output (activity) one obtains a increase in survival rates.

life years, quality adjusted life years) in Dawson et al. (2005).[7] In this case the production technology in equation (1) becomes: $T=\left\{\left(\mathbf{x},\mathbf{z}^u\right)\in\mathbf{R}_+^{M+K} \mid \mathbf{x}\text{ can produce }\left(\mathbf{z}^u\right)\right\}$, This specification assumes that all effort is put into quality improvement and the underlying economic objective in the simplest case of quality represented by one effect is minimising average cost per unit of effect (e.g., minimise cost per survivor). However, minimising cost per unit effect has been rejected by many health economists for failing to reflect the incremental and non-tradable nature of effects of care (Grossman 1972; Drummond et al. 1987; Mcguire, Henderson and Mooney 1988; Weisbrod 1991; Drummond et al. 1997; Drummond et al. 2005).

As we consider in detail in section 3, maximising net benefit has been established in health care as a more appropriate objective than minimising average cost per unit of effect given these characteristics. Further, we show that application of a correspondence result permits the construction of a measure of economic efficiency that is consistent with maximising net benefit, which can be decomposed into the radial TE measure in equation (6) and an allocative efficiency component. In addition, we outline how shadow price measures for quality variables can be derived using this method.

v) Quality as an exogenous factor

One simple option is to assume that the level of quality in each hospital is exogenously determined in some manner, and then introduce these quality variables as ways of explaining differences in observed levels of efficiency. For example, in the study of Zuckermann (1994) hospitals with standardised mortality rates in either the lower or upper decile (highest or

[7] Strong disposability in bad outputs implies that if the point $(\mathbf{x}_1,\mathbf{y}_1,\mathbf{z}_1)$ is feasible, then so too is any point $(\mathbf{x}_1,\mathbf{y}_2,\mathbf{z}_2)\le(\mathbf{x}_1,\mathbf{y}_1,\mathbf{z}_1)$. Alternatively, weak disposability in bad outputs implies that if the point $(\mathbf{x}_1,\mathbf{y}_1,\mathbf{z}_1)$ is feasible, then so too is any point $(\mathbf{x}_1,\alpha\mathbf{y}_2,\alpha\mathbf{z}_2)$, where $0\le\alpha\le1$. The former implies the latter but the converse need not apply.

lowest quality of care respectively) had their costs adjusted in comparison to hospitals in the tenth to ninetieth percentile. However, this exogenous modelling of standardised mortality as a quality variable resulted in both the highest and lowest quality providers having their performance (expected relative to actual costs at their level of mortality) increased relative to other providers. In general, exogenous specification of quality variables has a number of drawbacks, such as (i) implying that managers in hospitals have no control over quality levels; (ii) an inability to properly model the resource implications of changes in quality; and (iii) the resulting model does not allow one to derive shadow price measures for quality. Hence, an endogenous rather than exogenous specification of quality variables is suggested.

3. Methodology

Net benefit as the underlying objective in health care

Concerns about specifying quality in efficiency measures so as to create appropriate economic incentives relate to the appropriateness of the underlying objective function that efficiency measures represent. Many health economists have stressed the importance of evaluating strategies relative to a comparator and informing decision makers of incremental rather than average cost–effectiveness ratios (Drummond et al. 1987; Australian Department of Health and Aged Care 1993; Ministry of Health of Ontario 1994; Drummond et al. 1997; National Institute of Clinical Excellence 2001; Drummond et al. 2005). This rejection of average cost effectiveness ratios in favour of incremental cost effectiveness ratios is based on the incremental and non-tradable nature of health effects of care in treated populations (McGuire et al. 1988, p.32; Eckermann 2004, pp.134-135).

Considering incremental health effects relative to the incremental cost of alternative strategies in processes of health technology assessment was suggested by Claxton and Posnett (1996) as being equivalent to maximizing the net value of incremental effects of a technology at a threshold willingness to pay (WTP) for effects minus incremental costs. Stinnett and Mullahy (1998) and Zehrhaus and Tambour (1998) describe this net value of incremental effects less incremental costs for a strategy relative to a comparator as incremental net benefit. Formally, incremental net monetary benefit (*INMB*) per patient can be represented for a particular strategy, relative to a comparator (*c*), as:

$$INMB = k(E - E_c) - (C - C_c)\ , \tag{11}$$

where k represents a threshold value per unit of effect, E is effect per patient, and C is cost per patient. The maximisation of net benefit has consequently become established in health technology assessment as the objective underlying public decision making in comparing alternative health care strategies allowing for costs and effects of care.

More generally, Graham (1992) provides a formal justification of the net benefit criteria, outlining necessary and sufficient conditions for Pareto efficient public expenditure under uncertainty, where the threshold value k represents the minimum marginal cost of producing a unit of effect given current technology and resources (budget). Hence, if efficiency measurement for services, such as those provided by a hospital, are to align with Pareto efficient solutions, an objective function for including effects in efficiency measurement involving the maximisation of net benefit following Graham (1992) is suggested.

Measuring economic efficiency consistent with maximizing net benefit

We would like economic efficiency measures across health care providers, such as hospitals, to be consistent with maximising net benefit so as to provide incentives supporting Pareto efficiency. However, while the net benefit formulation in equation (11) represents an objective which can appropriately trade off the value of incremental effects and costs of (quality of) care, it does not lend itself to the types of efficiency measurement methods described earlier. We now provide a transformation which can link these concepts.

First, we assume that providers face a common comparator (in practice this means costs and effects should be adjusted across providers for differences in patient population risk factors such as age) and hence in a comparison across providers the objective becomes to maximise:

$$NMB = kE - C \tag{12}$$

Next we translate the utility enhancing effect (E) per patient into a utility reducing effect (z) via a linear transformation of the form: $z = \alpha - E$, where α is an appropriate constant. For example, if E is survival, then z is mortality and α is 1, while if E is life years, then z is life years lost and α is maximum life-years. Thus equation (12) becomes:

$$NMB = k(\alpha - z) - C = k\alpha - kz - C\,. \tag{13}$$

Given that k and α are constants (the same for every provider compared), the maximization of NMB in equation (13) is equivalent to the minimization of $kz + C$, which we will call *quality inclusive cost* (QIC). Furthermore, given that we potentially have multiple input variables and multiple quality variables (each of which should be included to ensure coverage of effects consistent with net benefit), we can rewrite $kz + C$ as:

$$QIC = \mathbf{v}'\mathbf{z} + \mathbf{w}'\mathbf{x}\,, \tag{14}$$

where $\mathbf{w} \in \mathbf{R}_{+}^{K}$ is a vector of k=1,2,...,K input prices for traditional inputs $\mathbf{x}$, and $\mathbf{v} \in \mathbf{R}_{+}^{S}$ is a vector of s=1,2,...,S quality prices, for quality variables (framed from a disutility perspective). Finally, we drop the per-patient assumption associated with equation (11) and replace it with the assumption that the calculation is for a given bundle of services that the provider produces (i.e., the vector of outputs, $\mathbf{y}$). Using the technology and notation defined earlier, we obtain the point of minimum quality inclusive cost as:

$$QIC(\mathbf{y},\mathbf{x},\mathbf{z}) = \min_{\mathbf{x},\mathbf{z}} \left\{ \mathbf{w}'\mathbf{x} + \mathbf{v}'\mathbf{z} \mid \left(\mathbf{x},\mathbf{y},\mathbf{z}\right) \in T \right\}. \tag{15}$$

This relationship provides a multi-output, multi-quality generalisation of the net benefit correspondence theorem in Eckermann (2004).

A generalised net-benefit correspondence theorem

There is a one-to-one correspondence between maximising the net benefit of a bundle of services, and minimising quality inclusive cost of that service bundle, ($\mathbf{w}'\mathbf{x}$) plus the value of effects framed from a utility reducing perspective ($\mathbf{v}'\mathbf{z}$), where the following conditions are satisfied:

(i) The vector of quality variables framed from a disutility perspective (**z**) covers effects included in net benefit (coverage condition);

(ii) Expected differences in costs and effects due to exogenous factors are adjusted for (common comparison condition).

Applying the net benefit correspondence to efficiency measurement

The net benefit correspondence theorem provides a general method for comparing the efficiency of providers that is consistent with an economic objective of maximizing net benefit. Net benefit is maximised when quality inclusive cost is minimised.

One can then define an economic efficiency measure as:

$$EE(\mathbf{y},\mathbf{x},\mathbf{z}) = \frac{QIC(\mathbf{y},\mathbf{x},\mathbf{z})}{\mathbf{w}'\mathbf{x}+\mathbf{v}'\mathbf{z}}, \tag{16}$$

which is the ratio of minimum *QIC* to observed *QIC*. This EE measure will take a value between zero and one, with a value of one indicating full economic efficiency.

One can also decompose this economic efficiency measure into technical and allocative components. For example, one could use TE_6 as a measure of technical efficiency and then obtain a measure of allocative efficiency in a residual manner as:

$$AE(\mathbf{y},\mathbf{x},\mathbf{z}) = \frac{EE(\mathbf{y},\mathbf{x},\mathbf{z})}{TE_6(\mathbf{y},\mathbf{x},\mathbf{z})}. \quad (17)$$

The *TE* and *AE* measures also take a value between zero and one.

These measures can be illustrated by considering the simple example in Figure 3, which is a generalisation of the example in Figure 2. In this new figure we have inserted an iso-cost line which has slope equal to –w/*v* (which reflects the relative prices of the traditional inputs and of the quality effects).[8] For firm *D*, minimum *QIC* is obtained at point *C*, which is the point of tangency between the iso-cost line and the isoquant.[9] Technical efficiency is equal to the ratio $TE = 0D_6 / 0D$. Economic efficiency and allocative efficiency can also be obtained using ratios in this diagram. That is, $EE = 0H / 0D$ and $AE = 0H / 0D_6$.[10]

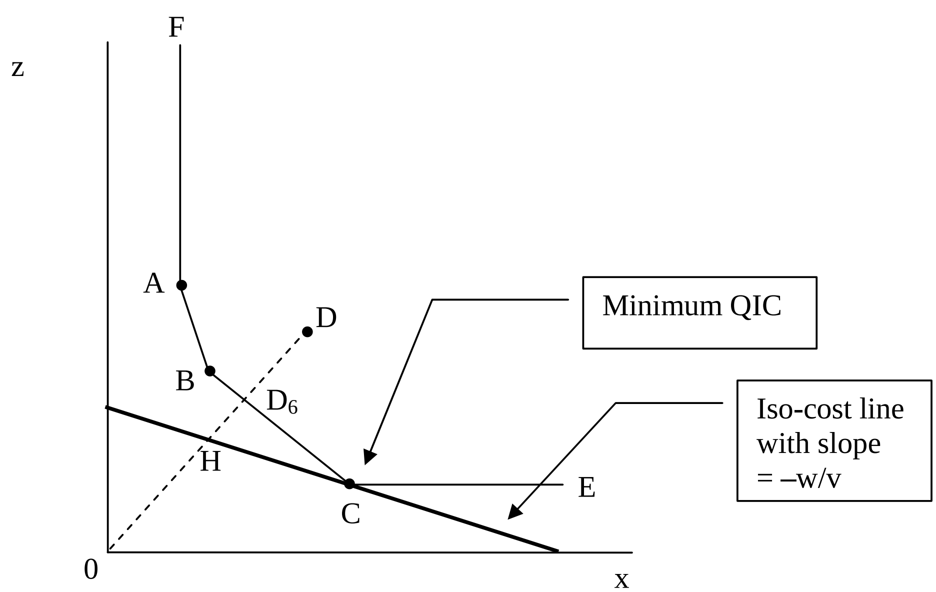

Figure 3: Efficiency decomposition

[8] To be precise, we should call this line an iso-*QIC* line, since quality variables are included in the input vector. However, to reduce the introduction of too much additional terminology, we use the iso-cost terminology, which is a widely used term.

[9] An iso-cost line closer to the origin will not be feasible because it does not intersect the technology. Alternatively, a higher iso-cost line will intersect with feasible points in the technology but will imply a higher QIC.

[10] The logic behind these ratios can be seen by noting that one could draw additional iso-cost lines through points D_6 and D.

It is important to note that being on the efficiency frontier in Figure 3 is a necessary but not sufficient condition for net benefit maximization. For example, if the provider operating at point *B* faced the relative prices reflected in the given iso-cost line, it is clear that even though it is technically efficient, it has economic inefficiency because it does not minimise *QIC* and hence does not maximize net benefit.

Implicit value of quality (shadow price)

In Figure 3, provider *C* is operating at a point of minimum *QIC*, given the specified price ratio (reflected in the slope of the iso-cost line). However, providers *A*, *B* and *D* are judged as being allocatively inefficient, if they also faced this price ratio. For each provider one could ask the question: What price ratio would lead one to conclude that this provider is allocatively efficient? The subsequent price ratio obtained for a particular provider is said to be an estimate of its *shadow price ratio* (w^s / v^s). For example, for the case of provider *D* in Figure 3, the shadow price ratio would be negative of the slope of the line *BC*. In the event that one has information on the price of the input, *w* (e.g., this could be nursing labour), and one assumes that the shadow price and observed price of this input coincide, then one can then easily calculate an estimate of the *shadow price of quality*, as $v^s = w/(w^s / v^s)$. Hence, the shadow price for quality can be estimated in the absence of prices for admission for individual providers or similarly for an indicative industry provider with average industry costs and outcomes.[11]

The above discussion of shadow price calculation has been presented in terms of the simple example in Figure 3. The calculation of shadow prices in cases where the model contains multiple input variables (e.g., nurses, doctors, equipment, etc.) and multiple quality variables

[11] Eckermann (2004) also illustrates that an ‘industry’ shadow price can be alternatively estimated as the value where cost share weighted industry allocative, or equivalently economic, efficiency is maximized (noting that technical efficiency is invariant to changes in values).

(e.g., mortality, infection, etc.) is also straight forward. In the situation where the frontier is calculated using a parametric method, derivative calculations are involved. For example, see Grosskopf et al (1995). Alternatively, when a non-parametric frontier estimation method is used, such as the data envelopment analysis (DEA) method used in this study, the calculation of the shadow prices are obtained as a by-product of the linear programs involved. For example, see Coelli et al (2005, p163).

Estimation of the frontier technology

The efficiency scores and shadow price measures described above can be calculated when one has obtained an estimate of the frontier technology. There are various methods that can be used to estimate a frontier technology. These methods can be generally grouped into one of two categories: parametric methods (such as stochastic frontier analysis or SFA) and non-parametric methods (such as DEA). These different methods have particular advantages and disadvantages. For example, DEA has the advantage that one does not need to assume a particular functional form for the technology (such as Cobb-Douglas), while SFA has the advantage that the issue of data noise is explicitly addressed. In this study we have chosen to use the DEA method because it is easy to implement and widely applied in health sector studies (e.g., see Hollingsworth 2003). The DEA methods used in this paper are equivalent to the technical efficiency and cost efficiency DEA linear programs listed in efficiency measurement books such as Färe et al (1994) or Coelli et al (2005).

4. Application to acute care hospitals

In this section we analyse the performance of 45 Australian acute care public hospitals in the State of New South Wales, Australia, with respect to treating patients for DRG E62a (respiratory infection). The comparison is based on 1998-99 cost and admission data provided by the Australian National Hospital Cost Data Collection (NHCDC) as part of the annual sample used to construct DRG weights (Australian Government Department of Health and Aged Care 2000), along with data on in-hospital mortality rate provided by the New South Wales Health Department. The average costs per admission and mortality rates for these forty-five hospitals (in treating patients for DRG E62a) are plotted in Figure 4, with cost per admission on the vertical axis and mortality rate on the horizontal axis. Summary statistics are also provided in Table 1, where we observe that the mean number of admissions per year is 63, with an average cost of $6,332 and an average mortality rate of 22%.

It is important to emphasise that the application in this section has been intentionally simplified so as to more clearly illustrate the new methods.[12] In this empirical example there is just one output variable (patients admitted with this type of respiratory infection), one quality variable (mortality) and one input variable (cost). Various simplifying assumptions are made in our study. First, we implicitly assume that there are no economies of scope between this output and other outputs in the hospitals (e.g., hip replacement surgery). Second, in order to allow us to plot the estimated frontier in two dimensions, we assume a constant returns to scale technology. Third, we make use of a single aggregate input variable, namely cost. This will be appropriate if all hospitals face similar prices for all inputs (e.g., nursing labour, medicines).[13] Fourth, we assume that all hospitals admit patients with similar distributions of risk factors (e.g., age, co-morbidities).

[12] The method can be implemented without these simplifications, however in our assessment the extra detail would make the illustration less informative.
[13] It should also be noted that any measures of "technical efficiency" calculated may also contain a component of allocative efficiency if a hospital does not combine (traditional) inputs in optimal proportions given the prevailing price ratios.

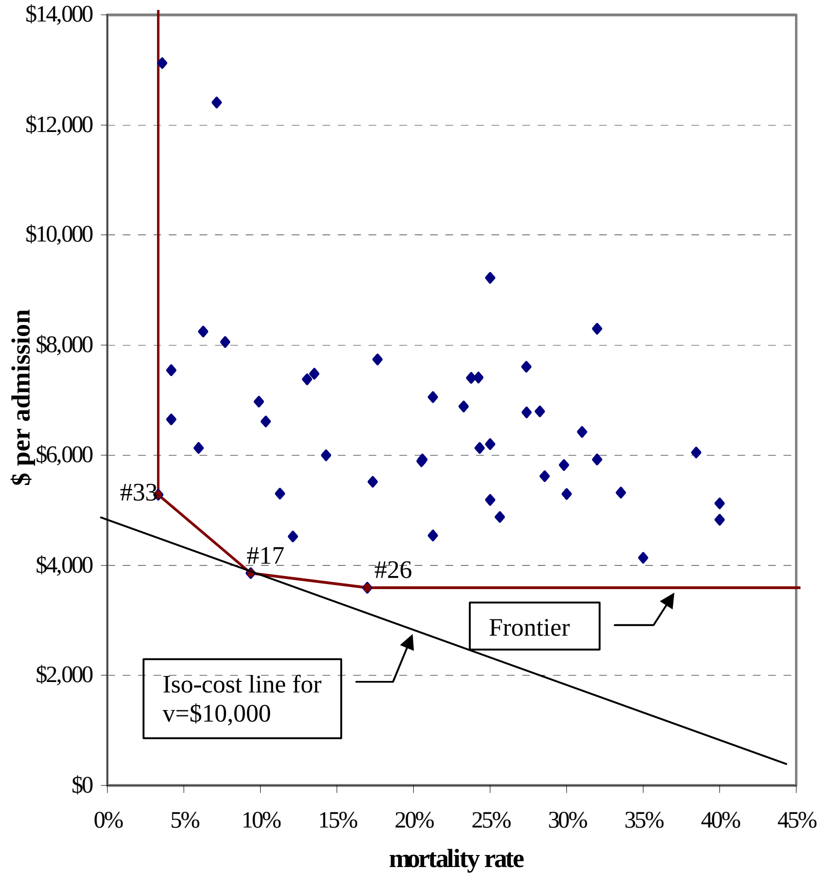

Figure 4: Efficiency measurement for DRG E62a

In Figure 4, the DEA frontier is plotted, along with an iso-cost line that corresponds to a price of *v*=$10,000. Given the simplified nature of the empirical example, the frontier in this case can be represented using a unit isoquant in two dimensions. The frontier is defined by hospitals, 33, 17 and 26. These hospitals are technically efficient, in the sense that one cannot proportionally reduce the input variables (cost and quality indicator variable) and still remain within the estimated frontier. For the given iso-cost line, hospital 17 is economically efficient, in the sense that quality inclusive cost (*QIC*) per admission is minimised,[14] while all other hospitals are economically inefficient because they could potentially reduce their *QIC* per admission.

[14] Refer to equation (15).

Economic efficiency (EE) measures, obtained using equation (16), are listed in Table 2 for each hospital, for four different values of *v*: \$0, \$10,000, \$25,000 and \$50,000 per mortality avoided. Looking first at the case of *v*=\$10,000, we observe that hospital 17 has an EE score of 1 as expected. The sample average EE score is 0.57, suggesting that the average hospital could reduce QIC by 43% per admission. The ranks indicate that hospital 14 is the least efficient, with an efficiency score of 0.27, implying a potential 73% reduction in QIC.

In some instances, efficiency levels can vary with hospital size. For example, smaller hospitals in regional locations may have low capacity utilization in some periods.[15] If this was the case, a simple raw average measure may provide a misleading indication of the level of efficiency in the industry. As a consequence, we have also reported weighted means, where the weights are either number of admissions or total costs. However, the values obtained differ from the unweighted mean by no more than a few percentage points, suggesting that this is not a big factor in this case.

As noted earlier, Table 2 contains EE scores corresponding to four different values of *v*. A value of *v*=\$0 implies that quality has no value. This can be visualised as being equivalent to inserting a vertical iso-cost line in Figure 4. In this case hospital 26 has the highest EE and mean EE is essentially unchanged at 0.57. When *v* values of \$25,000 and \$50,000 are considered, the iso-cost line becomes flatter, so that hospital 33 has the highest EE and mean EE drops to 0.55 and 0.45, respectively. The rankings of the frontier hospitals (17, 26 and 33) do not change substantially as the value of *v* changes, but for some hospitals there are substantial changes. For example, as *v* increases, the rank of hospital 7 increases from 3rd to

[15] Also note that since constant returns to scale (CRS) has been imposed on the production technology in this empirical illustration, if scale economies do exist, one could find that efficiency levels may vary with hospital size for this reason as well.

39th while that of hospital 11 decreases from 37th to 5th. This makes clear that if quality is ignored in the efficiency analysis, when the true value of quality is say $50,000, per mortality prevented one can obtain very misleading relative efficiency measures and rankings.

The economic efficiency (EE) measures in Table 2 can be decomposed into technical efficiency (TE) and allocative efficiency (AE) components, by calculating TE using equation (8) and then calculating AE in a residual manner using equation (17). These measures are reported in Table 3, for the case of *v*=$25,000. The results indicate that TE is the main contributor to EE, with a mean of 0.66 for TE versus a mean of 0.85 for AE. The value of 0.85 suggests that, if the average hospital was technically efficient (operating on the frontier), it could reduce QIC by a further 15% if it were to use an optimal mix of inputs (traditional inputs and quality measures) given the specified price ratios. These additional savings would not have been identified if a value was not assigned to quality.

The importance of assigning a value to quality, instead of focusing on technical efficiency or average cost effectiveness (i.e., cost per survivor) is illustrated in Table 4, where we list the efficiency scores obtained using these three methods, along with the corresponding ranks. In some cases the ranks do not change a lot, while in other cases there are large changes. For example, in the case of hospital 7, the rank is 5 and 7 for TE and average C/E, respectively, while it falls to 29 when EE is considered.

Shadow prices

Analysts can use the above methods to advise policy makers regarding economic efficiency levels corresponding to different assumed values for the quality of services. However, they can also obtain estimates of the implicit value being placed on quality, as reflected in the current behaviour of providers. That is, one can derive the shadow price for quality of each provider. In this application, the shadow price of quality for each hospital can be interpreted as the amount of money needed to avoid one mortality if it were technically efficient.[16]

Estimated shadow prices are listed in Table 5. These shadow prices differ according to which part of the frontier the hospital is projected onto. For individual hospitals they range from $0 (where hospitals are projected onto the horizontal part of the frontier with hospital 26 as the only peer)[17] to more than $24,356 (i.e., arbitrarily large) where hospitals are projected onto the vertical portion of the frontier, with hospital 33 as the only peer. An estimate of the industry-level shadow price for quality is found to be $3,523 per death avoided, calculated at the median cost and mortality rate across hospitals (see in Table 5). This industry shadow price for quality may appear low. However, given that hospital administrators generally face strong budgetary pressure to minimise cost per admission, with only indirect (e.g. social) pressures to seek quality outcomes, it is not surprising to find a shadow price which is not far from the zero price that would result from quality incentives being completely absent. Such shadow prices of quality cannot be estimated with output specifications of quality variables in the absence of prices for admissions in public hospitals.

Correspondence conditions

Application of the net benefit correspondence theorem has been presented illustratively with the explicit assumption that coverage and comparability conditions are satisfied. Satisfying the comparability condition in practice would require that costs and effects across hospitals are adjusted for differences in patient risk factors. Satisfying the coverage condition in practice would require that the scope of measured effects was widened and effects and costs

[16] Shadow prices are derived from the slope of the estimated frontier and hence are estimates that (to be precise) only correspond to a firm that is operating on the frontier itself. Hence, for technically inefficient firms, these measures would be applicable if they became technically efficient.
[17] A "peer" hospital is one which is used to the frontier for a particular inefficient firm. An inefficient firm can have one or more peers, depending on the point of projection onto the estimated frontier.

~~point~~ beyond point of separation were accounted for, either directly with data linkage (Holman et al.1999; Wolfson et al. 2002) or by modelling expected costs and effects conditional on patient health state at point of separation (Weinstein at al. 1980; Petitti 2000; Hunink et al. 2001; Eckermann 2004). Eckermann (2004, 2006) demonstrates that satisfying these comparability and coverage conditions are necessary and sufficient to prevent efficiency measures creating incentives for choosing less complex patients (cream-skimming) and cost (and outcome) shifting. Hence, the empirical findings in the illustration should be qualified to the extent they fail to adjust for differences in patient risk and effects beyond separation and hence create incentives for cream-skimming and cost-shifting, respectively. However, whatever specification of quality were used, satisfying coverage and comparability conditions would be required to avoid the cream-skimming and cost-shifting incentives that plague efficiency measures in health care.

5. Conclusions

The maximisation of net benefit is an appropriate economic objective where societal value of quality is an important consideration in areas such as health, public services and environmental economics (Graham 1981, 1992; Claxton and Posnett 1996; Stinnett and Mullahy 1998; Zehrhaus and Tambourne 1998; Willan and Lin 2001; Drummond et. al. 2005; Willan and Briggs 2006; Eckermann, Briggs and Willan 2008).[18] The objective of this paper has been to clarify the use of quality variables in efficiency measures to reflect (and create) economic incentives for appropriate quality of care, and in particular identify a method for comparing the economic efficiency of providers consistent with maximising net benefit.

[18] Cost-shifting and cream skimming are also important considerations in creating incentives for appropriate quality of care in health and public service industries.

A method that enables quality variables to be incorporated into standard efficiency measurement methods, which is consistent with maximising net benefit, has been identified and its application illustrated. The input specification of quality effects framed from a utility reducing (disutility) perspective has been shown to, unlike alternative specifications, allow:

1. estimation of economic efficiency, and its decomposition into technical and allocative efficiency, consistent with maximising net benefit and;
2. estimation of the shadow price for quality of care, in the absence of prices for services *per se*, such as admissions in hospital.

Input specifications for quality variables have previously been applied to estimate technical efficiency in health (Morey 1992), as well as in environmental and other areas (Giannakis, Jamasb and Pollitt (2005) in electricity and Reinhard, Lovell and Thijssen (1999)). However, the additional advantages of allowing economic (and allocative) efficiency measures consistent with maximising net benefit and shadow prices in the absence of prices for outputs have not been previously noted.

Consequently, the methods presented offer a general framework for performance measurement to reflect and hence create incentives for net benefit maximising quality of services. The methods have been illustrated in comparison of hospitals, but are suggested to be appropriate wherever maximisation of net benefit is an appropriate objective, or equivalently where societal value of quality is an important consideration. The proposed framework and method illustrated in this paper could, for example, be analogously applied to pollution abatement in industrial or agricultural settings, where efficiency measures that are consistent with maximising net benefit are desirable.

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Table 1: Summary Statistics

	Admissions	Cost per admission	Mortality rate
mean	63	$6,332	22.42%
std dev	49	$1,851	10.56%
minimum	10	$3,590	3.33%
maximum	184	$13,128	40.00%

Table 2: Economic efficiency conditional on threshold value of death avoided

Hospital	**$0**	**rank**	**$10,000**	**rank**	**$25,000**	**rank**	**$50,000**	**rank**
1	0.74	7	0.54	29	0.41	41	0.28	44
2	0.39	43	0.41	43	0.4	43	0.32	40
3	0.45	40	0.54	28	0.61	15	0.58	12
4	0.29	44	0.37	44	0.43	39	0.43	22
5	0.7	8	0.53	31	0.4	42	0.28	43
6	0.44	41	0.54	27	0.62	14	0.61	8
7	***0.87***	***3***	***0.63***	***13***	***0.47***	***29***	***0.32***	***39***
8	0.6	20	0.65	10	0.64	11	0.53	13
9	0.49	33	0.55	24	0.57	16	0.5	14
10	0.54	27	0.68	8	0.8	5	0.8	3
11	***0.48***	***37***	***0.6***	***18***	***0.71***	***8***	***0.72***	***5***
12	0.43	42	0.42	42	0.38	45	0.29	42
13	0.59	23	0.48	40	0.39	44	0.27	45
14	0.27	45	0.36	45	0.44	37	0.47	17
15	0.54	26	0.63	12	0.66	9	0.59	9
16	0.58	24	0.55	23	0.49	25	0.37	28
17	**0.93**	**2**	**1**	**1**	**0.99**	**2**	**0.81**	**2**
18	0.48	36	0.49	39	0.45	34	0.36	30
19	0.79	5	0.84	4	0.81	3	0.66	6
20	0.59	22	0.56	21	0.5	23	0.38	27
21	0.48	35	0.54	26	0.56	18	0.49	16
22	0.74	6	0.64	11	0.54	20	0.39	25
23	0.61	19	0.6	17	0.56	17	0.43	21
24	0.68	12	0.58	19	0.48	28	0.34	34
25	0.79	4	0.72	6	0.62	13	0.46	18
26	**1**	**1**	**0.91**	**2**	**0.78**	**6**	**0.58**	**11**
27	0.59	21	0.71	7	0.8	4	0.76	4
28	0.46	39	0.5	37	0.5	22	0.43	20
29	0.68	11	0.75	5	0.75	7	0.64	7
30	0.61	18	0.53	30	0.44	36	0.32	38
31	0.65	14	0.66	9	0.62	12	0.49	15
32	0.53	29	0.5	36	0.45	33	0.34	33
33	**0.68**	**10**	**0.85**	**3**	**1**	**1**	**1**	**1**
34	0.51	32	0.6	16	0.65	10	0.58	10
35	0.48	34	0.49	38	0.46	31	0.36	29
36	0.69	9	0.62	14	0.53	21	0.39	24
37	0.62	16	0.54	25	0.46	30	0.34	32
38	0.52	30	0.52	33	0.48	27	0.38	26
39	0.56	25	0.5	35	0.43	38	0.32	37
40	0.61	17	0.6	15	0.55	19	0.43	19
41	0.64	15	0.57	20	0.48	26	0.35	31
42	0.51	31	0.52	32	0.49	24	0.39	23
43	0.67	13	0.55	22	0.45	32	0.31	41
44	0.47	38	0.46	41	0.42	40	0.33	36
45	0.53	28	0.5	34	0.44	35	0.33	35
Mean	**0.57**		**0.57**		**0.55**		**0.45**	
Admis. wtd	**0.59**		**0.58**		**0.54**		**0.43**	
Cost wtd	**0.57**		**0.56**		**0.51**		**0.40**	

Table 3: Technical, allocative and economic efficiency

Hospital	TE	AE (k=$25000)	EE (k=$25000)
1	0.74	0.55	0.41
2	0.41	0.98	0.40
3	0.61	1.00	0.61
4	0.47	0.91	0.43
5	0.70	0.57	0.40
6	0.62	1.00	0.62
7	***0.87***	***0.54***	***0.47***
8	0.65	0.98	0.64
9	0.58	0.98	0.57
10	0.80	1.00	0.80
11	***0.80***	***0.89***	***0.71***
12	0.44	0.86	0.38
13	0.59	0.66	0.39
14	0.93	0.47	0.44
15	0.67	0.99	0.66
16	0.59	0.83	0.49
17	**1.00**	**0.99**	**0.99**
18	0.51	0.88	0.45
19	0.85	0.95	0.81
20	0.60	0.83	0.50
21	0.57	0.98	0.56
22	0.74	0.73	0.54
23	0.63	0.89	0.56
24	0.68	0.71	0.48
25	0.79	0.78	0.62
26	**1.00**	**0.78**	**0.78**
27	0.80	1.00	0.80
28	0.51	0.98	0.50
29	0.76	0.99	0.75
30	0.61	0.72	0.44
31	0.68	0.91	0.62
32	0.54	0.83	0.45
33	**1.00**	**1.00**	**1.00**
34	0.65	1.00	0.65
35	0.51	0.90	0.46
36	0.69	0.77	0.53
37	0.62	0.74	0.46
38	0.54	0.89	0.48
39	0.56	0.77	0.43
40	0.63	0.87	0.55
41	0.64	0.75	0.48
42	0.54	0.91	0.49
43	0.67	0.67	0.45
44	0.49	0.86	0.42
45	0.54	0.81	0.44
Mean	**0.66**	**0.85**	**0.55**
Admis. wtd	**0.64**	**0.84**	**0.54**
Cost wtd	**0.63**	**0.82**	**0.51**

Table 4: Comparing TE, EE and average cost effectiveness

Hospital	TE	rank	EE (k=$25000)	rank	Average C/E	rank
1	0.74	12	0.41	41	0.53	21
2	0.41	45	0.4	43	0.35	42
3	0.61	27	0.61	15	0.49	28
4	0.47	43	0.43	39	0.32	44
5	0.70	14	0.40	42	0.50	26
6	0.62	25	0.62	14	0.48	31
7	***0.87***	***5***	***0.47***	***29***	***0.67***	***7***
8	0.65	20	0.64	11	0.61	12
9	0.58	32	0.57	16	0.50	26
10	0.80	7	0.80	5	0.61	12
11	***0.80***	***7***	***0.71***	***8***	***0.54***	***19***
12	0.44	44	0.38	45	0.35	42
13	0.59	30	0.39	44	0.43	40
14	0.93	4	0.44	37	0.31	45
15	0.67	18	0.66	9	0.58	14
16	0.59	30	0.49	25	0.52	24
17	**1.00**	**1**	**0.99**	**2**	**1.00**	**1**
18	0.51	39	0.45	34	0.44	38
19	0.85	6	0.81	3	0.83	3
20	0.60	29	0.50	23	0.53	21
21	0.57	33	0.56	18	0.49	28
22	0.74	12	0.54	20	0.65	8
23	0.63	23	0.56	17	0.57	15
24	0.68	16	0.48	28	0.56	17
25	0.79	10	0.62	13	0.74	5
26	*1.00*	*1*	*0.78*	*6*	*0.98*	*2*
27	0.80	7	0.80	4	0.65	8
28	0.51	39	0.50	22	0.45	36
29	0.76	11	0.75	7	0.71	6
30	0.61	27	0.44	36	0.49	28
31	0.68	16	0.62	12	0.64	10
32	0.54	35	0.45	33	0.46	34
33	**1.00**	**1**	**1.00**	**1**	**0.78**	**4**
34	0.65	20	0.65	10	0.55	18
35	0.51	39	0.46	31	0.44	38
36	0.69	15	0.53	21	0.62	11
37	0.62	25	0.46	30	0.51	25
38	0.54	35	0.48	27	0.47	32
39	0.56	34	0.43	38	0.46	34
40	0.63	23	0.55	19	0.57	15
41	0.64	22	0.48	26	0.54	19
42	0.54	35	0.49	24	0.47	32
43	0.67	18	0.45	32	0.53	21
44	0.49	42	0.42	40	0.41	41
45	0.54	35	0.44	35	0.45	36
Mean	**0.66**		**0.56**		**0.55**	
Admis. wtd	**0.64**		**0.54**		**0.54**	
Cost wtd	**0.63**		**0.51**		**0.52**	

Table 5: Shadow prices

Hospital	Cost per admission	Mortality rate	Peers	Shadow price
1	4,830	40.00%	26	$0
2	9,224	25.00%	26, 17	$3,523
3	8,056	7.69%	17, 33	$24,356
4	12,409	7.14%	33	>$24356
5	5,123	40.00%	26	$0
6	8,249	6.25%	17,33	$24,356
7	***4,138***	***35.00%***	***26***	***$0***
8	6,000	14.29%	17, 33	$24,356
9	7,382	13.04%	17, 33	$24,356
10	6,649	4.17%	33	>$24,356
11	***7,545***	***4.17%***	***33***	***>$24,356***
12	8,301	32.00%	26, 17	$3,523
13	6,052	38.46%	26	$0
14	13,128	3.57%	33	>$24,356
15	6,616	10.34%	17, 33	$24,356
16	6,199	25.00%	26, 17	$3,523
17	**3,858**	**9.38%**	**None**	**$3523 to $24356**
18	7,411	24.24%	26, 17	$3,523
19	4,520	12.12%	26, 17	$3,523
20	6,134	24.32%	26, 17	$3,523
21	7,484	13.51%	17, 33	$24,356
22	4,878	25.64%	26	$0
23	5,890	20.51%	26, 17	$3,523
24	5,296	30.00%	26	$0
25	4,543	21.28%	26, 17	$3,523
26	**3,590**	**16.98%**	**None**	**$0 to $3,523**
27	6,132	5.97%	17, 33	$24,356
28	7,744	17.65%	17, 33	$24,356
29	5,302	11.27%	17, 33	$24,356
30	5,920	32.00%	26	$0
31	5,518	17.33%	26, 17	$3,523
32	6,779	27.38%	26, 17	$3,523
33	**5,283**	**3.33%**	**None**	**$24,356 or more**
34	6,977	9.89%	17, 33	$24,356
35	7,407	23.76%	26, 17	$3,523
36	5,189	25.00%	26	$0
37	5,820	29.82%	26	$0
38	6,887	23.28%	26, 17	$3,523
39	6,424	31.01%	26	$0
40	5,921	20.59%	26, 17	$3,523
41	5,618	28.57%	26	$0
42	7,057	21.28%	26, 17	$3,523
43	5,324	33.55%	26	$0
44	7,605	27.37%	26, 17	$3,523
45	6,797	28.26%	26, 17	$3,523
Industry*	6,134	21.28%	**26, 17**	**$3,523**

* The Industry figures are medians.