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Hospital Performance Evaluation in Uganda: A Super-Efficiency Data Envelope Analysis Model

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Standard Data Envelope Analysis models result in a large fraction of the observations becoming 100 percent efficient. The article measures the technical efficiency of 25 district referral hospitals from three regions of Uganda over the 1999-2003 period. It applies a super-efficiency Data Envelopment Analysis model. The application of a super-efficiency model was occasioned by the failure of standard data envelopment analysis models to rank the efficient set of hospitals which attain an efficiency score of unity. The results of the standard data envelopment analysis models indicate the existence of different degrees of technical and scale inefficiency in Uganda's district referral hospitals. With the super-efficiency model, a ranking of the efficient units is possible. When super-efficiency models are executed, hospitals can be ranked and categorised into four groups: strongly super-efficient; super-efficient; efficient and inefficient.

1. Introduction[1]

Since the early 1980s, Data Envelopment Analysis (DEA) has been used as an alternative method of classification to evaluate the relative efficiency of independent homogenous units which use the same inputs to produce the same outputs (Cooper, Seiford and Tone, 2000). However, a serious inconvenience in the utilisation of DEA as a method of classification is the possibility of having units tied with relative efficiency equal to 100 percent. That is, units at the frontier of relative efficiency. Various authors have tackled this inconvenience using various devices to break the tie, such as crossed evaluation (Green et al., 1996), super-efficiency (Anderson and Peterson, 1993) or assurance regions (Cooper et al., 2000), among others. Based on the super-efficiency ranking method of Anderson and Peterson (1993), which ranks only the efficient units, Hadad et al. (2003), have recently developed a super efficiency multi-stage ranking which ranks the inefficient units using a similar procedure at each stage.

Ranking organisational units in the context of DEA has become an acceptable approach as done in Multi-Criteria Decision Analysis (MCDA) (see for example Belton and Stewart (1999) and Green and Doyle (1995)). Using the availability of a model in commercial software as an indication of its popularity, then the super-efficiency ranking method developed by Anderson and Peterson (1993) is the

most widespread ranking method.

Ranking is a well established approach in the social sciences (Young and Hammer, 1987). It is historically much more established than the dichotomic classification of DEA to efficient and inefficient organisational units (Adler et al., 2002). Rank scaling in the DEA context has become well established in the last decade. Sexton (1986) was the first to introduce full rank scaling of organisational units in the DEA context, by utilising the Cross-Efficiency Matrix. Anderson and Peterson (1993) developed the super efficiency approach for rank-scaling that was followed by other researchers. The ranking in relation to rank-scaling has the advantage that it can be tested statistically by nonparametric analysis (Friedman and Sinuany-Stern, 1997; Sinuany-Stern and Friedman, 1998; and Sueyoshi and Aoki, 2001).

This article seeks to demonstrate how the super-efficiency DEA model introduced by Andersen and Petersen (1993) solves the problem of standard DEA, namely that many decision making units (DMU) are rated as efficient and tie for the top position in the ranking. The super-efficiency score enables one to distinguish between the efficient observations. In particular, the super-efficiency measure examines the maximal radial change in inputs and/or outputs for an observation to remain efficient, i.e. how much can the inputs be increased (or the outputs decreased) while not become inefficient. The larger the value of the super-efficiency measure the higher an observation is ranked among the efficient units. Super-efficiency measures can be calculated for both inefficient and efficient observations. In the case of inefficient observations the values of the efficiency measure do not change, while efficient observations may obtain higher values. Values of super-efficiency are therefore not restricted to unity (for the efficient observations), but can in principle take any value greater than or equal to unity.

The rest of the article is organised as follows: we first review materials and methods in DEA. This is covered in section 2. We look at the data and modelling choices in section 3 while section 4 discusses the results of the study. The article is concluded in section 5.

2. Materials and Methods

Examining Efficiency using Standard DEA

DEA is a linear programming procedure designed to measure the relative efficiency in situations when there are multiple inputs and multiple outputs and no obvious objective function that aggregates inputs and outputs into a meaningful index of productive efficiency. DEA was developed by Charnes et al. (1978). The method provides a mechanism for measuring a DMU's efficiency compared with other DMUs. The approach has been extensively employed in diverse industries and environments (a review of DEA applications over the 1978-1995 period is provided by Seiford (1996)). A review of nonparametric methods and their applications in health care is presented in Hollingsworth et al. (1999).

Efficiency measurement begins with Farrell (1957), who drew upon the work of Debreu (1951) and Koopmans (1951) to define a simple measure of firm efficiency which could account for multiple inputs. Farrell (1957) proposed that the efficiency

of a firm consists of two components: technical efficiency, which reflects the ability of a firm to obtain maximal output from a given set of inputs, and allocative efficiency, which reflects the ability of a firm to use inputs in optimal proportions, given their respective prices and the production technology. Technical efficiency was measured by means of non-parametric DEA. A combination of technical and allocative efficiency yields a measure of total economic efficiency. In the context of health care, this implies maximum health gain for a given level of expenditure.

The three measures of efficiency, technical, allocative and economic, are bounded by zero and unity. They are measured along a ray from the origin to the observed production point. Hence, they hold the relative proportions of inputs (or outputs) constant. One merit of these radial efficiency measures is that they are units invariant. This means that changing the units of measurement (for instance, measuring the quantity of labour either in person hours as against person years) will not change the value of the efficiency measure (Coelli, 1996). The final dimension of efficiency is scale efficiency. A production unit is "scale efficient" when its size of operation is optimal. At the optimal scale, when the size of operation is either reduced or increased its efficiency will drop. A scale efficient unit is one that operates at optimal returns to scale.

The non-parametric nature of DEA is particularly suitable for analysing the technical efficiency of health care facilities since the underlying health production process is still unknown. DEA requires no assumptions as to the functional form of the production models (i.e., how inputs are converted into outputs). DEA can measure efficiency under two orientations: input orientation and output orientation. Most studies use input-oriented specifications, whereby the focus is on the minimum input usage for given output levels. Any hospital utilising more inputs to produce the same amount of outputs as compared to its peers would be deemed inefficient. Alternatively, an output-based model is used to demonstrate possible increases in outputs given fixed levels of inputs. The choice of model depends on the objective in question. The present study uses input-oriented DEA models due to the fact that hospital managers and administrators cannot influence the demand for healthcare services (dictated by the healthcare seeking behaviour of the patients) they provide, but rather the supply of healthcare services.

***The Constant Returns to Scale DEA Mode*l**

Charnes et al. (1978) propose a DEA model which had an input-orientation and assumed Constant Returns to Scale (CRS). They specify a fractional linear programme that computes the relative efficiency of each DMU by comparing it to all the other observations in the sample. Their exposition proceeds as follows:

Suppose that there is data on K inputs and M outputs on each of N firms or DMUs as they are referred to in the DEA literature. For the ith DMU these are represented by the vectors x_i and y_i, respectively. The KxN input matrix, X; and the MxN output matrix, Y; represent the data of all the DMUs. DEA constructs a non-parametric envelopment frontier over the data points such that all observed points lie on or below the production frontier.

By means of duality in linear programming, the input-oriented CRS DEA model can be specified as:

$$\begin{aligned} &\underset{\theta,\lambda}{Min\ \theta} \\ &\text{subject to;} \\ &-y_i + Y\lambda \geq 0; \\ &\theta x_i - X\lambda \geq 0 \text{ and} \\ &\lambda \geq 0 \end{aligned} \qquad (1)$$

where θ is a scalar and λ is an Nx1 vector of constants. This envelopment form entails fewer constraints than the multiplier form (K+M < N+1). It is, therefore, the generally preferable form to solve. The value of θ obtained will be the efficiency score for the ith hospital. It will satisfy $0 \leq \theta \leq 1$, with a value of 1 showing a point on the production frontier and therefore a technically efficient hospital according to Farrell's (1957) definition. It is worth noting that the linear programming problem must be solved N times, once for each hospital in the sample to yield a value of θ.

The Variable Returns to Scale DEA Model and Scale Efficiencies

The CRS assumption is only appropriate when all hospitals operate at an optimal scale. Constraints in the operating environment, for instance, imperfect competition, financial and human resource constraints, amongst other factors, may cause a hospital to operate at non-optimal scale. Banker et al. (1984) suggest an extension of the CRS DEA model to provide for Variable Returns to Scale (VRS) situations. The use of the CRS specification when not all hospitals are operating at the optimal scale will result in a measure of technical efficiency which is confounded by scale efficiency. The use of the VRS DEA specification permits the calculation of scale inefficiency.

The CRS linear programming problem can be modified to account for VRS by adding the convexity constraint: $N1'\lambda = 1$ to equation (1) where N1 is an Nx1 vector of ones (Coelli, 1996). This approach forms a convex hull of intersecting planes which envelope the data points more tightly than the CRS canonical hull and thus provides technical efficiency scores which are equal to or greater than those obtainable by means of the CRS model.

DEA Super-Efficiency Model

We introduce the super-efficiency model as a DEA approach particularly useful for hospital performance evaluation. Its discriminatory power provides insights that cannot be gained with the standard DEA model. The DEA score for the inefficient unit is considered by Andersen and Petersen (1993) as its rank scale. In order to rank scale the efficient units they allow the efficient units to receive an efficiency score greater than 100 percent by dropping the constraint that bounds the score of the evaluated unit. Apart from the constraint $\lambda_o = 0$, the optimisation problem in equation (2) denotes

the standard, input-oriented DEA model with the assumption of a variable returns to scale technology or the so-called BCC specification (Cooper, Seiford and Tone, 2000):

$$\underset{\theta,\lambda,s^+,s^-}{Min} \qquad z_o = \theta_o - \varepsilon s^+ - \varepsilon s^-$$

subject to

$$\begin{aligned} Y\lambda - s^+ &= Y_{o;} \\ \theta_o X_o - X\lambda - s^- &= 0; \\ e\lambda &= ; \\ \lambda_o &= 0 \text{ and} \\ \lambda, s^+, s^- &\geq 0 \end{aligned} \qquad (2)$$

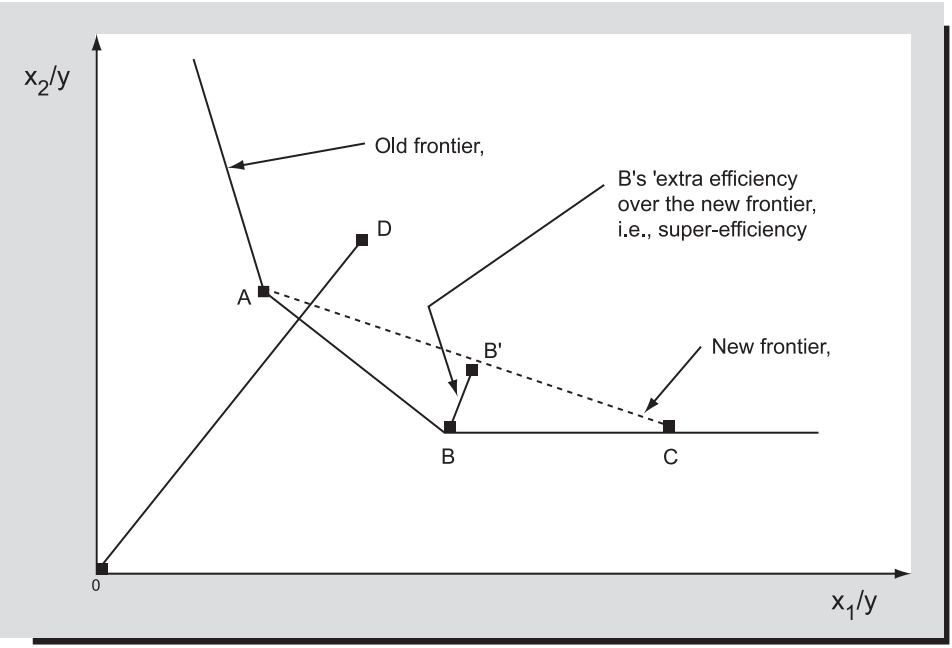
In the above problem $1 - \theta_o$ denotes the maximum proportional input reduction or radial contraction that can be attained by an inefficient hospital if it applies the same input-output transformation as the referent technology, i.e., if it produces efficiently. The efficiency score θ_o is transformed into the so-called slack-augmented score z_o by adding output slacks s^+ and input slacks s^- multiplied by ε - the non-Archimedean infinitesimal.

The efficiency score is determined by comparing actual parameter values of $hospital_o$, a k x 1 vector for inputs and an m x 1 vector Y_o for outputs to the corresponding vectors $X\lambda$ and $Y\lambda$ of the reference unit where e is an n x 1 row vector of ones and n represents the number of data points in the sample size. A standard DEA specification results when a constraint is ignored with the consequence that all efficient hospitals have a score of unity. When $\lambda_o = 0$, hospitals in the efficient set get a score that exceeds unity. This determines the factor by which the inputs of an efficient hospital can radially be expanded such that the hospital under consideration just stays efficient.

It should be noted that equation (2) may not have a feasible solution (Seiford and Zhu, 1999 and Xue and Parker, 2002) in which case the score is set to infinity, i.e., $\theta_o = \infty$. Nevertheless, the standard DEA result can always be obtained by scaling all scores $\theta_o \rangle 1$ to unity. Thus, no information is lost when making use of the super-efficiency model.

In standard DEA DMUs are identified as fully efficient and assigned an efficiency score of unity if they lie on the efficient frontier. Inefficient DMUs are assigned scores of less than unity. To illustrate, figure 1 shows four DMUs producing a single output and consuming two inputs $x_1 = x_2$. Minimum input combinations lie on the frontier connecting A, B and C, i.e., no other DMU produces the same output with a lower input combination. Unit D is dominated by the other three DMUs and produces the same output although with a higher input combination. The inefficiency of unit D can be measured by its radial distance to the frontier along the ray extending from the origin to D and intersecting the AB segment of the frontier.

Figure 1: Standard and Super-efficient DEA Input-oriented Models



Source: Author's construction

Further ranking of the efficient set of DMUs is possible by computing efficiency scores in excess of unity. Consider unit B in figure 1. If it were excluded from the frontier, a new frontier would be created comprising only units A and C. The super-efficient score for unit B is obtainable by calculating its distance to the new frontier whereby this 'extra' or 'additional' efficiency denotes the increment that is permissible in its inputs before it would become inefficient. The consequence of this modification is to allow the scores for efficient units to exceed unity. For instance, a score of 1.25 for unit B would imply that it could increase its inputs by 25 percent and still remain efficient. This so-called super-efficient model (Andersen and Petersen, 1993) is applied in the analyses using the approach described in Zhu (2003). Both standard and super-efficient DEA models have been used in the analyses described later in this article.

3. Data and Modelling Choices

We investigated the technical efficiency of district referral hospitals. As such, the unit of analysis is the district referral hospital. Twenty five district referral hospitals were drawn as follows: seven from the Eastern, eight from Western and ten from the Central regions of Uganda. These constitute the study sample. Bundibugyo district referral hospital from the Western region was left out due in part to insecurity and poor accessibility during data collection. The Northern region was

left out due to security concerns during data collection and because the operating environment of hospitals in this region is not comparable to that of their counterparts in the remaining regions. The reason for this being that the region has been insecure for the last 18 years or so and therefore including it would bias the sample. Table 1 shows the twenty five out of the thirty eight district referral hospitals in Uganda that have been covered.

Table 1: Sample District Referral Hospitals by Region

Region	Hospital
Central	Entebbe, Gombe, Kalisizo, Kawolo, Kayunga, Kiboga, Nakaseke, Mityana, Mubende and Rakai.
Eastern	Bududa, Bugiri, Busolwe, Iganga, Kapchorwa, Pallisa and Tororo.
Western	Bwera, Itojo, Kagadi, Kambuga, Kiryandongo, Kisoro, Kitagata and Masindi.

There is a conscious attempt to account for the heterogeneity of the hospital environment. The sample of hospitals is limited to district referral hospitals indicating that the 'care mix' can be assumed to be fairly comparable. The assumption is that hospitals of similar organisational form produce similar types of health care. Because the sample hospitals have the same scope of service, it is reasonable to assume homogeneity in the range of health care services they provide.

The choice of the sample size, number of inputs as well as the number of outputs was guided by the rule of thumb proposed by Banker and Morey (1989), that $n \geq 3(m+s)$, where: n is the number of DMUs included in the sample; m is the number of inputs; and s is the number of outputs included in the analysis. The rule captures two issues, sample size and number of factors [$(m+s)$]. However, Pedraja-Chaparro et al. (1999) note that the rule ignores two other issues, the distribution of efficiencies as well as the covariance structure of factors. Nevertheless, we still use the rule of thumb as a guide in the absence of any a priori view on the number of factors. A schedule containing the data needed for the study (hospital inputs as well as outputs) was constructed. The schedule was piloted on three district referral hospitals which included Nakaseke, Kayunga and Entebbe. There was a discrepancy between the initial research instrument and the Health Management Information System (HMIS) databases. After the pilot study, the schedule was adjusted to the HMIS databases.

A panel data set was assembled and a common set of input and output indicators was constructed to support the estimation of DEA models. Input as well as output data were gathered for the twenty five hospitals over the 1999-2003 period. The potential gains from using panel data to measure technical efficiency appear to be quite large. A panel obviously contains more information about a particular DMU than does a cross-section of the data.

The HMIS launched in 1997 is the source of the data for the study. However, the study concentrates on the period 1999-2003 because this period yielded a balanced panel. Data on the hospital inputs and the outputs were sought from the HMIS databases of each hospital. Twenty five out of thirty eight district referral hospitals

were selected in the regions of Western, Eastern and Central Uganda due to the decentralised delivery of healthcare services and their being conducive for data collection compared to the Northern region. Comparability of data across hospitals was ensured by a common database that all public district referral hospitals are required to submit to the District Director of Health Services on a monthly and annual basis. The HMIS captures data on a calendar year basis. Administrative data and annual reports were collected at each hospital to generate the dataset. Unfortunately, financial data on a majority of hospitals were not readily available and as a consequence, the variable total operating costs have been left out.

The specific choice input and output variables for the DEA are considered in detail further below. Data on admissions, deaths, in-patient days by ward as well as surgical operations, outpatient department attendances were collected from the Hospital Annual Reports. In-hospital mortality was used to account for quality of care, whilst a length of stay-based case-mix index was computed to provide for the heterogeneity of admissions.

Standard DEA models are estimated by means of the DEAP version 2.1; a DEA Programme developed by Coelli (1996) while super-efficiency models are estimated by means of Zhu's (2003) DEA Excel Solver. In order to check the stability and sensitivity of DEA results, a multi-pronged approach is adopted in the analysis of the DEA results. This includes an assessment of the efficiency of the sample hospitals, inclusion and exclusion of inputs and outputs, providing for case-mix in each hospital's patient load, analysing the correlation between different models over time, running the models both on the cross-sectional and pooled datasets and assessing the performance of hospitals across all models based on their efficiency scores and rankings.

Choice of Inputs and Outputs

A typical healthcare institution like a hospital embraces a variety of resources (human, material and knowledge amongst others), which are used in a series of processes that ultimately aim to improve upon the medical condition of the patient and contribute to healthier communities.

The estimation of technical efficiency requires the careful choice of the sample size as well as the number of factors (number of inputs plus the number of outputs). Any DEA study requires the careful selection of inputs and outputs. This is due to the fact that the distribution of efficiency is likely to be affected by the definition of outputs and the number of inputs and outputs included (Magnussen, 1996).

Theoretically, improved health status is the ultimate outcome that hospitals or the health care system generally aim for through their delivery of various outputs. Nevertheless, the measurement of health status poses difficulties because health is multi-dimensional and there is subjectivity involved in assessing the quality of life of patients (Clewer and Perkins, 1998). Because of the difficulty of accurately measuring improvement in health status, hospital output is measured as an array of intermediate outputs (health services) that improve health status (Grosskopf and Valdmanis, 1987).

The measures used in the study represent the general areas of direct services which hospitals provide to patients. Attempts are made to incorporate a fairly comprehensive list of inputs and outputs which reflect the general scope of hospital activities in order to obtain informative and robust results. However, the fact that DEA operates more powerfully when the number of DMUs exceeds the number of the combined total of inputs and outputs by at least twice (Drake and Howcroft, 1994) restricts the input and output measures chosen for the study.

Input Variables: Four inputs are constructed. These include, doctors, nurses, other staff, and beds. The study used absolute numbers of human resources providing health care services to approximate the labour resources employed due to the lack of information on full time equivalent staff. We combine labour categories into three variables: “doctors”, “nurses” and “other employees”. This is to minimise the variation in how the hospitals record their staff in the registers. The variable “doctors” includes all senior medical officers, medical officers and dental surgeons. The variable “nurses” includes senior nursing officers, nursing officers, Uganda registered nurses, midwives, enrolled midwives, enrolled nurses, nursing assistants, and nursing aids. Finally, the variable “other staff” includes clinical officers, dispensers, anesthetics officers, radiographers, orthopedic officers, laboratory technologists and technicians, laboratory assistants, hospital administrators, accountants, clerical officers, supplies officers, stores assistants, telephone operators, stenographers, copy typists, records assistants, dark room attendants, mortuary attendants, drivers, kitchen attendants, security guards, artisans (carpenters), electrical technicians and plumbers. All the three staffing measures include only salaried hospital staff. It should be noted that the inclusion of only salaried staff might understate the hospitals’ human resource complement.

There were no data for capital inputs, for instance, buildings and equipment. Consequently, capital is approximated by the number of beds per hospital. Beds are often used to proxy for capital stock in hospital studies. This is because a reliable measure of the value of assets is rarely available. District referral hospitals are distinguished from other public hospitals as being 100-bed hospitals. Nevertheless, the bed stock has been on the increase in some hospitals as they try to cope with increasing numbers of admissions. Moreover, in most hospitals due to limited bed capacity, there are what can be termed “floor admissions”. Hospital records do not clearly distinguish “bed admissions” from “floor admissions” which complicates its tracking across hospitals and through time for a given hospital. They are all lumped together as admissions. In the ideal world no hospital would admit when its bed stock is exhausted. However, being the only hospital with relatively “free” healthcare in the district, admissions beyond available bed capacity are admissible given that patients may lack alternatives due partly to the high levels of poverty. These will, unfortunately, make some hospitals appear more efficient than others with respect to bed capacity as some of the hospitals’ inpatients have no beds. This will also have implications for total factor productivity measures and in particular technology change.

Output Variables: The output measures focus on the process type or production volume style estimates of hospital output. The study examined a number of measures of district referral hospitals’ output. These include

admissions, deliveries, operations, and outpatient department attendances.

Inpatient Care: Inpatient care output for each district hospital was measured in two ways: first as annual cases treated, specifically annual admissions, and then as "case-mix adjusted" admissions. Case-mix adjusted admissions are defined as annual admissions times the case-mix index. The index is the (normalised) weighted sum of the proportions of the hospital's inpatients in different wards where the weights reflect the length of stay of its patient load. Case-mix adjusted admissions transform admissions into ward homogeneous patient loads. For a given level of admissions, the adjusted measure captures output differences due solely to case-mix variation. In particular, it controls for the fact that hospitals whose wards exhibit relatively longer average length of stay may be due to a more complex mix of patients compared to wards with relatively short average length of stay. The adjusted measure captures output differences due to variations in average length of stay, and by proxy, case-mix. While the data prohibits more detailed estimation of case-mix differences, this approach attempts to adjust output into more homogeneous and comparable groupings.

Deliveries: Deliveries include all deliveries in the hospital without adjusting for neonatal deaths because resources are expended irrespective of the status of the birth.

Surgical Operations: Surgical operations include major and minor operations and Caesarian sections.

Outpatient Department Attendances: Outpatient department attendances include new cases as well as re-attendances.

A summary of the variable definitions is provided in table 2 while table 3 contains descriptive statistics for the input and output variables for each sample year.

Table 2: Definitions and Measurement of Input and Output Variables

Variables	**Definition and Measurement**
Inputs	
Beds	Total Number of beds
Doctors	Total Number of medical doctors (physicians, pharmacists, dentists, etc., including residents and interns)
Nurses	Total Number of nurses, including professional, enrolled, registered, community nurses, and nursing aids.
Other Employees	Total Number of paramedics and assistants, technicians and assistants; administrative staff; and other general staff.
Outputs	
Admissions	Total Annual Admissions
Outpatient Dept. Attendances	Annual Total Number of outpatient department attendances
Surgical Operations	Annual Total Number of surgical operations
Deliveries	Annual Total Number of deliveries in the hospital

The mean and standard deviation of inputs and outputs analysed by the study are shown in table 3. The means and standard deviations reported suggest that there are substantial variations across the sample with respect to the input and output variables.

Table 3 Mean and Standard Deviation of Input and Output Variables

Variable/Year	**1999 (n=25)**	**2000 (n=25)**	**2001 (n=25)**	**2002 (n=25)**	**2003 (n=25)**	**1999-2003 (n=25)**
Inputs						
Beds	113.1	114.7	115.1	115.8	117.7	115.3
	[19.6]	[23.5]	[23.1]	[22.9]	[23.1	[22.2]
Doctors	4.5	4.6	4.8	4.8	4.8	4.7
	[1.7]	[1.7]	[1.7]	[1.8]	[1.8]	[1.7]
Nurses	58.9	57.6	58.2	55.9	57.2	57.6
	[21.5]	[21.9]	[20.7]	[19.4]	[19.4]	[20.3]
Other Staff	64.4	66.0	67.4	65.7	65.6	65.8
	[28.0]	[28.6]	[27.3]	[24.9]	[25.2]	[25.4
Outputs						
Admissions (unweighted)	7049.5	7063.3	7850.9	8185.4	8541.4	7738.1
	[4314.2]	[4738.1]	[5981.6]	[6363.1]	[6664.6]	[5627.3]
Casemix Adjusted Admissions	7052.6 [4298.0]	7058.7 [4725.4]	7845.4 [6400.6]	8238.8 [6413.2]	8571.1 [6284.0]	7753.3 [5640.1]
Outpatient Attendances	29467.9	30482.0	35467.9	37373.4	36243.4	33806.9
	[14179.2]	[14033.7]	[14981.3]	[15046.6]	[17079.3]	[15201.7]
Surgical Operations	775.8	826.9	886.8	1046.5	1040.8	915.3
	[472.7]	[433.4]	[437.6]	[459.3]	[466.1]	[460.3]
Deliveries	1192.9	1148.1	1358.6	1474.5	1495.5	1333.9
	[475.8]	[506.2]	[529.8]	[612.3]	[666.9]	[571.6]

Table 4 presents the Pearson correlation matrix of input and output variables. The mean and standard deviation vary marginally by year across the study period and for the pooled dataset. This implies that on average the variables display some degree of stability on a year to year basis across the study period and for the pooled dataset. In table 4, supply-side factors are correlated, as are some measures of outputs (as expected) and where possible we tried to maintain parsimonious specifications and reduce double counting.

Table 4 Pearson Correlation Matrix of Input and Output variables (n=125), 1999-2003

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Admissions (1)	1									
Patient Deaths (2)	0.3719*	1								
CAA (3)	0.9444*	0.2759*	1							
OPD (4)	0.2527*	-0.0112	0.2481*	1						
S/Operations (5)	0.2220*	0.5197*	0.1212	0.0581	1					
Deliveries (6)	0.1483	0.4622*	0.0465	0.2469*	0.3941*	1				
Beds (7)	0.1169	0.3844*	0.0474	-0.1106	0.4062*	0.4455*	1			
Doctors (8)	-0.1238	0.2098*	-0.0689	0.2637*	0.0954	0.2859*	0.3487*	1		
Nurses (9)	-0.0234	0.1141	-0.0222	0.3836*	0.1685	0.1577	0.2794*	0.4636*	1	
Other Staff (10)	0.0245	0.0539	0.0178	0.2207*	0.1272	0.3335*	-0.0065	0.2457*	0.3364*	1

*Significant at 5 percent level

Notes:

CAA	=	Case-mix Adjusted Admissions
OPD	=	Outpatient Department Attendances
S/Operations	=	Surgical Operations (minor, major and Caesarian sections)

Table 5 presents the five models estimated in the measurement of efficiency. Modelling input-oriented DEA technical efficiency scores, model 1 includes four inputs: beds, doctors, nurses and other staff, and four outputs: admissions (un-weighted), outpatient department attendances, surgical operations and deliveries. Model 2 keeps the same inputs and outputs as Model 1 but replaces admissions (un-weighted) with case-mix adjusted admissions. Model 3 includes the same inputs as Models 1 and 2, as well as two outputs, case-mix adjusted admissions and outpatient department attendances. Models 4 and 5 have two inputs, beds and all staff grouped together; Model 4 includes the same outputs as Model 3 while Model 5 includes the same outputs as Model 2. The five models were run for individual years and the pooled dataset over the 1999-2003 period.

In order to check the stability and sensitivity of DEA results, a multi-pronged approach is adopted in the analysis of DEA results. This includes simultaneous assessment of the efficiency of the sample hospitals and the inclusion and exclusion of inputs/outputs. In order to capture the variations in efficiency over time, Boussofiane et al. (1991) described the following method. According to them, given *n* units with data on their input/output measures in *k* periods, then a total of *nk* units are assessed simultaneously. The study utilises this method in its analysis. Following the methodology by Boussofiane et al. (1991), given twenty five hospitals and data on their input/output measures over a five year period, a total of 125 hospitals are assessed simultaneously. This data pooling allows for a greater sample size and a comparison of efficiency estimates.

Table 5: Five DEA Model Specifications

Model 1	Model 2	Model 3	Model 4	Model 5
Inputs	***Inputs***	***Inputs***	***Inputs***	***Inputs***
Beds	Beds	Beds	Beds	Beds
Doctors	Doctors	Doctors	All staff grouped together	All staff grouped together
Nurses	Nurses	Nurses		
Other staff	Other staff	Other staff		
↓	↓	↓	↓	↓
Outputs	***Outputs***	***Outputs***	***Outputs***	***Outputs***
Admissions (un-weighted)	Admissions (case-mix adjusted)	Admissions (case-mix adjusted)	Admissions (case-mix adjusted)	Admissions (case-mix adjusted)
Outpatient attendances	Outpatient attendances	Outpatient attendances	Outpatient attendances	Outpatient attendances
Surgical operations	Surgical operations			Surgical operations
Deliveries	Deliveries			Deliveries

Providing for Case-mix

If the analysis used inpatient days, deliveries and operations, as proxies for hospital output, a serious shortcoming in the analysis would exist: the failure to control for case-mix differences between hospitals. Specifically, while it might be the case that one hospital produces more outputs (e.g. inpatient days, operations, deliveries) for a given combination of inputs than another hospital, the first might be no more efficient if it consistently treats a relatively less sophisticated mix of cases, that is, a mix of cases requiring relatively fewer inputs per unit of output. Any study of hospital technical efficiency must then attempt to control for differences in the case mix between different hospitals.

Lacking data on individual hospital case mix as well as billing or cost data; the study adapted the English Department of Health's Casemix (Hernandez, 2002). The case-mix index (HI_i) for hospital is approximated by means of the average length of stay to control for the case-mix among different hospitals as follows:

$$HI_i = \frac{\sum_j NALOS_j * Ad_{ji}}{TALOS * \sum_j Ad_{ji}}, \qquad (3)$$

Where:

HI_i = case mix index for hospital i;

$NALOS_j$ = national weighted average length of stay for ward j;

Ad_{ji} = number of admissions in ward (in hospital i);

$TALOS$ = average weighted length of stay of wards;

Ad_{ji} = total number of admissions treated by hospital i.

And

$$NALOS_j = \frac{\sum_i LOSAd_{ji} * Ad_{ji}}{\sum_i Ad_{ji}}, \quad (4)$$

Where:

$LOSAd_{ji}$ = unit length of stay of ward j's admissions in hospital i;

Ad_{ji} = number of admissions in ward j (in hospital i);

$\sum_i Ad_{ji}$ = sum of ward j's admissions for all hospitals.

And

$$TALOS = \frac{\sum_j \sum_i LOSAd_{ji} * Ad_{ji}}{\sum_j \sum_i Ad_{ji}}, \quad (5)$$

Where:

$LOSAd_{ji}$ = unit length of stay of ward j's admissions in hospital i;

Ad_{ji} = number of admissions in ward j (in hospital i);

$\sum_j \sum_i Ad_{ji}$ = sum of all admissions for all hospitals.

The above approach to approximating the case mix index for a given hospital is premised on the assumption that the wards produce very similar types of output across hospitals. However, the length of stay-based case-mix index has a number of shortcomings which include but are not limited to: (i) it is not based on individual level patient data (it does not account for age, gender, complexity); (ii) hospital wards may not use homogeneous definitions across hospitals; (iii) there is a likelihood of different length of stay policies across hospitals; (iv) length of stay is susceptible to outlier data (hospitals provide more than curative care for instance

palliative care, and social care); and (v) discharges might be linked to the degree of integration with community care in which case hospitals might keep patients longer if there are weak community health service links.

4. Results and Discussion

The principal technical efficiency results reported in this section were derived by imposing the assumption of input-oriented DEA and VRS on standard DEA models. Super-efficiency DEA models were estimated by imposing the same orientation and were run under both CRS and VRS technology. The five models result in different measures of technical efficiency and the mean efficiency scores differ depending upon the model specification. Tables 6 reports the efficiency scores from the five standard DEA models.

To check the robustness of the models to changes in the measurement of admissions, models 1 and 2 were run. Comparing models 1 and 2 indicates that, in general, the efficiency scores of hospitals rise when the admissions are adjusted by means of the case-mix index. For instance, the mean efficiency score rises from 97.2 percent for Model 1 to 97.4 percent for Model 2 in 1999. This, therefore, implies that not adjusting admissions to the structure of the patient load understates the efficiency scores of hospitals. Thus, in 1999, Uganda's district referral hospitals realised approximately 97 percent of their potential output. The same potential output is produced even when efficiency is estimated from the pooled dataset. On average, 19 out of the 25 hospitals operated on the production frontier over the sample period when Models 1 and 2 are estimated.

Comparing models 3 and 4 generally shows that lumping human resources into one variable reduces the efficiency scores by an average of 1.6 percent and reduces the number of hospitals on the frontier from 19 to 9 (for Model 3) and to 5 (for Model 4). When models 4 and 5 are compared, it is revealed that the incorporation of more output variables increases the efficiency scores by an average of 4 percent and increases the number of hospitals on the production frontier by 6 hospitals (for Model 3) and 9 hospitals (for Model 4). These results are driven by the choice of variables in the modeling process. Also in line with expectations (Smith, 1997), the models with larger numbers of inputs and outputs yield higher average efficiencies.

Models 1 and 2 have the most factors, thus most hospitals end up on the frontier (Nunamaker, 1985). The only shortcoming of these two models is that they are less discriminating. It is noteworthy that models 1 and 2 perform as well as the corresponding pooled dataset both in terms of efficiency scores and hospitals on the frontier. The similarity between the results for models 1 and 2 (n=25) vis-à-vis those for the pooled dataset (n=125), shows that DEA models perform better with large samples (Pedraja-Chaparro et al., 1999).

Table 7 shows the Pearson correlation matrix of efficiency scores across the five DEA models for individual years. Table 8 shows the matrix for the pooled dataset. This was done to check model stability over time. The year 1999 has the same number of Pearson correlation coefficients as 2000. Likewise, 2002 and

2003 have the same number of significant coefficients. This, therefore, implies that the five models are stable for the years 1999, 2000, 2002 and 2003 but not stable for 2001 and for the pooled (1999-2003).

Table 6: Efficiency Scores from Five Standard DEA Models, 1999 – 2003

	1999	2000	2001	2002	2003	Pooled 1999-2003
Model 1						
Mean	0.972	0.943	0.975	0.982	0.968	0.972
Standard deviation	0.058	0.107	0.063	0.060	0.070	0.058
Minimum	0.786	0.606	0.757	0.728	0.698	0.786
Maximum	1.000	1.000	1.000	1.000	1.000	1.000
Number on Frontier	19	17	20	22	17	19
Model 2						
Mean	0.974	0.946	0.975	0.983	0.971	0.973
Standard deviation	0.054	0.104	0.061	0.060	0.069	0.055
Minimum	0.804	0.630	0.770	0.730	0.698	0.804
Maximum	1.000	1.000	1.000	1.000	1.000	1.000
Number on Frontier	19	18	20	22	18	19
Model 3						
Mean	0.921	0.922	0.944	0.923	0.917	0.921
Standard deviation	0.103	0.105	0.100	0.118	0.131	0.103
Minimum	0.594	0.642	0.602	0.602	0.591	0.594
Maximum	1.000	1.000	1.000	1.000	1.000	1.000
Number on Frontier	9	13	16	14	12	9
Model 4						
Mean	0.902	0.905	0.938	0.916	0.888	0.902
Standard deviation	0.101	0.112	0.109	0.126	0.127	0.101
Minimum	0.594	0.660	0.602	0.602	0.591	0.594
Maximum	1.000	1.000	1.000	1.000	1.000	1.000
Number on Frontier	5	12	16	13	6	5
Model 5						
Mean	0.961	0.932	0.957	0.961	0.935	0.960
Standard deviation	0.077	0.120	0.104	0.091	0.102	0.077
Minimum	0.743	0.580	0.630	0.693	0.657	0.743
Maximum	1.000	1.000	1.000	1.000	1.000	1.000
Number on Frontier	15	15	20	20	11	15

Table 7: Pearson Correlation Matrix of Efficiency Scores Across Five Standard DEA Models for Individual Years

1999	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Model 1	1.0000				
Model 2	0.9787*	1.0000			
Model 3	0.1639	0.2416	1.0000		
Model 4	0.2102	0.2524	0.8962*	1.0000	
Model 5	0.9261*	0.9473*	0.2451	0.2941	1.0000
2000	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Model 1	1.0000				
Model 2	0.9965*	1.0000			
Model 3	0.0156	0.0334	1.0000		
Model 4	0.0612	0.0808	0.9348*	1.0000	
Model 5	0.9725*	0.9658*	0.0383	0.1401	1.0000
2001	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Model 1	1.0000				
Model 2	0.9996*	1.0000			
Model 3	0.2978	0.3004	1.0000		
Model 4	0.3727	0.3745	0.9910*	1.0000	
Model 5	0.8390*	0.8364*	0.4629*	0.5660*	1.0000
2002	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Model 1	1.0000				
Model 2	0.9999*	1.0000			
Model 3	0.5087*	0.5063*	1.0000		
Model 4	0.5528*	0.5501*	0.9940*	1.0000	
Model 5	0.7201*	0.7165*	0.5535*	0.6208*	1.0000
2003	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Model 1	1.0000				
Model 2	0.9670*	1.0000			
Model 3	0.5042*	0.5445*	1.0000		
Model 4	0.4773*	0.4761*	0.9065*	1.0000	
Model 5	0.7333*	0.7748*	0.5727*	0.6256*	1.0000

1999-2003	Model 1	Model 2	Model 3	Model 4	Model 5
Model 1	1.0000				
Model 2	0.9787*	1.0000			
Model 3	0.1639	0.2416*	1.0000		
Model 4	0.2102*	0.2524*	0.8962*	1.0000	
Model 5	0.926104*	0.9473*	0.2451*	0.2941*	1.0000

Note: *Significant at 5 percent level

The efficiency scores estimated for the standard DEA models are truncated to lie between zero and unity which complicates the ranking of the efficient set of hospitals. To address this shortcoming of standard DEA models, super-efficiency DEA models along the lines of Andersen and Petersen (1993) were estimated for the five DEA specifications.

Table 8 presents the individual hospital super-efficiency scores across the five models for 1999. This was done because the results for the standard DEA models for the pooled dataset (1999-2003) were generally similar to those of 1999.

In general, the five models had feasible solutions under CRS technology for all hospitals. However, under the VRS technology, some hospitals had infeasible solutions. Three hospitals (Bugiri, Entebbe and Iganga) had infeasible solutions under models 1, 2 and 5, whilst two hospitals (Bugiri and Entebbe) had infeasible solutions under models 3 and 4. This is in line with results by others who have found estimates for operating units undefined because of the infeasibility of the set of constraints of the modified DEA model (Pastor et al., 1999; Boljuncic, 1999).

If super-efficiency is used as an efficiency stability measure, then based upon Seiford and Zhu (1998b), infeasibility means that an efficient DMU's efficiency classification is stable to any input changes if an input-oriented super-efficiency DEA model is used (or any output changes if an output-oriented super-efficiency DEA model is used). Therefore, one can use positive infinity ($+\infty$) to represent the super-efficiency score. i.e., infeasibility means the highest super-efficiency.

Table 9: Individual Hospital Super-efficiency Scores (%) across the Five Models, 1999

	Model 1		Model 2		Model 3		Model 4		Model 5	
Hospital	**CRS**	**VRS**	**CRS**	**VRS**	**CRS**	**VRS**	**CRS**	**VRS**	**CRS**	**VRS**
Bududa	138.15	203.45	155.00	214.41	153.21	214.41	63.06	98.23	77.72	100.91
Bugiri	333.96	Infeasible	290.10	Infeasible	290.10	Infeasible	263.02	Infeasible	263.02	Infeasible
Busolwe	124.64	179.93	124.64	176.90	100.38	105.69	68.31	82.98	95.04	100.53
Bwera	96.08	99.96	96.08	99.96	95.26	99.94	64.30	97.76	68.42	97.76
Entebbe	110.96	Infeasible	110.96	Infeasible	109.51	Infeasible	100.90	Infeasible	107.78	Infeasible
Gombe	79.66	88.32	75.68	82.71	66.35	78.67	40.08	73.92	60.67	80.69
Iganga	146.60	Infeasible	146.60	Infeasible	42.03	58.82	36.02	58.21	117.96	Infeasible
Itojo	77.56	85.87	77.57	85.87	76.69	85.66	63.67	84.79	70.05	85.27
Kagadi	86.18	96.65	99.85	100.52	56.98	93.80	44.14	92.71	84.22	97.04
Kalisizo	88.61	99.59	88.61	99.59	88.61	99.59	60.03	97.23	60.03	97.23
Kambuga	100.63	103.36	100.43	103.32	84.94	103.15	77.18	99.80	98.87	102.82
Kapchorwa	85.46	100.07	86.01	99.75	31.01	95.75	29.00	95.46	82.89	98.81
Kawolo	93.63	104.62	93.63	104.62	89.70	100.41	65.00	97.32	80.66	100.15
Kayunga	76.85	95.05	76.86	94.99	64.82	94.49	63.47	93.14	76.07	94.08
Kiboga	59.44	80.33	66.46	80.61	41.33	76.04	36.58	76.04	63.02	80.44
Kiryandongo	65.93	177.78	79.35	177.78	64.55	177.78	40.27	122.58	61.35	122.58
Kisoro	144.39	148.08	144.39	148.07	143.78	148.07	134.36	144.73	134.93	144.97
Kitagata	71.27	95.55	70.08	93.90	52.53	89.54	49.47	82.64	67.11	88.95
Masindi	81.63	95.51	89.53	95.83	66.58	84.45	43.10	80.03	84.57	94.82
Mityana	137.19	137.89	137.19	137.89	76.32	99.55	64.83	97.14	117.04	120.22
Mubende	120.31	125.75	120.31	125.75	117.31	118.74	113.56	113.59	119.01	121.96
Nakaseke	95.50	95.95	96.27	96.39	88.46	94.85	80.29	92.69	90.44	94.35
Pallisa	229.39	292.11	229.39	292.11	112.13	123.59	66.16	83.39	147.38	164.10
Rakai	73.19	101.66	74.56	101.61	55.16	97.80	46.39	96.18	74.56	100.75
Tororo	85.75	117.95	85.75	116.62	85.75	116.62	73.99	83.48	73.99	83.48

In order to fully rank hospitals, hospitals with infeasible solutions were ranked as follows: having estimated the models under both CRS and VRS technology, the super-efficiency score under CRS was used to rank hospitals with infeasible solutions. This is because units with infeasible solutions are deemed strongly super-efficient and top the ranking. Under VRS, hospitals were ranked by means of their individual super-efficiency scores. Table 9 shows the ranking of individual hospitals across the five models.

Table 9: Hospital Ranking by Model, 1999

Hospital	Model 1	Model 2	Model 3	Model 4	Model 5
Bududa	5	5	3	7	10
Bugiri	1	1	1	1	1
Busolwe	6	7	9	18	10
Bwera	15	16	11	7	15
Entebbe	3	3	2	2	3
Gombe	23	24	23	24	24
Iganga	2	2	25	25	2
Itojo	24	23	21	17	22
Kagadi	18	15	18	14	16
Kalisizo	15	16	11	9	16
Kambuga	13	13	10	6	9
Kapchorwa	15	16	16	13	14
Kawolo	12	12	11	9	13
Kayunga	22	21	18	14	19
Kiboga	25	25	24	23	25
Kiryandongo	7	6	4	4	6
Kisoro	8	8	5	3	5
Kitagata	19	22	20	18	21
Masindi	19	19	22	22	18
Mityana	9	9	11	9	8
Mubende	10	10	7	5	7
Nakaseke	19	20	17	14	19
Pallisa	4	4	6	18	4
Rakai	14	14	15	12	10
Tororo	11	11	8	18	23

The ranking of hospitals is model-specific and thus the ranking of hospitals is contingent upon the model specification. The hospital ranking across the five models is analysed by looking at the top, middle and bottom five hospitals. The top five hospitals are ranked one through five, the middle five, 11 through 15; while the bottom five are assigned ranks 21 through 25. Three hospitals have an interesting

pattern of ranking across the five models, namely Bugiri, Gombe and Kiboga. It is apparent that Bugiri hospital tops the ranking across the five models while Gombe and Kiboga are generally in position 24 and 25, respectively, across the five models.

Xue and Harker (2002) have shown that if infeasibility occurs for some efficient DMUs in the super efficiency DEA models under alternate returns to scale (RTS) assumptions, it is still possible to obtain the ranking of the entire observation set based on their relative efficiency. They identify a special subset of the set of the strongly efficient DMUs (E) and the super-efficient DMUs (SE). Additionally, they identify a special subset of the super-efficient DMUs and the strongly super-efficient DMUs (SSE). In general the relative efficiency of units in the four categories can be ranked from higher to lower as:

Super Efficient (including Strongly Super Efficient)→Strongly Efficient→Efficient→Weakly Efficient, i.e., SE (including SSE) →E→E'→F while SSE⊂SE⊂E.

They have shown that the necessary and sufficient condition for a DMU's primal problem to be infeasible in the super-efficiency model is that it is a super-efficient DMU. With the full ranking of the whole DMU set, further statistical analysis of the efficiency ranks of the DMUs and other post-DEA analysis founded on ranks are possible.

Following a variant of the methodology by Xue and Harker (2002), hospitals were categorised into four groups (strongly super-efficient; super-efficient; efficient and inefficient) depending on their level of technical super-efficiency score. The strongly super-efficient hospitals are those for which the super-efficiency model was infeasible; super-efficient had a score above unity; the efficient had a score equal to unity whilst the score was less than unity for inefficient hospitals. Table 11 presents the classification of hospitals according to their super-efficiency score for the parsimonious model 2 over the 1999-2003 period.

This study has demonstrated how the super-efficiency model of DEA introduced by Andersen and Petersen (1993) solves the problem of standard DEA, namely that many hospitals are rated as efficient and tie for the top position in the ranking.

Table 11: Classification of Hospitals using Model 2, 1999-2003

Year	Strongly Super-efficient	Super-efficient	Efficient	Inefficient
1999	Bugiri, Entebbe & Iganga	Bududa, Busolwe, Kambuga, Kawolo, Kiryandongo, Kisoro, Mityana, Mubende, Pallisa, Rakai & Tororo	Kagadi	Bwera, Gombe, Itojo, Kalisizo, Kapchorwa, Kayunga, Kiboga, Kitagata, Masindi & Nakaseke
	[12%]	[44%]	[4%]	[40%]
2000	Bugiri, Entebbe & Iganga	Bududa, Busolwe, Kapchorwa, Kawolo, Kiryandongo, Kisoro, Nakaseke, Pallisa & Rakai	Mityana	Bwera, Gombe, Itojo, Kagadi, Kalisizo, Kambuga, Kayunga, Kiboga, Kitagata, Masindi, Mubende & Tororo
	[12%]	[36%]	[4%]	[48%]
2001	Bugiri, Entebbe & Iganga	Bududa, Busolwe, Bwera, Kagadi, Kapchorwa, Kawolo, Kiryandongo, Kisoro, Kitagata, Masindi, Mityana & Pallisa	Kalisizo, Kambuga, Mubende & Rakai	Gombe, Itojo, Kayunga, Kiboga, Nakaseke & Tororo
	[12%]	[48%]	[16%]	[24%]
2002	Bugiri, Entebbe & Iganga	Busolwe, Bwera, Kagadi, Kambuga, Kapchorwa, Kawolo, Kayunga, Kiryandongo, Kisoro, Kitagata, Masindi, Mityana, Pallisa & Rakai	Bududa, Kalisizo & Mubende	Gombe, Itojo, Kiboga, Nakaseke & Tororo
	[12%]	[56%]	[12%]	[20%]
2003	Bugiri, Entebbe, Iganga & Tororo	Bududa, Busolwe, Kagadi, Kambuga, Kawolo, Kiryandongo, Kisoro, Kitagata, Masindi, Mityana, Mubende, Pallisa & Rakai	Bwera	Gombe, Itojo, Kalisizo, Kapchorwa, Kayunga, Kiboga & Nakaseke
	[16%]	[52%]	[4%]	[28%]

It is important to note that the results obtained in this study depend to a large extent upon the definition of inputs and outputs. The results of the DEA analyses do not provide detailed recommendations concerning a particular hospital. However, a number of alternative input and output measures are possible (and more realistic) thereby mitigating or modifying the specific findings of this particular study. Thus, it may be argued that for any hospital deemed inefficient (or, efficient for that matter) there may exist a number of special operating circumstances that might bring the findings of a specific DEA result into question. The ability to test

alternative model specifications, in fact, is a very important strength of the DEA approach. That is, one can systematically evaluate the impact of alternative factors (for both inputs and outputs) on alternative model designs. These analyses should provide a strong indication of the adequacy of model specification as well as appropriate benchmarks.

DEA possesses a target-setting capability that can be used to develop policy making scenarios which can enable healthcare managers identify the operating response to different managerial priorities (Athanassopoulos et al., 1999).

The DEA model selected here was an input-oriented model, which seeks to identify technical inefficiency as a proportional reduction in input usage. It is also possible to measure technical efficiency as a proportional increase in output production. However, the former appears to be a more adequate model for managers of healthcare related organisations. This is because healthcare providers have objectives to fulfill which are typically set by the national health policy or having an altruistic social responsibility of providing healthcare to the citizenry. Hence the input quantities appear to be the primary decision variables.

Despite its popularity there are several criticisms against the Andersen and Petersen ranking method. The method accepts the DEA score as a rank scale for the inefficient units. In order to differentiate between the efficient units (which receive a score of unity in standard DEA), they developed a method to score them with values greater than unity. Cooper and Tone (1997) argue that DEA classifies the units into two dichotomic sets: efficient and inefficient. They do not rank the efficient units since they claim that they all are on the efficient frontier. Moreover, they do not accept the DEA score as a ranking score for the inefficient units since their weights vary from unit to unit. However, they suggest another ranking method based on the slack variables of the dual problem. Wilson (1995) argues that the Andersen and Petersen ranking model does not provide ranking. It mainly identifies outliers; namely, efficient units that receive very high scores are identified as outliers.

The article has shown that the standard DEA is limited in its applicability in the context of hospital performance evaluation because it results in performance rankings where typically a large number of hospitals tie for the top position. The use of standard DEA models results in a large fraction of the observations becoming 100 percent efficient. With the super-efficiency model, a ranking of the efficient units is possible.

It is noteworthy that although this study has employed super-efficiency DEA to rank efficient hospitals, there are other methods that can be used to increase discrimination in DEA. These include, but are not limited to, cross-efficiency (Sexton et al., 1986); benchmark ranking method, (Torgersen et al., 1996); multivariate statistical tools (Friedman and Sinuany-Stern, 1997); Multiple Criteria DEA (Li and Reeves, 1999); and Measure of Inefficiency Dominance (Bardhan et al., 1996). Nevertheless, the application of some of the above methods is bedevilled in part by the lack of appropriate software.

5. Conclusion

This article sought to apply the super-efficiency DEA model introduced by Andersen and Petersen (1993) and use the results to demonstrate how this solves a common problem of the standard DEA. The review of methods and materials revealed that in the standard DEA many DMUs are rated as efficient and tie for the top position in the ranking. On the other hand, as the results of this article show, the super-efficiency score enables us to distinguish between the efficient observations.

In particular, in the standard DEA we find, among other things, that not adjusting admissions to the structure of the patient load in the DEA modelling understates the efficiency scores of hospitals. In relation to the human resource variable, we find that the results are sensitive to the lumping of human resources into one variable (or treating labour as homogeneous) in the modelling, reducing the efficiency scores by an average of 1.6 percent and reducing the number of hospitals on the production possibilities (efficiency) frontier.

Applying a super-efficiency DEA modelling approach it is observed that in general, the five models estimated in the article had feasible solutions under CRS technology for all hospitals. However, under the VRS technology, some hospitals had infeasible solutions. Generally it is also noted that the ranking of hospitals is model-specific and thus the ranking of hospitals is contingent upon the model specification.

The article demonstrates how the super-efficiency model of DEA solves the inherent problem of standard DEA. It disaggregates the rating of hospitals that are tied for the top position in the efficiency ranking. We note that the results obtained in this study depend to a large extent upon the definition of inputs and outputs. We also note that the results of the DEA analyses should always be treated with caution as they do not readily allow for making detailed recommendations concerning any particular hospital.

A number of alternative input and output measures are possible under the DEA framework, which mitigates or modifies the specific findings of this study. The implication of alternative specifications is that for any hospital deemed inefficient or efficient there may exist a number of special operational circumstances that might bring the findings of a specific DEA result into question. The ability to test alternative model specifications is in fact an important strength of the DEA approach. It offers the possibility of systematically evaluating the impact of alternative factors (for both inputs and outputs) on alternative model designs. Such analysis offers a strong indication of the adequacy of various model specifications.

Note:

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References

Adler, N.; L. Friedman; and Z. Sinuany-Stern. 2002. “Review of Ranking Methods in the DEA Context.” *European Journal of Operational Research*, 140:249–265.

Andersen, P. and N. C. Petersen. 1993. “A Procedure for Ranking Efficient Units in Data Envelopment Analysis.”’ *Management Science*, 39:1261-1264.

Athanassopoulos, A. D.; N. Lambroukos; and L. Seiford. 1999. “Data Envelopment Scenario Analysis for Setting Targets to Electricity Generating Plants.” *European Journal of Operational Research* 115, no. 3: 413-428.

Banker, R. D. and R. C. Morey. 1989. “Incorporating Value Judgments in Efficiency Analysis.” *Research in Government and Nonprofit Accounting*, 5:245-267.

Banker, R. D.; A. Charnes; and W. W. Cooper. 1984. “Models for Estimating Technical and Scale Efficiencies in Data Envelopment Analysis.” *Management Science* 30, no. 9: 1078-1092.

Bardhan, I. I; W. F. Bowlin; W. W. Cooper; and T. Sueyoshi. 1996. “Models for Efficiency Dominance in Data Envelopment Analysis. Part I: Additive Models and MED Measures.” *Journal of the Operations Research Society of Japan*, no. 39: 322–332.

Belton, V. and T. J. Stewart. 1999. “DEA and MCDA: Competing or Complementary Approaches.” In *Advances in Decision Analysis*, ed. N. Meskens and M. Roubens. Norwell: Kluwer Academic Publications.

Boljuncic, V. 1999. “A Note on Robustness of the Efficient DMUs in Data Envelopment Analysis.” *European Journal of Operational Research* 112, no. 1: 240-244.

Charnes, A ; W. W. Cooper; and E. Rhodes. 1978. “Measuring the Efficiency of Decision Making Units.” *European Journal of Operational Research*, 2:429– 444.

Clewer, A. and D. Perkins. 1998. *Economics for Health Care Management*. London: FT Prentice Hall.

Coelli, T. J. 1996. “A Guide to DEAP Version 2.1: A Data Envelopment Analysis (Computer) Program.” *Centre for Efficiency and Productivity Analysis* (CEPA) Working Paper 96/8. Department of Econometrics, University of New England, Australia.

Cooper, W. W.; Lawrence M. Seiford; and Kaoru Tone. 2000. *Data Envelopment Analysis: a Comprehensive Text with Models, Applications*, *References and DEA-Solver Software*. Boston: Kluwer Academic Publishers.

Cooper, W. W. and K. Tone. 1997. “Measures of Inefficiency in Data Envelopment Analysis and Stochastic Frontier Estimation.” *European Journal of Operational Research*, 99:72–88.

Debreu, G. 1951. ‘The Coefficient of Resource utilisation.’ *Econometrica*, 19:273-292.

Drake, L. and B. Howcroft. 1994. “Relative Efficiency in the Branch Network of a UK Bank: An Empirical Study.” *OMEGA* 22, no. 6 :429-444.

Farrell, M. J. 1957. “The Measurement of Productive Efficiency.” *Journal of the Royal Statistical Society*, Series A CXX Part 3:253-290.

Friedman, L. and Z. Sinuany-Stern. 1997. “Scaling Units via the Canonical Correlation Analysis in the DEA Context.” *European Journal of Operational Research* 100, no. 3: 629-637.

Green, R. H. and J. R. Doyle. 1995. “On Maximising Discrimination in Multiple Criteria Decision Making.” *Journal of Operation Research Society* 46, no. 2:192–204.

Green, R. H.; J. R. Doyle; and W. D. Cook. 1996. “Preference Voting and Project Ranking

using DEA and Cross-Evaluation." *European Journal of Operational Research*, 90:461-472.

Grosskopf, S. and V. Valdmanis. 1987. "Measuring Hospital Performance: A Non-Parametric Approach." *Journal of Health Economics*, 6:89-107.

Hadad, Y.; L. Friedman; Z. Sinuany-Stern; and A. Mehrez. 2003. "DEA Super Efficiency Multistage Ranking." *Computer Modelling & New Technologies* 7, no. 1: 37-46.

Hernandez, R. A. 2002. "Casemix Indices for Acute and Specialised Hospitals in England,' Unpublished MSc Health Economics Dissertation, University of York, UK.

Hollingsworth, B.; P. J. Dawson; and N. Maniadakis. 1999. "Efficiency Measurement of Health Care: A Review of Non-parametric Methods and Applications." *Health Care Management Science*, 2:162-172.

Koopmans, T. C. 1951. "An Analysis of Production as Efficient Combination of Activities." In: *Activity Analysis of Production and Allocation*, ed. Tjalling C. Koopmans. New York: Cowles Commission for Research in Economics.

Li, X. and G. R. Reeves. 1999. "A Multiple Criteria Approach to Data Envelopment Analysis." *European Journal of Operational Research*, 115:507-517.

Magnussen, J. 1996. "Efficiency Measurement and the Operationalisation of Hospital Production." *Health Services Research*, 31:21-37.

Pastor, J. T.; J. L. Ruiz; and I. Sirvent. 1999. "A Statistical Test for Detecting Influential Observations in DEA." *European Journal of Operational Research* 115, no. 3: 542-554.

Pedraja-Chaparro, F.; J. Salinas-Jimenez; and P. C. Smith. 1999. "On the Quality of the Data Envelopment Analysis Model." *Journal of the Operational Research Society* 50, no. 6: 636-644.

Seiford, L. M. 1996. "The Evolution of the State-of-Art (1978-1995)." *Journal of Productivity Analysis*, no. 7: 99-137.

Seiford, L. M. and Joe Zhu. 1998b. "Sensitivity Analysis of DEA Models for Simultaneous Changes in all the Data." *Journal of the Operational Research Society*, no. 49: 1060-1071.

Seiford, L. M. and J. Zhu. 1999. "Infeasibility of Super-efficiency Data Envelopment Analysis Models." *INFOR* 37, no. 2: 174-187.

Sexton, T. R. 1986. "The Methodology of DEA." In *Measuring Efficiency: An Assessment of DEA*, ed. R.H. Silkman. San Francisco: Jossey-Bass; 7–29.

Sexton, T. R.; R. H. Silkman; and A. J. Hogan. 1986. "Data Envelopment Analysis: Critique and Extensions." In *Measuring Efficiency: An Assessment of Data Envelopment Analysis*, ed. Richard H. Silkman. San Francisco, CA: Jossey-Bass.

Sinuany-Stern, Z. and L. Friedman. 1998. "DEA and the Discriminant Analysis of Ratios for Ranking Units." *European Journal of Operations Research*, 111:470–478.

Sueyoshi, T. and S. Aoki. 2001. "A Use of Nonparametric Statistic for DEA Frontier Shift: the Kruskal and Wallis Rank Test." *Omega*, 29:1-18.

Torgersen, A. M.; F. R. Forsund; and S. A. C. Kittelsen. 1996. "Slack-adjusted Efficiency Measures and Ranking of Efficient Units." *The Journal of Productivity Analysis*, 7:379–398.

Wilson, P. W. 1995. “Protecting Influential Observations in Data Envelopment Analysis.” *Journal of Productivity Analysis*, 4:27–45.

Xue, M. and P.K T. Harker. 2002. “Note: Ranking DMUs with Infeasible Super-efficiency DEA Models.” *Management Science*, 48:705-710.

Young, F. W. and R. M. Hammer. 1987. *Multidimensional Scaling*: *Theory and Application*. London: Lawrence Erlbaum Associates Publishers.

Zhu, J. 2003. *Quantitative Models for Performance Evaluation and Benchmarking; Data Envelopment Analysis with Spreadsheets and DEA Excel Solver*. Boston: Kluwer Academic Publishers.