DATA ENVELOPMENT ANALYSIS FOR MEASURING THE EFFICIENCY OF HEAD TRAUMA CARE IN ENGLAND AND WALES

by

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Table of Contents

List of Tables

List of Figures

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Declaration

I unequivocally declare that the contents of the present research are of original quality, apart from in relation to the specific references that are made regarding other scholars. This paper has not been submitted for consideration previously to the current university or a different one in the past. The entire content of the research is my own personal work and nothing has been formulated in collaboration with another, unless it is clearly specified in the literature.

ABSTRACT

This research develops a comprehensive model for evaluating the efficiency and productivity of the sector of head trauma injury (HTI) care in England and Wales, in order to reduce the costs associated with trauma care. After assessing the advantages and disadvantages of various efficiency measurement approaches, the data envelopment analysis (DEA) methodology is chosen for this research, including both the DEA-based Malmquist index model and the bootstrapping DEA model.

Since the variables selected for these models include some missing data, the approach known as multiple imputation by chained equations (MICE) is proposed to deal with such missing data situations, in order to ensure the accuracy of the inferential and predictive results that our analyses generate. In addition, an experimental study is provided to simulate this approach, in order to investigate its validity as a methodology for replacing such missing values within DEA applications. This experimental study is based on a real data set of 66 hospitals provided by the Trauma Audit and Research Network (TARN), within Salford Royal NHS Foundation Trust. The results of this experimental study show that MICE works well and gives an acceptable estimate of true efficiency.

Furthermore, this research introduces a framework that combines DEA with structural equation modelling (SEM) in order to investigate the effects of uncontrollable variables on efficiencies. While the use of DEA provides valuable results, our SEM analysis reveals additional findings that were not identified in previous studies. For example, unlike previous second stage analysis studies in DEA that focused on only the direct effects of environmental factors on the efficiency scores, this study uses SEM to investigate further any indirect effects and the total effects of these uncontrollable factors on the efficiencies. This additional information is shown to be more useful and more informative than the results generated by the previous studies.

The methodologies proposed and developed in this thesis are then applied to the full set of available TARN data in order to measure the efficiency and productivity of HTI care, demonstrating real possibilities for reducing the costs of head trauma care.

CHAPTER ONE: INTRODUCTION AND STRUCTURE

1.1 Introduction

Trauma is a major cause of death worldwide, with an estimated 5 million deaths each year. In the United Kingdom, at least one million patients, or 10% of all patients attending Accident and Emergency (A&E) services, present in hospitals each year with head injuries (Morris *et al*., 2008). Evaluations in recent times in regards to the trends of survival for post-trauma within the UK have indicated that minimal improvement has been achieved following 1994 (Lecky *et al*., 2002). It has been recommended by The Royal College of Surgeons and The British Orthopaedic Association that a system of trauma service should be implemented throughout the country which will be founded upon trauma systems of a geographical nature for the entirety of Britain (The Royal College of Surgeons, 2000). The idea was an attempt to improve the quality of trauma care by ensuring that the routine clinical practice of trauma in the UK is fully documented. This process involves the measurement of certain outcomes and costs involved.

Trauma care is expensive and a huge burden on healthcare systems, as well as national economies. There are many studies that have estimated and examined the cost of trauma (Haeusler *et al*., 2006; Morris *et al*., 2007; Morris *et al*., 2008). However, none of these studies examined the issue of reducing this cost for trauma care.

This current thesis uses an innovative approach to efficiency measurement, which is known as Data Envelopment Analysis (DEA), with the primary aim to calculate the minimum possible costs, which would allow optimal efficiency in trauma care. The approach is a relative technical efficiency measurement based on mathematical programming. DEA compares the performance metrics of a particular organisation, such as a hospital, with the relevant 'best practice' standards. Moreover, it can identify targets, improvements and practices required to help particular organisations to enhance their overall performance.

1.2 Background

Head trauma injury (HTI) is a specific type of sustained brain injury, which is sometimes referred to as traumatic brain injury (TBI). It can happen when the brain receives damage from a sudden trauma. There are various incidents that can result in HTI, such as when the head suddenly comes into contact with an object in a violent manner, or in a moment that a particular object penetrates the brain tissue through the casing of the skull. Moreover, depending on the extent of the damage to the brain, the definition of TBI is often classified as mild, moderate, or severe. This classification of injury severity is evaluated by using the Glasgow Coma Scale (GCS), which is a measure of consciousness and it was developed by Teasdale and Jennett (1974), as seen in Table 1 (adapted from Hawley *et al.*, 2004). Subsequently, the outcome after BTI is assessed by the Glasgow Outcome Scale (GOS), which was developed by Jennett and Bond (1975), as shown in Table 2.

Severity of HTI	**Definition**	**GCS**
Mild	An injury causing unconsciousness for less than 15 minutes	13-15
Moderate	An injury causing unconsciousness for more than 15 minutes	9-12
Severe	An injury causing unconsciousness for more than 6 hours	3-8

Table 1.1: Assessment of injury severity (adapted from Hawley *et al.*, 2004)

Outcomes	**Definition**	**GOS**
Death		1
Vegetative state	Patient shows unawareness with only reflex responses and periods of spontaneous eye opening usually	2
Severe disability	Patient is conscious, but dependent upon another person for daily support because of a mental or physical disability	3
Moderate disability	Patient is able independently to care for himself or herself, but may not resume work	4
Good recovery	Patient resumes normal life and work, but may suffer minor neuropsychological deficits	5

Table 1.2: Glasgow Outcome Scale (adapted from Jennett and Bond, 1975)

The National Institute for Health and Clinical Excellence (NICE) guidelines, which were published in 2014, provided statistics associated with HTI in England and Wales (NICE, 2014). Firstly, the statistics showed that the most frequent cause of both premature death and disabilities was from head injuries for people aged between 1 and 40 in England and Wales. Indeed, 1.4 million people are attended to accident and emergency A&E departments annually due to head injuries in England and Wales. In total, the average percentage of these patients being children under 15 years old stands at 33%-50%.

The second factor from (NICE, 2014) statistics is that around 200,000 people are admitted to other hospital departments (not A&E) on an annual basis with injuries to the head, of which about one-fifth present with a degree of skull fracture or an evidential nature of damage to the brain. Additionally, there are certain patients who experience disabilities of a long-term nature, as well as those who occasionally fail to survive the onset of complications that could be potentially eradicated through early detection and appropriate treatment. Nevertheless, the majority of patients do in fact recover without a course of specialised intervention, and the death rates caused by injuries to the head remain low, as the statistics stand at 0.2% of all admitted patients into A&E from head trauma. Comprehensively, only 5% of all those who attend A&E from a head injury are categorised in the moderate or severe head injury groups. Hence, 95% of patients who attend the emergency department due to a head injury have a conscious level that is defined as normal or minimally impaired (GCS greater than 12). Finally, 25–30% is the estimated figure for children aged below 2 years old who are hospitalised suffering from head injuries that have resulted from direct abuse.

1.3 Research Aims and Methodology

The primary aim of the current study is to establish a comprehensive model to evaluate the efficiency of the sector of HTI hospitals in England and Wales, in order to reduce the cost associated with trauma care through the use of DEA. Moreover, this study aims to evaluate the productivity of these HTI hospitals over the course of time 2009 to 2012 by using the DEA-based Malmquist index. Even though many studies were found in the literature that examined efficiency in the UK healthcare sector, such as Thanassoulis *et al.* (1995), Buck (2000), Ferrari (2006) and Amado and Dyson (2009), none of them were known to attempt an evaluation of the efficiency and productivity of head trauma care. Therefore, the present study ultimately aims to extend the established literature on healthcare efficiency using DEA in the UK healthcare sector and, more specifically, the relevant literature on reducing head trauma care costs.

In order to measure the efficiency of HTI hospitals by using DEA, input and output variables should be defined. One of the most important input variables can be seen in relation to the total cost of hospital, which is usually distinguished from the number of beds as a proxy for this input variable. However, a better proxy for this particular input is used in this research, which is an economic methodology proposed by Morris *et al*. (2008) for estimating the total cost associated with HTI care. In addition, during the process of choosing the data, some were found to be missing and for this reason an appropriate methodology was required in order to deal with such missing data. As the most suitable method, imputation is proposed by the chained equations approach to handle these missing data, which is the first time that this approach has been adapted in a DEA context.

Moreover, this study attempts to estimate the impact of the uncontrollable factors (environmental variables) on HTI hospital efficiency. These factors include the characteristics of hospitals and certain characteristics of head trauma patients. The exploration reveals many available models that can be used to study “uncontrollable” (environmental) variables, and their impact on efficiency scores that are estimated through using data envelopment analysis (DEA), but these approaches provide limited information, as well as a failure of agreement to which is the best method to achieve this. Consequently, a new methodology in the DEA context is adapted from recent research in other areas and applied to the second stage in order to evaluate the impact of the environmental variables on the efficiency scores. This approach is referred to as *Structural Equation Modelling (SEM)*, which allows the possibility not only to investigate the direct effect of various characteristics of both HTI hospitals and patients on the efficiency differences among hospitals, but also the indirect impact of these different characteristics of patients.

One of the disadvantages of DEA is that it does not account for the measurement of errors due to its nature as a deterministic approach. Subsequently, advanced methods have been developed in the literature to overcome this issue, such as sensitivity analysis and statistical testing. These methods are applied to very limited DEA studies in health care, as was recognised by Hollingsworth (2003) and more recently by Pelone *et al*. (2015). The latter study concluded that future DEA studies that include extensive uncertainty analysis are needed in order to fill this gap in the literature. In the current study, the DEA analysis results are followed by an extensive uncertainty and robustness analysis, which includes a combination of the bootstrap DEA (Simar and Wilson, 1998, 2000, 2007), internal validity (sensitivity analysis) and external validity tests (Parkin and Hollingsworth, 1997), together with statistical testing such as Friedman's test. Conducting these extensive analyses and tests will add to the literature, which could assist in filling the gap that is associated with the limited application of uncertainty analysis methodology in the DEA literature.

The implementation of the above methodology, in order to meet the objectives of the current research, results in contributions to the literature of DEA in terms of theory and practice, which could be considered as the primary motivation for this study.

1.4 Data Source

The Trauma Audit Research Network (TARN) kindly agreed to provide access to relevant data for the current study, as TARN's data had been utilised in different studies of health care that investigated specific trauma care trends and traits (Lecky, 2002). Moreover, neurosurgical care effects upon head injury outcomes (Patel *et al.*, 2005) were investigated, outcome prediction within trauma (Bouamra *et al*., 2006), the costs of acute treatment for brain trauma (Morris *et al.*, 2008) as well as mortality comparisons between Australia and the UK that followed hospitalisation (Gabbe *et al*., 2011). To the best of the researcher's knowledge, this is the first study to use a TARN dataset to investigate the possibility of reducing the costs of head trauma care while still maintaining efficiency.

Overall, TARN collates data from an average of one in every two English and Welsh hospitals that receive patients with head trauma. This figure relates to those patients who are either immediately admitted to hospital for 3 or more days following sustained injuries, which includes those who are admitted to an intensive care unit (ICU), or a neurocritical or high dependency unit (HDU), together with those patients who subsequently die within 93 days following the incident (Morris *et al.*, 2008). Additionally, there is a requirement to use external resources for this project, which are discussed in Chapter 3, in order to measure the costs of head trauma care.

1.5 Study Outline

This thesis includes seven chapters altogether as presented in Figure 1.1.

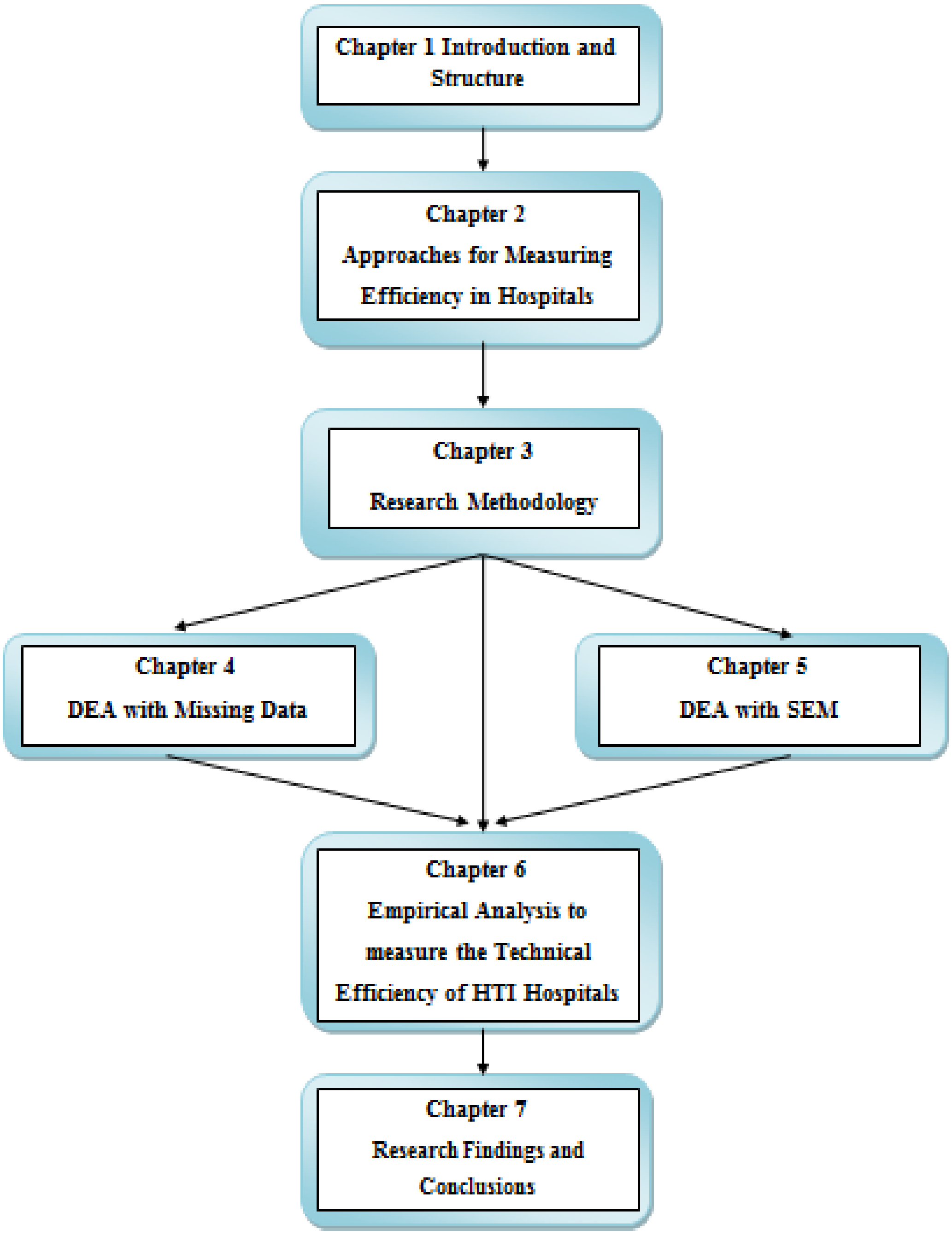

Figure 1 Thesis structure

The first chapter is an introduction, which provides a brief background into HTI care in England and Wales. Moreover, it presents the overall objectives of the study and indicates the methodological tools that will be implemented in the current study, as well as the rationale for conducting it.

In-depth, Chapter Two provides an overview of the approaches that have been taken in performance measurement and presents the efficiency measurement concepts as a foundation for the approach that is applied in the current study. A full methodological overview is provided in respect of the utilised form of efficiency measurements, which also documents a brief summary of various relevant methods of analysis, as well as an extensive review of previous empirical DEA studies in healthcare that are illustrated. The aim of the overview of techniques in efficiency measurement is to identify the most feasible and consistent approach in order to estimate efficiency of HTI care in the present research.

Chapter Three begins with the selection of research methodology. More precisely, the previous research and analysis indicate that the DEA approach should be employed in the empirical analyses of the current study. Therefore, full details of the DEA approach is presented in this chapter. Following this approach, bootstrapping DEA methodology and the DEA-based Malmquist index are discussed in order to be utilised for measuring efficiency and productivity of HTI hospitals. Furthermore, the data sources, including the choice of the relevant inputs and outputs for the empirical analysis of HTI hospital efficiency, are also described.

Chapter Four includes a background and literature review of missing data in DEA and multiple imputations through the use of the chained equations (MICE) approach as the proposed methodology for dealing with missing data in this research. A designed experiment to demonstrate this proposed method by using the actual data with artificially induced absent data is also presented. This designed experiment investigates the effects upon the DEA efficiency scores that are associated with different rates of absence.

Chapter Five introduces current methods to deal with the environmental factors in DEA and proposes a new method called structural equation modelling (SEM) to deal with such factors and provides a real example to highlight the advantage of the proposed method.

Chapter Six stipulates the measurement of the technical efficiency of HTI hospitals during the period 2009-2012 by using the variable returns to scale, input-oriented DEA method, which is followed by bootstrapping DEA in order to provide a robust analysis of the results obtained from the original DEA. Conclusively, the results provide a static picture of hospital performance in particular years. In order to ascertain a further comprehensive view of how hospital efficiency changes over time, extended investigation of the change in productivity of the hospitals over the period 2009-2012 is undertaken using the DEA-based Malmquist index. Finally, the proposed SEM approach is applied to this specific chapter as a second stage post-DEA in order to investigate the effects of some environmental factors on the DEA efficiency scores.

Chapter Seven is the final chapter, which presents a summary of all the results of the thesis and draws conclusions from the empirical work. The chapter also discusses the implications of the main findings and draws attention to the contributions of the current study, as well as pointing to whether further research is required in certain areas and the nature of any such investigations.

CHAPTER TWO: APPROACHES FOR MEASURING EFFICIENCY IN HOSPITALS

2.1 Introduction

The aim of this chapter is to review development theory, and to evaluate efficiency measurement techniques and hospital efficiency, which will also incorporate empirical literature, as the focus of the current research is to measure HTI care and its overall efficiency in order to reduce accumulated expenditure. Invariantly, a clear comprehension of the main components of performance measurement is needed and these are analysed in a general sense, with particular focus on efficiency measurements. Subsequently, it becomes feasible to apply assessment techniques for determining efficiency performance. Moreover, this chapter conveys an intricate summary and evaluation of the accumulated empirical literature regarding the efficiency of hospitals. Indeed, the principal intended insight of the present review is to analyse hospital efficiency, which is indelibly conducive to the set objective of the current research study, as the review focuses purely on hospital studies, with no reference to any separate health facility or research sector. Furthermore, the hospital production models are presented and evaluated, as they provide an important form of measurement for the efficiency of hospitals. Thus, an applicable guide process for the additional chapters will be implemented to comprehend the use of appropriate methods and variables, which will be devised from an extensive methodology review, empirical studies, and production models.

Overall, there are six main sections within this chapter, which fully detail the processes of our methodology. Firstly, the general performance measurement approaches are analysed in Section 2. The need to measure performance is discussed in Section 3. Section 4 presents details of the efficiency measurement concepts, which particularly focus on productivity measurements and the concept by Farrell (1957). In Section 5, a full methodological overview is provided in respect of the utilised form of efficiency and productivity measurements, which also documents a brief summary of various relevant methods of analysis. In Section 6, an extensive review of previous empirical studies is illustrated. Then, in Section 7, the hospital production models are distinguished, which ultimately helps identify suitable input and output factors that affect hospital efficiency and productivity analysis. In Section 8, the differences of efficiencies among hospitals are explained. Finally, a conclusion of the whole chapter is provided.

2.2 What is Performance Measurement?

Performance measurement is a structured process through which an organisation identifies, measures, and monitors important programs, systems, and processes. Hospitals could be commercial organisations, and other than the social impact they have, hospitals are expected to use their resources in an efficient manner, and show profits. The profits help the hospital to invest in infrastructure and equipment, and to hire resources (Cameron, 2010).

The term performance measurement is associated with the manufacturing industry, and it was identified by financial measures such as liquidity, leverage ratios and net profit. Commercial organisations are cost driven, and an organisation's performance is a function of its efficiency and productivity. These are measured as the ratio of costs of inputs required to the cost of the product (Shaw, 2003). However, these measures have been criticised for various reasons, even though they have also provided a slightly greater understanding of performance in operations. For instance, internal comparisons of costs and revenues have been emphasised by financial measures, although they have failed to demonstrate different factors of importance that can result in positive organisations (Otley, 2002). Additionally, when financial measures are the only utilised form in measuring performance measurement, it may be implied that cost reduction is the only focus from organisations, as well as profit margins and decision-making in the short-term, while ignoring a variety of environmental factors (both internal and external) that could be imperative to achievement in the long-term (Bourne *et al*., 2003).

Therefore, different definitions of the performance measurement for organisations are provided and several financial and non-financial measures are available to identify this organisational performance (Thor *et al*., 2007).

One school of thought considers that organisational performance, in the case of hospitals and healthcare units, should be measured in terms of the clinical outcomes. This is a complex subject, since it must consider qualitative measurements such as the patient's illness, nature of the illness, the patient's age and lifestyle habits, and several other patient dependent variables (Dijkstra *et al*., 2006). However, the inference is that a hospital may cure all patients, but may still be inefficient, as far as consuming resources and giving the desired output are considered. The term 'efficiency' therefore is complex, and subject to qualitative and quantitative interpretations.

Hofer (1983) argues that performance measurement is important since it forms an important component of the management decision-making process. Before taking up strategic planning, an organisation must first evaluate the performance. Results of the evaluation act as the basis for further management decisions. If the results are not satisfactory, then the problem areas can be identified and mitigation actions taken (Avkiran, 2002). However, measurement of organisational performance is not easy and straightforward, as mentioned previously. The problem becomes complex when the performance of non-cost centre departments, such as human resources, maintenance, design and others, must be measured.

Elbashir *et al*. (2008) agree with these arguments and indicate that organisational performance and organisation processes are related. A firm with low performance usually has inefficient processes. Several points emerge from these arguments, and they have a bearing on measuring the efficiency of the firm. Performance is not explicitly defined, and definitions among researchers differ, based on their objectives (Lebas and Euske, 2002). Performance is multi-dimensional measures with several variables, forming interdependencies. In addition, performance parameters vary among industries, and even among healthcare organisations. The standard financial measures of performance such as profits, leverage ratios, margins, debts, etc., are important. However, these financial ratios restrict themselves to only the financial performance, while ignoring other parameters (Bourne *et al*., 2005).

This section highlights the complexities of measuring organisational performance. The next section discusses the need to pursue this extensive and complex exercise in order to measure the performance.

2.3 Need to Measure Performance

This principle applies to any organisation, irrespective of the sector, which includes construction, manufacturing, agriculture, healthcare, retail and investors of funds and other resources. While production is an ongoing process to meet the organisation’s objectives, it is important to understand how efficiently these resources are consumed in the process. The objective is to link organisational performance with efficiency (Hibbert *et al*., 2013). When the performance is measured, the organisation understands how good or bad the performance is with reference to internal and external benchmarks. It can then take up steps to consume resources efficiently, improve the quality, ensure higher customer satisfaction, and meet the strategic objectives (Henri, 2004).

Standard financial measures provide assessments of the performance from the cost and financial aspects of the firm. Adopting such performance measures helps firms to look beyond internal cost comparisons and towards other factors. These include utilisation of resources, productivity in terms of availability and time used, waiting time, customer satisfaction, etc. By moving away from financial measures, the firm focuses on internal and external forces that have a long-term impact (Bourne *et al*., 2005). Many other functions and assets are examined from a different perspective and insight, and they lead to uses that are more efficient.

Measuring performance within the healthcare service sector presents a number of challenges. Hospitals cater to a wide segment of patients, from the poor who require subsidised and free treatment to the rich who can afford premium treatment. Hospitals also operate with multiple business objectives, and deliver a much more diversified range of service offerings, while operating in uncertain political environments (Kutzin, 2013).

Van Peursem *et al*. (1995) indicate that the basic performance measurement for healthcare must be identified by economy, efficiency, and effectiveness. Economy measures the relationship between the costs or expenses incurred for procuring certain inputs, and the output obtained from them. It represents the number of quality inputs, and the costs needed to complete a healthcare activity. Efficiency is a measure of the ratio between the output and the resources used. It refers to the activities that can be monitored and controlled. Effectiveness specifies the degree to which the required objectives are met. Factors such as the quality and quantity of the results are also important.

Several studies are extended to measure the performance of healthcare organisations. Grigoroudis *et al*. (2012) used both financial and non-financial measures to determine the performance of public health care organisations The non-financial measures included the satisfaction of internal and external customers, the self-improvement system of the organisation and the ability of the organisation to adapt and change. Smith (1990) researched the performance of the UK hospitals and used six categories for the indicators. These included epidemiology, resource provision, resource quality, resource costs, process, and outcome.

In contrast, the World Health Organisation (WHO, 2003) provided another set of measures to define the performance of healthcare units. These include efficiency, equity, quality, responsiveness and sustainability. Creteur and Poschet (2002) carried out another study to measure the performance of hospitals. They used indicators such as human resources, efficiency, patient satisfaction, quality of care and financial outcomes. It is thus clear that the measures and indicators must be carefully selected, keeping in mind the strategic objectives of the hospital and the availability of data.

In our research, we decide to use efficiency as a measurement of HTI hospital performance,. The reasons for this choice of method are as follows. Measurement of productive efficiency helps to evaluate the activities controlled by the management. In addition, efficiency explains the manner in which resources are used and the outcome obtained, and this helps to improve organisational performance. These factors help to improve the technical efficiency, increase revenues by increasing productivity, and meet the organisations' objectives (Smith and Mayston, 1987).

2.4 Concept of the Production Frontier and Efficiency

The concept of production frontier and efficiency was discussed and implemented practically in the work of (Farrell, 1957) for measuring efficiency based on the efficiency definition of (Koopmans, 1951) and (Debreu, 1951). The decision making unit (DMU) is efficient when it is impossible to improve any input or output without worsening some other input or output. In economics, the production process refers to the utilisation on certain inputs in order to generate a particular output. In a hospital setting, one example of an output could be the discharge of in-patients, with inputs such as technology, equipment, labour and number of beds. The production process could refer to the conversion of inputs into health care services with the ultimate goal to treat and discharge patients.

The production function provides a specific technical way in which inputs are combined in order to generate the output. Given that the technological change is fixed in the short-term, the production function may generate a set of different output quantities based on different input quantities. In the simple case of 'one input – one output', the production function may be represented by a curve, as shown in Figure 2.1. The *production frontier* is the combination of points corresponding to the *maximum* possible quantity of output that can be achieved at each particular input quantity ('output-orientation') and, alternatively, a particular output quantity may be achieved using the minimum possible quantity of input ('input-orientation'). All of these points correspond to *technically-efficient* production (*technical efficiency).*

Therefore, the concept of *technical efficiency* could be approached using either the "input" or the "output" orientation, as described in this section. In Figure 2.1, technically-efficient points are positioned on the actual production frontier, such as points B and C. However, point A is technically-inefficient because there are ways to generate larger output ($y^1 > y^0$) with the same quantity of input (x^1) or there are ways to produce the same output (y^0) using a smaller quantity of input ($x^0 < x^1$). In other words, better capacity utilisation could improve efficiency by moving from point A to point B or point C.

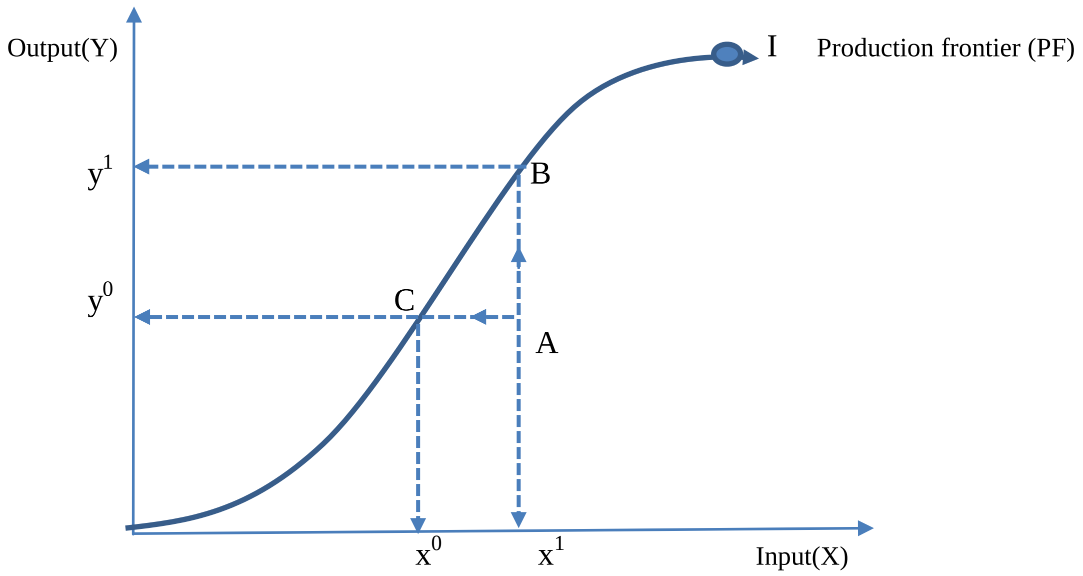

Figure 2.1: The production frontier

On the other hand, *allocative efficiency* refers to the combination of optimal proportions of inputs and outputs with a given set of prevailing prices. In other words, allocative efficiency aims at maximising the overall social benefit. In both the technical and the allocative efficiency[1], the identification of the 'best-practice' production frontier ('best frontier') may

[1] In microeconomics, the product of technical and allocative efficiency ratios provides the economic efficiency of a DMU. Further details would go beyond the scope of this study.

provide the benchmark against which each hospital can be compared in order to determine its efficiency levels. In practice, inputs and outputs for hospitals cannot be easily transformed into physical or monetary units. For this reason, many authors focused on the technical aspect of efficiency in an attempt to evaluate hospitals' relative performances (Tobin, 1958; Sahin and Ozcan, 2000; Xue and Harker, 1999). In this study, the focus will be on technical efficiency only.

2.5 The Measurement of Efficiency

The previous section discusses at length the concepts of efficiency and the relationships between them. However, it is important to evaluate efficiency numerically. This importance of measuring efficiency was first practically recognized by Farrell (1957). Efficiency, as mentioned previously, has two components, technical and allocative, that are combined to measure the economic efficiency. Technical efficiency is the capacity of an organisation to maximise the output from a certain number of inputs, which are needed to provide the outputs. Allocative efficiency is the capacity of a firm to combine the outputs and inputs in adequate proportions, assuming set prices and with the available technology (Hollingsworth, 2012). Economic efficiency, also called productive or cost efficiency, is simply a combination of the technical and allocative efficiencies. It is used to reduce inputs and increase outputs proportionately at minimum costs. Therefore, the economic efficiency must be measured with reference to other organisations in similar sectors (Farrell, 1957). A private hospital in the UK, offering only super specialty treatment for heart surgery, would be more efficient than a general hospital run by the NHS. Figure 2.2 illustrates the efficiency measures of hospitals as an example.

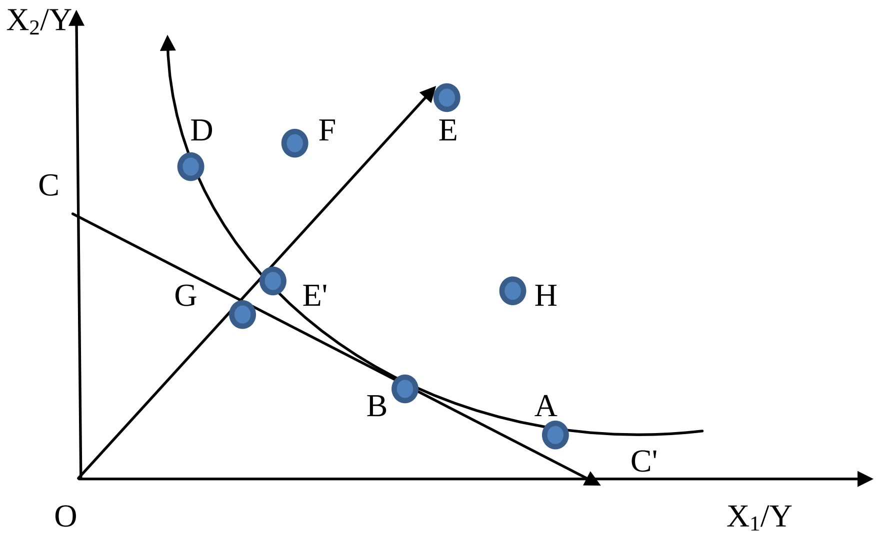

Figure 2.2: Farrell's efficiency measures

In Figure 2.2, the hospitals are assumed to have two variable inputs, X_1 and X_2. These are used in different quantities to produce an output Y. The production frontier can be defined by means of the following expression (Hollingsworth *et al*., 1999):

$$Y = f(X_1, X_2)$$

In Figure 2.2, the points A-H are different hospitals that use different combinations of inputs to produce a given unit of patients for treatment. Assuming that the hospitals work with constant returns to scale, the hospital with the best practice frontier is represented by the curve passing through the points D, B, and A. These hospitals use the least amount of inputs to generate the required outputs. These hospitals are on the efficient frontier and they are technically efficient, since other hospitals cannot produce the same level of output with proportionally fewer inputs. The efficiencies of these hospitals are calculated as the ratios OD/ OD, OB/ OB, and OA/ OA respectively. The efficiencies of these hospitals are therefore all 1.

At the same time, the hospitals on the interior of the frontier curve, identified by points H, E and F, are technically not efficient. These hospitals can deliver more output without extra input, or they can use fewer inputs to maintain the output level. For example, the technical efficiency of hospital E is calculated as OE'/ OE, and this value lies in the finite interval (0,1]. The ratio defines

Technical Efficiency (TE) = OE'/ OE

where $0 < TE \leq 1$.

The allocative efficiency and economic efficiency can be measured when the prices of inputs and the output units are available. Referring to Figure 2.2, when the line defined by CC' indicates that the ratio of the prices between inputs is known, then the optimal input mix for the hospital to produce a unit of output is at B, which is the tangent point between CC' and the production frontier. In such a condition, the allocative efficiency of E is (Farrell, 1957):

Allocative Efficiency (AE) = OG/ OE'

where $0 < AE \leq 1$.

The above equation signifies the possible percentage reduction in production related costs when hospital B is considered at the allocative point. Hospitals at points D and A are technically efficient. However, they are not allocatively efficient since they do not combine other inputs to lower their production costs. The economic efficiency is made up of allocative and technical efficiency, and a hospital is economically efficient when both these components are efficient. The economic efficiency is therefore defined as follows:

Economic Efficiency (EE) = OG/ OE

where $0 < EE \leq 1$.

In other words,

Economic Efficiency = [Technical Efficiency] x [Allocative Efficiency]

or

OG/ OE = OE'/ OE x OG/ OE'

The ratio GE/ OE signifies the production cost reduction that is possible when the hospital shifts from E to G, which is the effect of minimising cost.

The input orientation method is used to measure the efficiencies given in Figure 2.2. The method measures input variations, formed among the hospitals, when a standard output is produced. The output orientation method can also be used, where the two components of the economic efficiency are obtained by increasing the outputs produced from the inputs.

All concepts discussed in this section are developed in order to form the parametric and non-parametric approaches for measurement of efficiency.

2.6 Methods of Efficiency Measurement

It is necessary to stipulate the main approaches for efficiency evaluation as they present the foundation for the methodological framework, which is implemented in our further analytical empirical research. The origins of the term *"efficiency"*, as a definition and measurement, stem from the research by Koopmans (1951), Debreu (1951) and Shepherd (1953). In particular, originally within the first definition, DMU was distinguished as becoming efficient through the impossibility of producing additional output without creating a reduction of another output (Koopmans, 1951). Subsequently, distance functions in an output-expanding direction were implemented as a form for multiple-output technology modelling, and increasingly as a manner of radial distance measurements of a DMU from a frontier (Debreu, 1951). Additionally, this form of multiple technology modelling was introduced into an input-conserving direction (Shepherd, 1953). Nevertheless, the overall functionality in production had never been realised, which is precisely why observed data through the use of a nonparametric or a parametric function were suggested for estimation (Farrell, 1957). Consequently, as a development from these two approaches, contrasting models were devised. In fact, the selection between the models depends on the predefined purpose for measuring the efficiency within an investigation, as well as on data availability in various instances.

The alternative methodologies of efficiency measurement are examined in the following section. To create functional efficiency measurements of a unit of production, it is necessary to apply conventional methods. For instance, it is possible to utilise ratio analysis and regression analysis from the base of the average frontier, or by using one of the parametric or non-parametric frontier methods, which have been based on the frontier that is deemed to have the most beneficially constructed frontier. Consequently, both the conventional approaches and the frontier approaches are discussed in this section in order to select methods of efficiency measurement that are included in empirical analysis, as the focus will determine the underlying concepts and assumptions, together with the strengths and weaknesses, instead of the methodology's technical details.

2.6.1 Ratio Analysis

Ratio analysis is the simplest approach for measuring the technical efficiency using different indicators as ratios. Common indicators include bed occupancy rate, turnover ratio, turnover interval and average length of stay in hospital (Zere *et al*., 2006). Efficiency is captured through the effective utilisation of a particular input, and for this reason commonly-used ratios involve a single output and a single input as the nominator and the denominator, respectively. In order to estimate the overall efficiency for a hospital, a number of ratios should be calculated simultaneously.

However, partial indicators of efficiency may provide misleading results (Sherman, 1984; Thanassoulis *et al*., 1996; Nyhan and Martin, 1999). For example, the bed occupancy rate provides information about the required occupancy of beds every year compared to the availability of beds. This is an indicator of efficiency because too many available beds would indicate a waste of resources, whereas too few available beds would indicate dysfunctionality of some hospital departments. However, an optimum bed occupancy rate may not necessarily be an indicator of efficiency because there are no available data regarding the cost associated with each treated patient. For example, if a different ratio provided information about the average cost per treated patient, and it was found to have increased, the bed occupancy rate would not be very informative in terms of the overall hospital efficiency, Ehreth (1994).

2.6.2 Regression Analysis

Regression analysis involves the exploration of a relationship between a dependent variable (output) and certain independent variables (inputs). This relationship is usually represented by a fixed structural form (function), whose estimation in our context aims at identifying the efficiency.

In the health care sector, this approach could be used to provide information about the technical efficiency of a DMU, such as a hospital. For example, the production function of a hospital could represent the services provided by the hospital as the overall expected output, while financial and human resources or technological equipment could be the utilised inputs. This relationship could be explained using a parametric econometric method, such as multiple linear regression analysis (Nyhan and Martin, 1999; Simar and Wilson, 2000).

Figure 2.3 shows the simple 'one-input and one-output' linear regression case. The estimated dependent variable ("output") essentially provides the expected average quantity of output for each quantity of input used by the DMU, and this is represented by the drawn line segment, which shows the "fitted" values of the regression estimation.

The linear estimated production function could be perceived as the indicator of average technical efficiency[2] for every input utilised (average efficiency rate). Therefore, any divergence from the fitted line would correspond to divergence from average efficiency levels, corresponding to a source of inefficiency. Stated differently, the smaller the impact of unobservable factors (random errors), the better the regression estimation and therefore, the more efficient a particular DMU is expected to be.

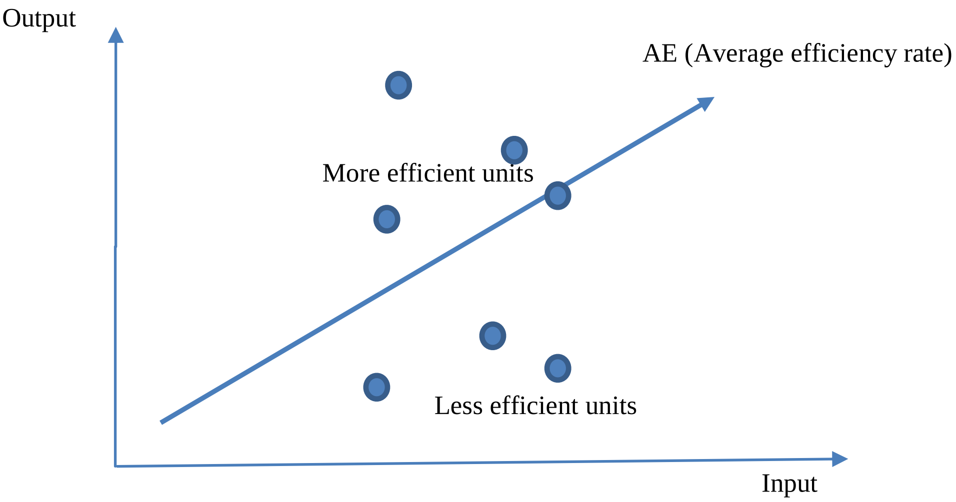

Figure 2.3: Regression analysis

The major advantage of regression analysis is the method's capability to accommodate multiple independent variables as inputs for a particular output. This is not possible with ratio analysis. However, although regression analysis may involve multiple inputs, it cannot include more than one output in a single investigation. A series of investigations, run simultaneously, could provide information for each different output. Nevertheless, this is a potential disadvantage of the method given that there is no widely-acceptable way for interpreting performance of multiple-source random errors. Multivariate generalisations of

[2] The specificity of this term is provided in prevous sections. For the purposes of this section, it makes no difference whether we use the term overall efficiency or technical efficiency.

regression analysis exist, though these models introduce more parameters to represent correlations among the dependent variables, with a corresponding reduction in power and precision. Furthermore, unlike ratio analysis, regression analysis requires a very specific production function associating an output with different inputs. In practice, this is not usually feasible given the extensive nature of the hospital services provided and the large number of inputs and outputs involved in the measurement process.

Nonetheless, the most important drawback of regression analysis in measuring efficiency is the mere fact that the method calculates efficiency in average terms. Although a comparative static analysis of efficiency indicators across different hospitals may be informative, there is no qualitative information available about the particular source of inefficiency in each hospital.

2.6.3 Frontier Analysis

The general method of frontier analysis offers two main approaches for measuring efficiency, based upon nonparametric and parametric frontiers. These approaches were first suggested by Farrell (1957) as practice techniques for measuring efficiency. This measurement approach included the technical efficiency and the allocative efficiency, which were then combined to provide a measure of total economic efficiency. Both of those efficiencies were estimated from the relevant production frontier—the "best frontier"—by using observed data.

2.6.3.1 Parametric Frontier Analysis

The parametric approach requires us to specify a prior structural form for the production function. This production function could be a Cobb-Douglas or translog function. Two methods were developed in this category with the aim of estimating all coefficients associated with the production function, corresponding to a deterministic parametric frontier and a stochastic parametric frontier. The deterministic frontier is a non-statistical method which does not account for any random factor in the data, such as random noise or measurement errors, and it is estimated either by implementing mathematical programming or by means of econometric regression techniques; Jacobs (2001) and Murillo-Zmorano (2004). Conversely, the stochastic frontier approach assumes random factors for the data and it is evaluated by using econometric regression techniques only. These are briefly described in the following sections.

a. The Deterministic Parametric Frontier

The deterministic parametric frontier approaches the production function as a deterministic relationship between the output and the inputs (Cazals *et al*., 2008). For this reason, it is essential that a very specific structural form of a production function is defined. The inputs represent independent variables which attempt to explain the variations of the dependent variables, that is the output. The deviation from the frontier (residual) is considered to be the actual *technical inefficiency* of the DMU. Therefore, the production function is assumed to be fully *deterministic* in terms of technical efficiency; Smith and Street (2005). There are two techniques for estimating the parameters of inefficiency, the mathematical programming method, first developed by Aigner and Chu (1968), and regression analysis. The second method includes corrected ordinary least squares (COLS) and modified ordinary least squares (MOLS), and are considered by some authors to be conventional methodology (Cazals *et al*., 2008).

The major advantage of the deterministic parametric frontier method is the fact that there is no need to define the distributional properties of inefficiency. The disadvantage of the method is the assumption that any random errors could be attributed to technical inefficiency without the possibility of accommodating measurement errors and random shocks associated with unobservable or externally-defined variables. Figure 2.4 presents an example of a deterministic parametric frontier. Both of the units (A and C) are technically inefficient as they lie on the production frontier.

On the other hand, unit B lies below the production frontier, indicating that it is technically inefficient. Due to the deterministic assumption, the line segment BC, which is the deviation of unit B from the frontier, is attributable fully to inefficiency.

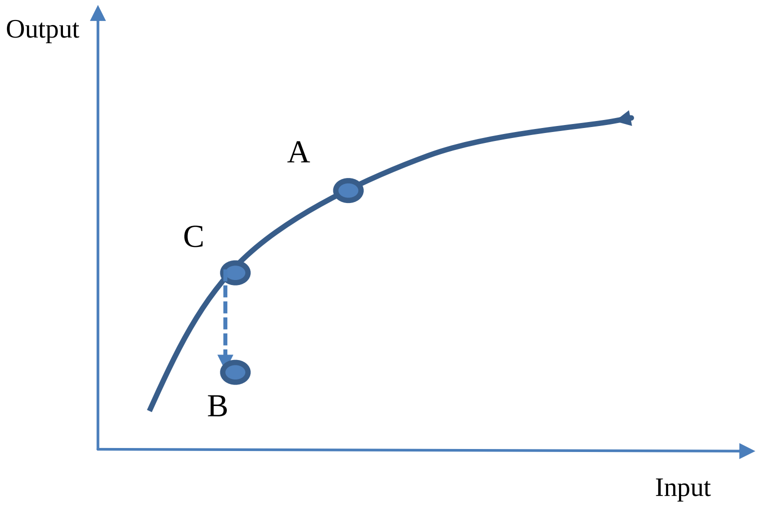

Figure 2.4: The deterministic production frontier

b. Stochastic Frontier Analysis (SFA)

The stochastic frontier model was proposed by Aigner *et al.* (1977) and Meeusen and van den Broeck (1977). The idea of this approach is essentially to expand the deterministic frontier by broadening the component elements included in the random error of the production function. In other words, the units that deviate from the frontier may not be totally under control. Therefore, these two studies suggest that we should add a further random error to the non-negative random variable, to model this inefficiency.

As a result, the main advantage of this method is its capacity to treat separately the component of technical inefficiency and any random shocks or measurement errors, which might have influenced the dependent variables, that is the production output.

This method requires a specific distributional form for the component of technical inefficiency and the remaining random errors. Furthermore, in order to be able to treat technical inefficiency separately, a rule of technological change is also required, in the form of a technology function. It is commonly assumed that technical inefficiency, which is non-negative, follows a truncated normal, half-normal or gamma distribution (Smith and Street, 2005).

These are restrictive assumptions, and may present a major challenge to the effectiveness of this method. For example, if the technological function is mis-specified, the ability of the method to separate the effects of technical inefficiency and the effects of the remaining random errors will be eliminated.

Figure 2.5 illustrates the stochastic production frontier case using a simple production function. Point D represents a technically-efficient DMU with a positive stochastic part. This means that the random errors include no inefficiency but rather positive external shocks contribute to higher output. On the other hand, point B represents an under-performing case, which corresponds to a DMU that operates at a technically-inefficient point. Unlike the deterministic approach, line segment BC can now be separated into BE and EC, corresponding to the technical inefficiency and the remaining random errors, respectively.

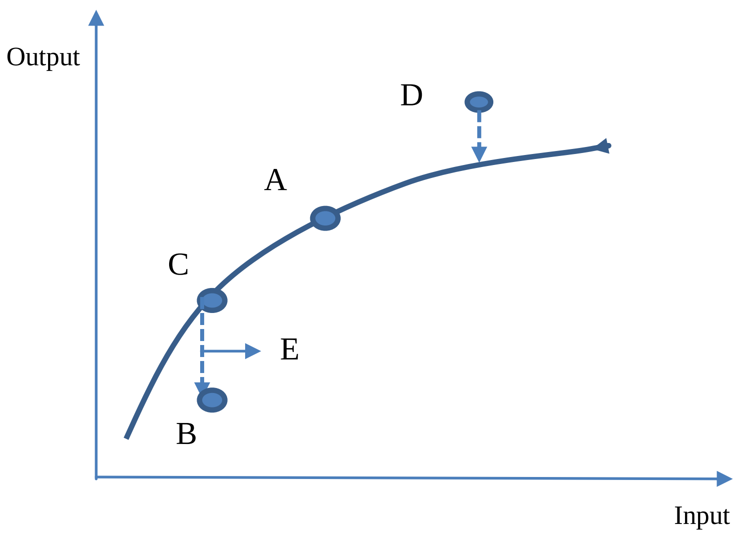

Figure 2.5: The stochastic production frontier

2.6.3.2 Non-parametric Frontier Analysis

Non-parametric frontier analysis is based on a production frontier generated without the need to parameterise the production function. This means that the production function may remain unknown, and there is no need to define its distributional properties either. The non-parametric methods are based on linear programming analysis, and they consider any deviation from the frontier as actual inefficiency. There are two approaches to non-parametric frontier analysis, the deterministic approach and the stochastic approach. These are presented next.

a. Non-parametric Deterministic Frontier

The non-parametric deterministic methods do not require a specified functional form. There are two representative non-parametric deterministic methods, which are briefly discussed next: data envelopment analysis and free disposal hull analysis.

a.1 Data Envelopment Analysis (DEA)

DEA is a non-parametric linear programming method for estimating efficiency and capacity utilisation, effectively identifying the production frontier. The method was first introduced by Charnes *et al.* (1978) as a measure of efficiency for 'not-for-profit' entities participating in public programmes in the United States.

DEA is based on the principle that the performance of each DMU must be compared relative to the 'best-practice' frontier, that is a benchmark continuum of highly-efficient, virtual DMUs. The 'best-practice' virtual frontier is essentially the convex combination of all efficient points of operation. In this method any deviation from the 'best-practice' frontier must be an indication of technical inefficiency. This research uses the DEA method for measuring the efficiency of HTI care in England and Wales and is described in considerably more detail in the next chapter.

a.2 Free Disposal Hull (FDH)

The FDH method relaxes the convexity assumption and, for this reason, it may be considered a more general case of the main DEA modelling approach. It was first introduced by Deprins *et al.* (1984).

The rationale of this method is to narrow attention to the observable performance of a DMU by relaxing the input-substitutability assumption required in the DEA method. In other words, the FDH method assumes that a significant degree of complementarity between inputs exists, which essentially suggests that certain inputs must be freely-disposable at no additional cost in order to continue producing. In other words, inputs fail to replace one another in the production of a fixed amount of output when they are non-substitutable, and these inputs need to be used in a set measurement proportion in order to process their output, while excessive input from what is originally required becomes wasted. In this regard, the production function would appear like a *staircase,* as demonstrated in Figure 2.6.

Although the method may be better in terms of approaching the real operational behaviour of a hospital, it may not provide accurate estimates of its efficiency score because the lack of input-substitutability prevents the producer from achieving all of the optimum production points possible.

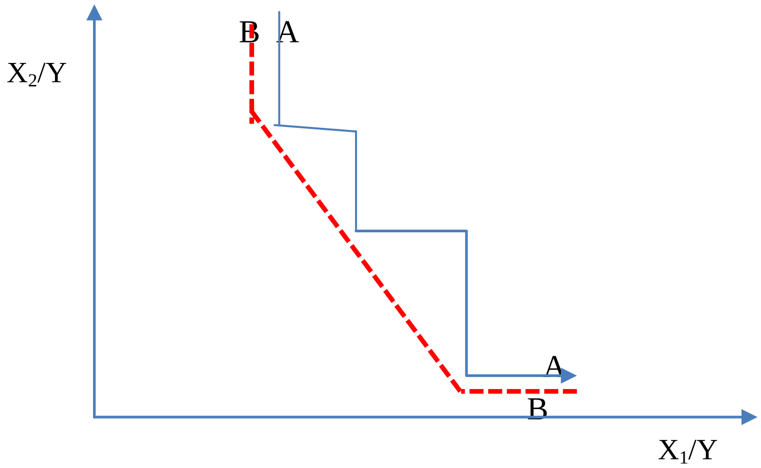

Figure 2.6: The FDH approach to efficiency

In Figure 2.6, the perfect complementarity characterising inputs X_1 and X_2 corresponds to the set of points that are shown by the *staircase* curve AA. The AA curve is essentially the isoquant (indifference curve) representing the fixed (equal) maximum output that can be achieved with different combinations of inputs. As we will see in Chapter 3, the production frontier associated with the main DEA method would generate a convex linear combination of points for different ranges of input quantities. Therefore, one would reasonably expect that the DEA curve would 'envelop' the FDH curve, as demonstrated in Figure 2.6 by the BB and AA curves respectively.

b. Non-parametric Stochastic Frontier (Stochastic DEA)

As described previously, DEA modelling does not take into account the inherent random errors, due to the fact that its structure is created based only on observed data.

The stochastic DEA method aims at overcoming this disadvantage. Sengupta (1987) and Simar and Wilson (1998) used a stochastic version of DEA. In stochastic terms, the production function is unknown and, therefore, these researchers aimed at estimating empirically the true distribution of the output using resampling methods such as bootstrapping. In other words, this is a simulation process that draws observations out of the set, while allowing repeated draws of the same observations. The bootstrapping procedure could generate many ‘pseudo-samples’ from the original set of observations, and for this reason the approximation of the underlying distribution is expected to be fairly accurate. This could allow the calculation of the production frontier and efficiency scores without the need to derive a specific structural form for the production function. Statistical inference may also follow based on the derived distribution. In this thesis, bootstrap DEA is used and more technical details are provided in the next chapter.

2.7 Empirical Studies on Measuring Efficiency in Health Care

There is a vast amount of literature about the empirical measurement of technical efficiency in different health care sectors, such as primary and secondary care (Hollingsworth, 2003), and in different departments of hospitals (Chilingerian and Sherman, 2004) or different groups of professionals (Hollingsworth *et al*., 1999).

Hollingsworth *et al.* (1999) reviewed 91 studies involving DEA modelling for measuring technical efficiency in healthcare. The authors found that most of the studies were focused on measuring hospital efficiency, particularly in the United States. The most important observation was that DEA modelling was found to be more successful and more accurate in measuring overall hospital efficiency, rather than the efficiencies associated with certain departments or groups of medical professionals. For example, it was easier for the DEA linear programmer to calculate the technical efficiency of a hospital as a whole, given certain organisational and managerial restrictions, but it was much more challenging to identify differences in efficiency levels among hospital departments.

Furthermore, the review offered by Hollingsworth (2003) identified that half of the 188 reviewed studies involved non-parametric approaches to measuring technical efficiency in hospitals, revealing the importance of assessing hospital efficiency. This review showed that there have been significant attempts to introduce more advanced versions of DEA programming in studies measuring hospital efficiency, such as the two-stage DEA approach using the tobit model. In the same review, certain parametric approaches and the SFA found empirical validity, as well. However, the author concluded that DEA remains the predominant method used for measuring technical efficiency in the health care sectors. Nonetheless, these comprehensive reviews demonstrated that the availability of systematic data sets may also be a factor explaining why hospitals were found to be more appropriate than other health care institutions in terms of applying alternative methods for measuring technical efficiency.

Along the same lines, Worthington (2004) identified 38 studies which used the frontier analysis for measuring technical efficiency. As noted earlier, the two main methods of frontier analysis are DEA and SFA, and this author noted that DEA is the more frequently-used methodology. In addition to this, the author reported that the most frequently-used inputs for measuring efficiency were the conventional ones, which are capital and labour. On the contrary, the output selection was much more variable due to the spectrum and different qualities of the health care services provided.

Hollingsworth (2008) offers a review, which is based on the measures of frontier efficiency from 317 independent studies. The principal technique that has been incorporated is through the analysis of non-parametric data envelopment analysis, although the utilisation of parametric techniques (i.e. stochastic frontier analysis) is increasing. Moreover, there has been a re-evaluation and summarisation of the process of application to organisations relating to health care and hospitals. In general, this study defines potential detrimental effects that may be enhanced from considering the conceptualisation of efficiency. Furthermore, this review establishes specific criteria in the assessment of efficient application and implementation, which will potentially assist researchers, together with individuals who are assessing whether to apply published findings to their investigations.

Recently, a systematic literature review has been provided by Pelone *et al*. (2015) into the analysis of primary care (PC) efficiency through the use of data envelopment analysis. In order to comprehend how results are impacted by methodological frameworks, as well as the information that policy makers receive, the researchers reviewed 39 specific DEA applications that are present within PC. This paper also described a combination of investigations that utilised the qualitative narrative synthesis. Additionally, data are reported from this study through each efficiency analysis in the context of evaluation, specification of model, application of methods in order to test the findings' durability, and the presentation of results. Overall, it is indicated by the results in relation to the application to PC that the DEA requires additional developments to enable the complex production of PC outcomes, although it is still a perpetually developing methodology. However, the improvement of the efficiency of PC organisations by policy makers and managers is supported by continual evaluations. Nevertheless, enhanced research remains a requirement to address certain areas of ambiguity in this particular field of investigation. For instance, the standardisation of methodologies and the development of outcome research in PC require improvement and clarification. Likewise, it is conclusive that additional research will have to be structured from beneficial evidence-based rationales and incorporate substantial uncertainty analyses. The researchers hav proposed to different academics and scholars that various considerations should be analysed in order to understand the process of decision making in PC from the utility of efficiency measurement.

Most of the literature reviews conducted for the measurement of efficiency in health care found that there is a lot to be learned from empirical studies, particularly regarding the interpretation of outcomes derived from frontier analysis. These studies exploring the technical efficiency in health care used their findings to inform policy decisions, such as to identify ways of achieving resource savings and possible improvement of efficiency scores. For example, Faze *et al*. (1989) evaluated the plant capacity of hospitals by applying non-parametric DEA modelling and using 'number of beds' as the proxy for capacity. The authors found that there were no major differences between rural and urban hospitals, in terms of 'capacity utilisation' and 'cost efficiency'. However, they did find that urban hospitals employed more doctors and other medical staff than rural hospitals.

A study by Ozcan *et al.* (1996) considered the efficiency levels of psychiatric hospitals as a separate group and compared those with hospitals of acute care for the time period 1986-1990. The study included 'not-for-profit' and 'for-profit' hospitals. The psychiatric hospitals appeared to be less efficient than acute care hospitals, while there were no statistically significant differences between the 'not-for-profit' and 'for-profit' groups of hospitals.

Harrison *et al.* (2004) included a larger sample of US hospitals in a non-parametric DEA approach in order to calculate and compare efficiency levels. The findings demonstrated the significant effects of inefficiency over the years and the potential to increase efficiency through better resource management. For example, the efficiency rate increased from 68% in 1998 to 79% in 2001. The proportion of highly-efficient hospitals also increased from 10% in 1998 to 16% in 2001.

Several smaller studies used non-parametric DEA modelling in order to assess the technical efficiency of general hospitals, such as those by Ersoy *et al.* (1997) on Turkish general hospitals, Giokas (2001) on Greek general hospitals, and Al-Shammari (1999) and Sarkis and Talluri (2002) on Jordan general hospitals. All these studies indicated that there was a significant improvement of efficiency levels over the years. The studies identified similar factors, which might have contributed to this improvement, such as better organisation of resources and better resource utilisation. It is interesting that the 'bed occupancy rate' was found to be inversely associated with the operating hospital cost (Giokas, 2001). This demonstrated the complexity in terms of identifying the most important factors influencing technical efficiency.

A few studies which applied DEA modelling in order to measure efficiency in African hospitals found some similar results (Kirigia *et al*., 2002, Osei *et al*., 2005, and Zere *et al*. 2006), as follows: i. public hospitals were found, on average, to be more efficient than private hospitals; ii. efficiency scores could be improved if the numbers of medical officers and technical staff decreased and the numbers of maternal and child care visits, deliveries and discharges increased; iii. several small-sized hospitals appeared to be more efficient than their capacity had allowed them due to "scale effects", that is increasing returns to scale might have reduced the magnitude of efficiency loss. For this reason, it was suggested that merging small hospitals in specific geographic areas could significantly improve the overall actual technical efficiency in secondary care.

Nayar and Ozcan (2008) studied the performance measures of quality for Virginia hospitals. The findings indicate that technically efficient hospitals showed good performance as far as quality measures were concerned. Some of the technically inefficient hospitals were also performing well with respect to quality. Kazley and Ozcan (2009) examined the relationship between hospital electronic medical record (EMR) use and efficiency among a large number of acute care hospitals. The findings indicate that small hospitals may benefit in the area of efficiency through EMR use, but medium and large hospitals generally do not demonstrate such a difference. Barnum *et al.* (2011) compared the efficiencies of 87 community hospitals. These results suggest that conventional DEA models are not suitable for estimating the efficiency of hospitals unless there is empirical evidence that the inputs and outputs are substitutable. Sulku (2012) compared the performances of public hospitals served in provincial markets of Turkey following the introduction of new programs. Inputs such as the numbers of beds, primary care physicians and specialists were examined for the outputs of inpatient discharges, outpatient visits and surgical operations that were investigated. The findings indicate that average technical efficiency gains took place because of the significantly improved scale efficiencies, as the average pure technical efficiency slightly improved.

O'Neill *et al.* (2008) carried out a longitudinal study of 70 research studies published in 12 countries. The findings indicate that in Europe, the focus is more on finding the allocative rather than the technical efficiency. Vitikainen *et al*. (2009) examined the robustness of efficiency results due to output and case mix measures. The findings indicate that episode measures are generally to be preferred to activity measures. Sahin *et al.* (2011) examined the efficiency of the Ministry of Health's 352 general public hospitals during 2005-2008. The results indicate that operational performances of these hospitals have a common tendency that the performance of 2005–2007 progressed over the previous year, while that of 2008 has regressed as compared to 2007. Hu *et al.* (2012) investigated regional hospital efficiencies in China during 2002–2008 to identify the impact of new policies. The findings indicate that the hospital efficiency is moderately increased slightly, and that a higher proportion of for-profit hospitals and high quality hospitals is helpful to enhance technical efficiency.

Alonso *et al.* (2015) used the DEA method with bootstrap to analyse and compare efficiency scores in traditionally managed hospitals and those operating with new management formulae. The study indicates that the skills and involvement of the management is a major factor. Mohammadi and Iranban (2015) used DEA to study the hospital efficiency in Iran. Inputs for the study included the costs of materials and service variables, as input indices and the safety standards in the archive, the number of new incoming certificates of the quality, and patient satisfaction were considered as output indices. Wang *et al.* (2015) used the DEA method to study the efficiency of 18 hospitals in Shanghai for 2008-2013. The study helped to assess the areas of inefficiency and methods to improve the efficiency.

2.7.1 Identifying a Hospital Production Model (Inputs and Outputs)

In order to measure the hospital efficiency, inputs and outputs must be defined in advance. Hospital inputs are much easier to identify than outputs because they are usually observable variables. Furthermore, they are relatively easy to quantify and measure compared to outputs which could appear to be abstract or qualitative in nature. Nonetheless, even in cases where inputs may be difficult to measure, they could be measured in cost units (Jacobs, 2006).

On one hand, hospital inputs can be categorised into recurrent inputs and capital inputs. For example, members of staff and operating expenses are considered to be recurrent, whereas bed capacity and service complexity are considered to be capital inputs (Hollingsworth and Parkin, 1995; Sahin and Ozcan, 2000; Parkin and Hollingsworth, 1997). Table 2.1 summarises the set of inputs used in hospital efficiency studies stated in this section.

Variable used as hospital input
Medical staff Number of beds Operational expenses Total costs Service complexity

Table 2.1: Examples of hospital inputs

On the other hand, several authors warned about the risk involved in identifying hospital outputs for measuring efficiency (Sahin and Ozcan, 2000; Maniadakis *et al*., 1999; Roos, 2002). There is an intrinsic difficulty in identifying and measuring hospital outputs due to the nature and broad range of health care services. It is customary to separate outputs as processes from end-point outcomes. However, certain authors attempted to provide a more comprehensive guide in assisting researchers with the identification of hospital outputs.

Linna *et al*. (2005) and Steinmann *et al*. (2004) used as outputs health activities with direct benefits for the patients, such as number of discharged patients, treated cases, psychotic episodes, etc. (Ozcan and Luke, 1993). On the contrary, Zere *et al*. (2001) and Ozcan (1992) used as outputs non-health activities with no direct benefit for patients, such as medical residents, nursing students, training hours, etc. Similarly, certain authors suggested that hospital efficiency should be based upon hospital activities, more generally, as hospital outputs. In this case, outputs could be admissions, numbers of surgeries, outpatient visits and laboratorial examinations (Pilyavsky *et al*. 2006; Hu and Huang, 2004; Morey *et al*., 1990).

Nonetheless, the most important approach to identifying hospital outputs remains the one which would allow better and more accurate measurement of technical efficiency, and this must be associated with health outcomes. Health outcomes, as outputs, could involve health status measures, quality-of-life measures, well-being measures, etc. (Roos, 2002; Maniadakis *et al*., 1999; Sahin and Ozcan, 2000). Table 2.2 indicatively presents a set of hospital outputs used in the studies mentioned in this section.

Variables used as hospital output
Outpatient visits Medical residents or students Ambulatory and emergency visits Number of treated patients Patient discharges Patient days

Table 2.2: Examples of hospital outputs

2.8 Explaining the Differences in Technical Efficiencies among Hospitals

A large number of empirical studies investigated the factors behind the large variations of technical efficiency in hospitals. One such factor is the type of hospital ownership. Grosskopf and Valdmanis (1987) compared private and public 'not-for-profit' hospitals in California, US, and found that public hospitals were more technically efficient due to better resource management and a better 'best practice' production frontier. However, a similar study conducted by Valdmanis (1990) found that private hospitals were able to provide a broader range of medical services compared to the public ones. A study by Chang *et al*. (2004) suggested that when the unit of intensive care is excluded from similar analyses, the privately owned hospitals are expected to be more efficient than their public counterparts.

An interesting study involving comparisons between hospitals owned by the US Department of Defense (DoD) was conducted by Ozcan and Bannick (1994). Using the DEA modelling approach, the authors estimated the efficiency scores for hospitals owned by the DoD (Army, Navy and Air-Force) and a large number of civilian hospitals. The authors found that the DoD hospitals were much more technically-efficient compared to the civilian ones. However, the authors concluded that DoD hospitals had some idiosyncratic aspects which should have taken into account, such as the different medical objectives, the different employment conditions of medical staff, different organisational patterns and, of course, different groups of patients served. Bannick and Ozcan (1995) conducted a similar study and found that DoD hospitals were more efficient than the Veteran Affairs (VA) hospitals. Nonetheless, this study provided empirical evidence supporting the applicability of the DEA approach in identifying and explaining 'within-sector' differences of technical efficiency levels.

The consequences of having different type of hospital ownership were also explored between countries in two studies. Mobley and Magnussen (1998) assessed efficiency levels of public and private hospitals in the United States and Norway. The private US hospitals were found to be at least equally-efficient as the publicly-funded Norwegian hospitals. The longer-term efficiency was found to be due to better utilisation of bed capacity in Norwegian hospitals, a significant source of inefficiency in both the US public and private hospitals.

The second study explored the differences in efficiency between German and Swiss hospitals (Steinmann *et al*., 2004). The German hospitals were found to be much more efficient than the Swiss ones. The authors did not arrive to conclusive results about the possible factors behind these differences. However, a similar study ran by Linna *et al*. (2005) compared the efficiency levels between Norwegian and Finnish hospitals, and found the latter to have a considerably higher score. The differences in input prices and medical cultures were attributed to be the most important factors associated with this difference.

Several studies attempted to explore the causal relationship of different independent variables with technical efficiency. For example, One particular study was conducted to evaluate how technical efficiency from a large urban and acute sample of general hospitals is affected by membership status, ownership levels, and payer mix (organised care contracts, percentage Medicare and percentage Medicaid) (Ozcan and Luke, 1993). It was highlighted that government hospitals scored the highest level of relative efficiency, whereas private hospitals for profit scored the lowest. Moreover, in relation to the payer mix, a negative was created from increased percentages of payments by Medicare, while an insignificantly beneficial effect was instilled by managed care contracts, as well as hospital efficiency not being affected by Medicaid. Furthermore, an insignificantly positive effect upon the performance of hospitals was demonstrated by the membership of the multi-hospital system, together with larger profit-making hospitals. Similarly, Hao and Pegels (1994) found that hospital size had a significant influence on technical efficiency. They found that higher numbers of outpatient visits was positively influencing efficiency, while a higher number of beds had no influence on efficiency. In all of these studies, the DEA modelling approach was applied.

Grosskopf *et al*. (2001) focused on the medical staff factor. They tried to determine whether or not medical residents could have been a source of technical inefficiency in hospitals. Using data collected from 213 hospitals in the US, they found that 20% of those were technically inefficient due to ‘congestion’ associated with medical residents. They further reported that the ‘congested’ hospitals were mostly public and had higher teaching intensity than teaching dedication.

Another study conducted by Nguyen and Giang (2007) investigated the effects of three determinants of technical efficiency, namely size, location, and capital or labour intensity. The DEA and tobit models were applied using data collected from 17 hospitals and 27 medical centres in Vietnam. The authors found that location did not influence efficiency levels and both groups of health care institutions were labour intensive. The only factor which was found to influence efficiency clearly was size. Despite the technical weaknesses of the study, this observation led the authors to suggest that hospitals were much more technically efficient than medical centres.

Finally, policy interventions were found to have a significant influence on technical efficiency. Several studies investigated a number of policy interventions which occurred in different countries. Such studies included changes in payment (Chern and Wan, 2000) and financing systems (Lopez-Valcarcel and Perez, 1996; Biorn *et al*., 2003;), the merging policy in the US (Borden, 1998; Harris II *et al*. 2000); change in hospital size (Maniadakis *et al*., 1999; McKillop *et al*., 1999); hospital closures (Ozcan and Lynch, 1992) and employment structure (Steinmann and Zweifel, 2003).

2.9 Conclusion

This chapter reviews the alternative approaches for measuring efficiency in hospitals. Ratio analysis is the simplest and, practically, most restrictive approach. The second approach is regression analysis, which, unlike ratio analysis, is capable of accommodating multiple outputs in the analysis. However, frontier analysis appears to be more advanced than regression analysis because it approaches efficiency based on the capabilities of every hospital. The non-parametric frontier analyses were found to be superior to the parametric ones mainly due to the fact that there is no need to define a production function explicitly. The most popular non-parametric method in the literature seems to be DEA because it always approaches efficiency in relative terms, that is it compares the efficiency of each DMU to a virtual 'best-practice' DMU with the ultimate goal of identifying specific sources of potential inefficiency. The DEA approach and the reasons behind our decision to adopt it in this study are further investigated in the next chapter.

Finally, this chapter closes with a comprehensive review of empirical studies on measuring technical hospital efficiency. Although the literature review is kept brief and non-systematic, it provides important information such as the degree of complexity associated with the identification and measurement of hospital outputs and inputs in calculating technical efficiency, as well as most factors that explain the differences of this efficiency among hospitals.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

The main objective for assessing hospital efficiency is the rising costs of health care services. Regardless of the economic nature of the health care system, whether that is publicly or privately funded, hospital efficiency is a critical indicator for ensuring the quality of patient care. As stated in Section 2.4, *technical hospital efficiency* refers to the maximum possible output that can be produced with the minimum quantity of input. In the literature, the focus on assessing hospital efficiency was mostly restricted to *technical efficiency,* as stated through the need of hospitals to compare their relative performance according to the way scarce resources are utilised. For example, hospitals compete for funding, donations, number of patients and affiliation with medical schools (Osei et al., 2005). Hence, although technical efficiency is only one indicator of the overall hospital performance, it is the necessary condition for ensuring the best-practice and good patient care. For this reason, the term 'hospital efficiency' is used throughout this chapter to refer to the technical efficiency indicator.

In Chapter 2, two alternative approaches for assessing technical hospital efficiency were described: the parametric and non-parametric approaches. Although the characteristics of each method were clearly-defined in terms of advantages or disadvantages, there is currently no actual consensus among evaluation experts in regards to which approach could be better in assessing hospital efficiency.

This chapter engages with the most important non-parametric method, which is the DEA. The most prevalent representative DEA models for modelling operational processes for the evaluation of hospital performance are subsequently discussed in Section 3.2, as follows: i. the Charnes, Cooper and Rhodes (CCR) model (1978), ii. the Banker, Charnes and Cooper (BCC) model (1984) and iii. the bootstrapping DEA methodology. Additionally, Section 3.3 presents DEA based Malmquist productivity index, while section 3.4 highlights other methodological considerations, in terms of choosing of inputs and outputs as well as the return to scale. Following this, Section 3.5 presents the sample, while the final Section 3.6 provides certain necessary conclusions from the chapter.

3.2 Data Envelopment Analysis (DEA)

As stated in Chapter 2, the DEA is a non-parametric linear programming method for estimating production efficiency and capacity utilisation, or as stated differently, *technical efficiency*. Charnes *et al*. (1978), who first introduced this method, used the term Decision Making Unit (DMU) to refer to the 'entities' for which the efficiency scores were calculated. The authors used linear programming to derive a non-parametric, piece-wise frontier 'enveloping' all input-output combinations (*production possibility set*) for each DMU. In relation to hospital efficiency, different hospitals may be represented by different DMUs, given that there is a high degree of homogeneous operations among hospitals.

The generated frontier was made possible for an efficiency indicator to be generated without the need to parameterise the production function, which means that the production function remained unknown. This method was developed based on Farrell's concept of relative efficiency, according to which the distance from the derived frontier, which indicates the maximum possible efficiency, provides an efficiency score for each DMU (Farrell, 1957). Farrell used one input-one output analysis and Charnes *et al*. (1978) extended the modelling in order to introduce multiple inputs and multiple outputs in the analysis. Therefore, the most attractive element of the DEA is exactly the capacity to incorporate multiple inputs and outputs in the analysis.

DEA involves the solution of a linear programming problem of the observed inputs and outputs (Charnes and Cooper 1962). The ratio of total weighted output to the total weighted input provides the relative efficiency indicator for a DMU. Moreover, the linear programmer requires the selection of weights, such as the constraints experienced by each DMU (in our case, a hospital), which are carefully considered in order to extract weights that are associated with the highest possible efficiency score for that particular DMU.

The first step involves the derivation of a virtual, composite DMU that corresponds to different combinations of production inputs and outputs of different actual DMUs. This composite DMU would essentially represent the production frontier to indicate the maximum possible efficiency for each input-output combination across different hospitals (peer-formed virtual DMU). The second step permits the calculation of the maximum quantity of inputs in order for a particular DMU to be able to produce its current output. If the ratio of efficiency equals 1, then there is no virtual DMU to outperform that particular DMU, and therefore, one can conclude that the DMU is efficient. On the contrary, if it is smaller than 1, the DMU is inefficient because there is a virtual composite DMU, which could produce the same outputs with just a fraction of the inputs used by that particular DMU.

Empirically, the DEA method was successfully used for the evaluation of hospital efficiency (Osei *et al*., 2005; Valdmanis *et al*., 2004; Rebba and Rizzi, 2006). Invariably, the DEA method could guide the management team of a hospital in order to identify potential sources of inefficiency by re-running the linear programming through using different weights. This is possible due to the fact that the DEA method allows a wide range of inputs and outputs to be included in the analysis. Furthermore, the DEA, as a non-parametric method, does not depend on a specific functional specification. As a consequence, the method is insusceptible to the most common estimation problem in econometrics, known as the model specification error.

When prices are available for all inputs, the DEA method could be used to estimate the overall economic efficiency, which involves *allocative efficiency* and *technical efficiency*, as described in Chapter 2. However, in practice, the DEA method was mostly applied to measure the technical efficiency of a hospital performance. Indeed, this is probably true because hospital operations involve many inputs and outputs, which by their very nature, cannot be transformed into physical or monetary units. Finally, unlike parametric econometric methods, such as multivariate regression, the DEA method does not require a large sample of inputs and outputs.

On the other hand, the DEA method has several disadvantages compared to conventional econometric methods. Firstly, the DEA method cannot incorporate stochastic variables. In other words, the method does not include an error term to represent the random influence of unobservable variables. Similarly, it is sensitive to the specification model, in terms of the selection of input and output variables. In addition, it provides no information regarding the possible factor that attributed to the difference of inefficiency among hospitals. For this reason, the comparison of the relative efficiency scores across different hospitals provides an indicator of performance. Thus, it is possible to inform which hospitals had performed better or worse than others. Nevertheless, the method is not capable of providing information about the reasons why this might have been the case (efficiency differences). In the DEA literature, many advanced methodologies have been proposed in order to deal with such problems and in the current study, extensive uncertainty analysis methodologies, included DEA bootstrap, are implemented in order to overcome with the deterministic nature of DEA, as well as the sensitivity of variable selection. Moreover, this research has applied the SEM approach as a second stage analysis following DEA in the first stage in order to account for possible factors that could explain the differences in efficiency, as is discussed in detail in Chapter 5.

3.2.1 Charnes, Cooper and Rhodes (CCR) Model

The CCR DEA model (1978) was developed based on Farrell's concept of relative efficiency, as described in the previous section. The authors considered homogeneous DMUs, which are organisations that function through common operational objectives and use similar inputs to generate similar outputs, as well as the constant return to scale (CRS) assumption that was assumed for this model. Subsequently, this model sometimes refers to the VRS-DEA model.

In a hospital setting, patient admissions and discharges are 'output' examples, whereas labour and general supplies are examples of inputs. The aim of the CCR model is to measure the performance of a DMU (in the current study, a hospital) relative to the best observed practice in a sample of n DMUs (n=1, 2,….., N), where each one of them utilises a vector of i inputs (i=1, 2,…., I) in order to produce a vector of m outputs (m=1, 2,…, M), which are the dimensions of the inputs and outputs vectors that are (I x *1*) and (M x *1*), respectively.

According to Cooper *et al*. (2006), the CCR model forms the *possibility production set* (the feasible set of points) P with four assumptions. Firstly, each observed point (x_n, y_n) belongs to P: $(x_n, y_n) \in P$. Secondly, the constant return to scale assumption states the point $(x_n, y_n) \in P$, then the point $(kx_n, ky_n) \in P$ for any positive k. The third assumption relates to any point $(x, y) \in P$, if there is a positive point $(\bar{x},\bar{y})$ where $\bar{x} > x$ and $\bar{y} < y$ then $(\bar{x},\bar{y}) \in P$. Finally, for any linear combination of the points located in P belong to P.

From the above assumptions of the CCR model, P can be defined as an expression of (Cooper *et al*., 2006):

$$P = \{(x, y) | x \geq \lambda X, y \leq \lambda Y, \lambda \geq 0\}$$

In order to better understand the CCR model, a mathematical representation is provided by the following linear programming problem for every DMU=DMU_a:

$$Max \ E_a = \frac{\sum_{m=1}^{M} e_m Y_{m,a}}{\sum_{i=1}^{I} c_i X_{i,a}} \qquad (3.1)$$

subject to the following constraint:

$$\frac{\sum_{m=1}^{M} e_m Y_{m,n}}{\sum_{i=1}^{I} c_i X_{i,n}} \leq 1 \quad ; n=1, 2, \ldots .. N$$

$$e_m \geq \varepsilon \ , \ c_i \geq \varepsilon \ ; \quad i = 1,2,\ldots\ldots, I \ , \ m = 1,2,\ldots\ldots, M$$

In this Equation, E_a is the efficiency score of hospital *a* which is assessed**,** ε is a non-Archimedean value to ensure strict positivity of the weights, $Y_{m,a}$ is the observed amount of output *m* produced by hospital *a*, $X_{i,a}$ is the quantity of input *i* used by hospital *a*, while e_m and c_i are the weights assigned by the linear programming to outputs *m* and inputs *I,* respectively. These weights represent the most favourable combined efficiency weightings of all hospitals and they differ across DMUs. Moreover, *N* is the number of hospitals, *I* is the number of inputs used by each hospital and *M* is the number of outputs produced by each hospital.

In the above fractional programming (Equation 3.1), the first part represents the objective function and provides the ratio of weighted outputs and weighted inputs for a particular DMU_α (technical efficiency ratio). The terms e_m and c_i represent the weights assigned to outputs and inputs, respectively. These weights differ across DMUs. The remainder of Equation (3.1) is comprised of the restrictions of the linear programming problem. These restrictions are imposed in order to establish that there is not an efficiency ratio higher than 1 by any DMU, other than the DMU_α. Thus, these restrictions ensure that the solution to the problem will provide the maximum relative efficiency levels for each $DMU=DMU_\alpha$.

The model, as presented above, is run iteratively and consecutively for each one of the *n* DMUs. The solution to the problem selects a set of *optimal* input and output weights for all

DMUs. Those weights satisfy the imposed restrictions and represent the most favourable efficiency view of every DMU, which means that the linear programming procedure constrains either the numerator or the denominator of Equation (3.1) to become equal to 1. Through doing this, there is not a DMU (or virtual combinations of DMUs) that produces more outputs than the DMU_a does if all *n* DMUs are using the same inputs. Equivalently, there is not a DMU (or virtual combinations of DMUs) that uses fewer inputs than the ones used by the DMU_α in order to produce the same outputs as DMU_a. The CCR model uses a standardisation (normalisation) process of the efficiency scores, so that an efficient score for every DMU lies between 0 (inefficient) and 1 (efficient). Consequently, this allows prioritisation of all DMUs according to their relative efficiency score. This sort of information may be used in comparative static analysis for managerial purposes. CCR model represented in Equation (3.1) can be solved by mathematical programming using either "multiplier" form or "dual" form. Both of these forms provide an equivalent solution.

The "multiplier" or "primal" CCR model is essentially the original model that has constrained the denominator to be equal to 1, which equates to the assumption that there is no other DMU that produces more outputs than the DMUα, if all DMUs utilise the same inputs. The "primal" CCR model is presented below:

$$Max \;\; E_a = \sum_{m=1}^{M} e_m Y_{m,a} \qquad (3.2)$$

subject to:

$$\sum_{i=1}^{I} c_i X_{i,a} = 1$$

$$\sum_{m=1}^{M} e_m Y_{m,n} - \sum_{i=1}^{I} c_i X_{i,n} \leq 0 \;\; ; n=1, 2, \ldots.. N$$

$$e_m \geq \varepsilon \;,\; c_i \geq \varepsilon \;; \quad i = 1,2,\ldots\ldots, I \;,\; m = 1,2,\ldots\ldots, M$$

This problem could be a weighted output maximisation problem when weighted input equals 1 (input orientation), or a weighted input minimisation problem when weighted output equals

1 (output- orientation). The first constraint in Equation (3.2) means that the weighted sum of inputs for the hospital being assessed equals one. Whereas, the second constraint ensures that all hospitals locate on or below the frontier, which means that the efficiency score of all hospitals has an upper bound of 1 (or 100%). Invariantly, the "primal" CCR model is the most commonly-used version. This is perhaps due to the fact that this version of the model is intuitively closer to conventional economic theory of production (Vassdal, 1982). However, the solution is computationally-burdensome because of the large number of constraints that depend on the number of *n* DMUs.

The "dual" or "envelopment" version of the CCR model has fewer constraints, as they depend on the number of inputs and outputs ($i+m$). In DEA, the number of DMUs is usually considerably larger than the number of inputs and outputs put together, hence, more time is required to solve the linear programming problem emanating from the multiplier form of the CCR model of the DEA than that which emanates from the envelopment form. Moreover, the "dual" form incorporates "slack" variables within the constraints, which transforms them from inequalities to equalities. The "slack" variables are extra sources of inefficiency that are not picked by the "multiplier" form. They could correspond to possible output deficits or input wastages. The "dual" CCR model is presented below:

$$Min\ \eta_a - \varepsilon(\sum_{i=1}^{I} S_i^- + \sum_{m=1}^{M} S_m^+) \qquad (3.3)$$

subject to:

$$\sum_{n=1}^{N} \lambda_n X_{i,n} + S_i^- = \eta_a X_{i,a} \ ; \ i = 1,2,......,I$$

$$\sum_{n=1}^{N} \lambda_n Y_{m,n} - S_m^+ = Y_{m,a} \ ; \ m = 1,2,......,M$$

$$S_i^-, S_m^+, \lambda_n \geq 0 \qquad ; \ \forall i,m,n$$

where: ε is a very small infinitesimal positive number, which adjusts the optimal value of the objective function (maximum efficiency) with the possible impact of the “slack” variables; λ_n is non-negative input and output weights; S_i^-, S_m^+ are the “slack” variables for inputs and outputs, respectively.

Furthermore, $0 \leq \eta_\alpha \leq 1$ is a scalar variable that indicates the efficiency score. The first constraint in the equation (3.3) determines a benchmark DMU, which consumes the smallest proportion of inputs of DMU_a as possible, while at least achieving its output amounts. The second constraint represents that the output levels of inefficient observations are compared to the output levels of a reference DMU that is composed of a convex combination of observed outputs. The last one of the constrains ensures that all values of the production convexity weights are greater than or equal to zero, so that the hypothetical reference DMU is within the possibility set.

As the technical efficiency of $\eta_a = 1$ reaches a maximum level corresponding to the minimum required levels of inputs for DMU_a. It approaches 1 when the DMU_α operates on the production frontier, which is shown as highly efficient. Hence, there is no other DMU that produces the same outputs with fewer inputs. Similarly, it approaches less than 1 when the DMU_α operates below the production frontier, which is relatively inefficient. Indeed, there may be other DMUs capable of producing the same levels of outputs with fewer inputs.

The minimisation process identifies the largest possible values for the “slack” variables for each DMU, and takes those into consideration according to Equation (3.3). As a result, the efficiency scores will be adjusted accordingly in order to ensure that the most efficient DMU operates at the production frontier, if and only if η_a equals 1 and the “slack” variables become 0.

For an inefficient DMU, we obtain its reference set (peer set) R_a from model 3.3 by:

$$R_a = \{n \,/\, \lambda_n > 0\} \; (n \in \{1, \ldots\ldots, N\}). \tag{3.4}$$

These references are used to be examples for this inefficient DMU in order to learn from those who are efficient. Thus, if the DMU_a is inefficient, we can project this DMU onto the efficient frontier by using the optimal values from Equation (3.3) in order to obtain the improved activity $(\hat{x}_{ia}, \hat{y}_{ma})$ as following formulae:

$$\hat{x}_{ia} = \eta_a^* \ x_{ia} - s_i^{-*} = \sum_{n \in R_a} x_{in} \lambda_n^* \quad ; \ i = 1,2,\ldots\ldots, I \tag{3.5}$$

$$\hat{y}_{ma} = y_{ma} + s_m^{+*} = \sum_{n \in R_a} y_{mn} \lambda_n^* \quad ; \ m = 1,2,\ldots\ldots, M \tag{3.6}$$

A representation of the CCR model is shown in Figure 3.1 below.

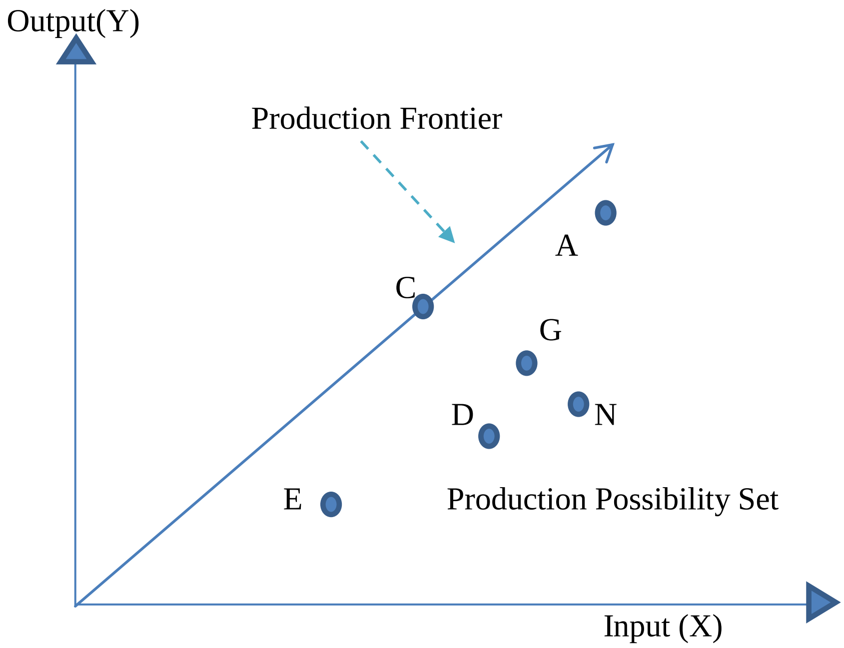

Figure 3.2: The CCR production frontier

adapted from Cooper *et al*. (2006, p. 84)

In Figure 3.1, under the simplistic assumption that there is only one input and one output, for the CCR model, due to the CRS assumption, the DMU at point C lying on the efficient (production) frontier is the only CCR-efficient DMU because its efficiency score η_a equals 1. The remaining DMUs (i.e. $\text{DMU}_{\text{A, D, E, G and N}}$) are inefficient due to their efficiency score being smaller than 1 (η_a<1). Additionally, the essence of the CCR DEA model is that there is no DMU lying in the area under the frontier (straight line), which could be more efficient than the DMU_C.

Similarly, no combination between the inefficient DMUs could generate higher efficiency score than the DMU_C.

The "dual" model presented in the system of Equation (3.3) is the "input-oriented" approach of the CCR model, which equates to the objective function that aims at minimising the required inputs for every output of each DMU. A very similar approach is the "output-oriented" approach of the CCR model, where the objective function aims to maximise the overall output that can be achieved with the same inputs. In that case, the equivalent "primal" CCR model would be very similar to the system represented in Equation (3.2), but the objective function would require the minimisation of the weighted inputs, whereas the weighted output will be normalised to 1.

The "primal" and the "dual" CCR models would lead to the same efficiency scores in both the "input-oriented" and the "output-oriented" approaches due to *Constant Returns to Scale (CRS).*

3.2.2 Banker, Charnes and Cooper (BCC) Model

The CCR model was based on the silent assumption of CRS. The term CRS implies that for every increase of the quantity of production inputs by a proportional factor, the overall output also changes by the same proportion. For example, if X inputs produce Y output, then input kX would produce output kY. Under this assumption, the size of each DMU is not important for the assessment of technical efficiency.

However, the size of every DMU remains relevant in the assessment of efficiency. In a hospital setting, social objectives, imperfect competition or labour constraints may influence the operations of the hospital, which make it unlikely to operate at an optimal scale (Coelli *et al.,* 2005). Therefore, it seems highly unlikely that the CRS would be a realistic assumption. The DEA modelling would suffer significantly if "economies" or "dis-economies" of scale (increasing or decreasing returns to scale[3]) were ignored.

For example, a very large central hospital in a big city, would act as an "outlier" within the DEA approach, and possibly lead to higher efficiency scores for the virtual DMU. Stated differently, efficiency scores that are generated by the CCR model involve both *scale efficiency* and *technical efficiency*. In case of inefficiency, the CCR model is not capable of

[3] IRS (DRS) refers to a higher (lower) than proportional increase in output following increase of the quantity of inputs by a particular proportional factor.

providing information in regards to the degree to which the identified inefficiency may be due to technical inefficiency or scale efficiency.

Banker, Charnes and Cooper (1984) created the BCC model as an attempt to extend and further elaborate the initial CCR model by adopting the *variable returns to scale* (VRS) assumption, which either increases or decreases returns to scale. Thus, Cooper *et al*. (2006) defined the BCC possibility production set *P* as:

$$P = \left\{ (x, y) \middle| x \geq \lambda X, y \leq \lambda Y, \sum_{n=1}^{N} \lambda_n = 1 \ \lambda \geq 0 \right\}$$

The BCC model adds an unconstrained scalar variable φ_α to the "primal" version of the CCR model as follows:

$$MaxE_a = \sum_{m=1}^{M} e_m Y_{m,a} - \varphi_a \qquad (3.7)$$

subject to:

$$\sum_{i=1}^{I} c_i X_{i,a} = 1$$

$$\sum_{m=1}^{M} e_m Y_{m,n} - \sum_{i=1}^{I} c_i X_{i,n} - \varphi_a \leq 0 \quad ; n=1, 2, \ldots.. N$$

$$e_m \geq \varepsilon \ , \ c_i \geq \varepsilon ; \quad i = 1,2,\ldots\ldots, I \ , \ m = 1,2,\ldots\ldots, M$$

φ_a is free of mathematical sign

The variable φ_a,which could be positive, negative or zero, ensures that the frontier has a number of convexity linear combinations of best practice, including regions of increasing and decreasing returns to scale. This means that each DMU is compared to others that are of a similar size.

The "dual" BCC model is shown below:

$$Min\ \eta_a - \varepsilon\left(\sum_{i=1}^{I} S_i^- + \sum_{m=1}^{M} S_m^+\right) \qquad (3.8)$$

subject to:

$$\sum_{n=1}^{N} \lambda_n X_{i,n} + S_i^- = \eta_a X_{i,a} \ ; \quad i = 1,2,......,I$$

$$\sum_{n=1}^{N} \lambda_n Y_{m,n} - S_m^+ = Y_{m,a} \ ; \ m = 1,2,......,M$$

$$\sum_{n=1}^{N} \lambda_n = 1$$

$$S_i^-, S_m^+, \lambda_n \geq 0 \qquad ; \forall i, m, n$$

The addition of the constraint $\sum_{n=1}^{N} \lambda_n = 1$ is an important intervention. If the sum of all weights of inputs and outputs becomes equal to 1, then all possible efficiency factors for comparison among different DMUs become convex combinations of real observations. The scalar η is the proportional reduction of all inputs required to improve efficiency. This reduction simultaneously applies to all inputs, and it is equivalent to production along the envelopment frontier. The presence of ε in the objective function allows the minimisation over η without the non-zero slacks. Thus, a DMU is efficient if η =1 and all slacks (S_i, S_m) are zero, whereas when η<1 and/ or slacks are non-zero, the DMU is inefficient.

The production frontier associated with the BCC model includes three different segments: the segment with increasing returns to scale (IRS; $\varphi < 0$), the segment of constant returns to scale (CRS; $\varphi = 0$), and the segment with decreasing returns to scale (DRS; $\varphi > 0$). *IRS (DRS*) refers to a higher (lower) than proportional increase in output following increase of the quantity of inputs by a particular proportional factor.

A small-sized DMU is compared with other small-sized DMUs, since they all belong to the segment with IRS. Symmetrically, a large-sized DMU will be compared with other DMUs of similar sizes that belong to the segment where DRS appears to be most probable on the production frontier. The BCC model is shown in Figure 3.2.

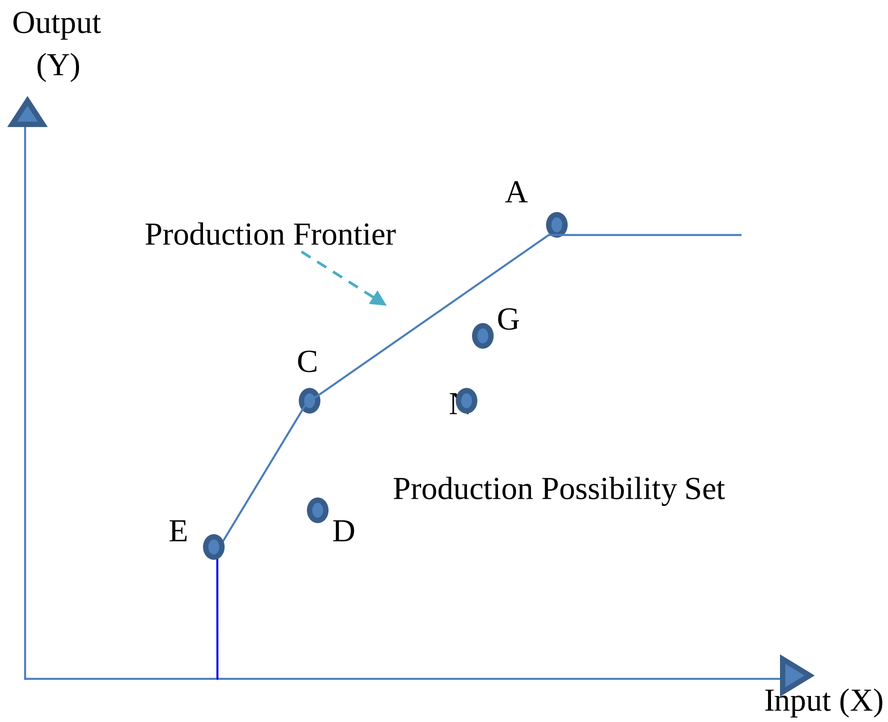

Figure 3.2: BCC Technical efficiency model

Adapted from Cooper *et al*. (2006, p. 84)

In the simplistic case of one input-one output, the production frontier of the BCC model appears to have three efficient DMUs, which are $DMU_{A,C,E}$. The line segment that links up point A and point C refers to the Increasing Return to Scale (IRS) portion of the efficient frontier, while the line segment that joins point C to point F corresponds to the Decreasing Return to Scale (DRS) segment of the efficient frontier. A Constant Return to Scale (RTS) occurs at point C.

Unlike the CCR, which measures the overall technical efficiency, the BCC model has the capacity to decompose technical from scale efficiency and identify the most productive scale size for each DMU. Moreover, by adjusting for “scale effects”, the BCC model is in a position to estimate the ‘pure’ technical efficiency. For this reason, it may be better than the CCR model in terms of providing policy recommendations, such as the introduction of performance measures to encourage operations at the most productive scale size or the adjustment of performance outcomes in order to be able to control for scale differences.

The importance of *scale efficiency* in the evaluation of hospital performance may be demonstrated when both the CCR and the BCC models are combined. This is shown in Figure 3.3.

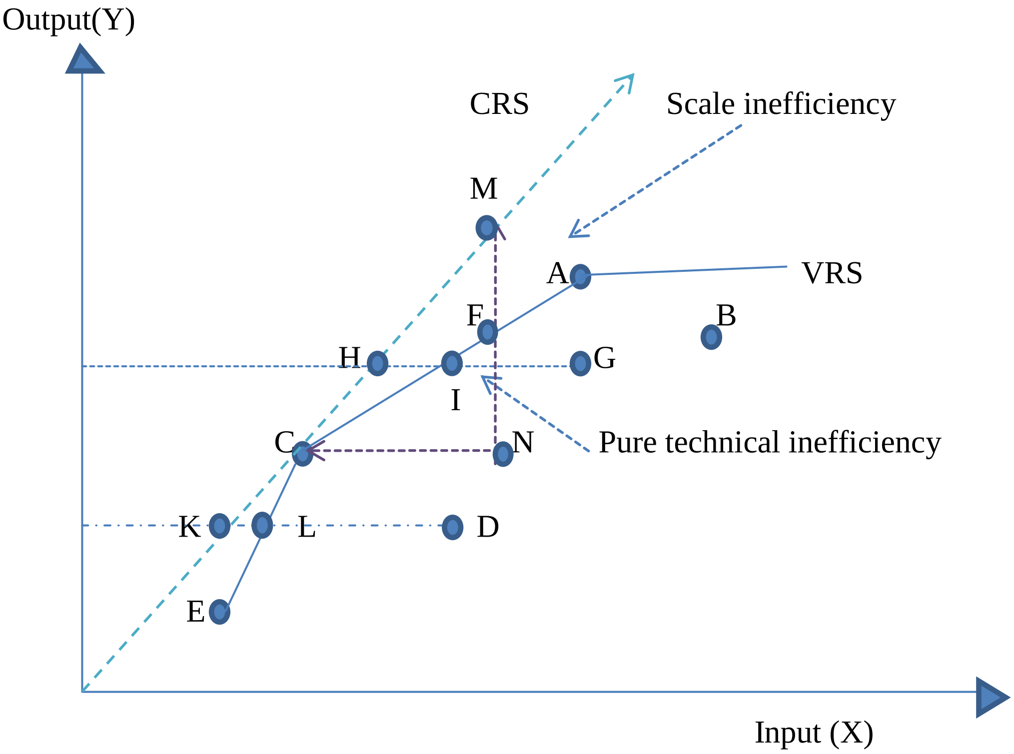

Figure 3.3: The difference between the CRS and VRS production frontiers
Adapted from Cooper *et al*. (2006, p. 86)

Through the use of Figure 3.3, it is easy to observe that the only hospital that appears to be CCR-efficient and BCC-efficient is hospital "C". Consequently, this is the only hospital with no "scale effects" in the assessment of its technical efficiency scores. The area representing the difference between the straight line (CCR model) and the curve (BCC model) indicates the "scale effects" in assessing technical efficiency. For example, the technical efficiency of hospital "G" is calculated to be segment IG according to the BCC model and segment HG according to the CCR model. Since HG > IG, the CCR model has essentially over-estimated the technical efficiency of hospital G. In comparison, the BCC model has more accurately estimated the 'pure' technical efficiency, as it appropriately subtracts the scale inefficiency, which is the amount of efficiency loss that is probably due to the large size of the hospital.

A similar observation can be made for hospital "D". However, on this occasion, the IRS (i.e. the over-proportional increase in output due to proportional increase in inputs) would offset (compensate for) part of the scale inefficiency. As a result, the over-estimation is only for the segment KL, which is a relatively small difference.

Nonetheless, unlike the CCR model, the "input-oriented" and "output-oriented" approaches would not generate the same efficiency scores. This is due to the fact that the two approaches conceptualise the 'returns to scale' differently. The input-orientation refers to savings of inputs for the production of the same output, whereas the output-orientation refers to maximising output with the use of the same inputs. In Figure 3.3, we can observe the different way of measuring technical efficiency and "scale effects" in the two approaches for hospital "N". The "input-oriented" approach would estimate the technical efficiency by analysing the horizontal distance between points C - N, which remains the same for both the BCC and CCR models. On the other hand, the "output-oriented" approach would estimate technical efficiency by using the vertical distance, that is, NF (BBC model) and NM (CCR model). Since NM = NC but NF < NC the two approaches would produce different technical efficiency scores depending on which model we apply.

In policy terms, if the management team of a hospital is in a position to observe more inputs than outputs, they should use the "output-oriented" approach. On the contrary, if more inputs are observable, the hospital should apply the "input-oriented" approach for more accurate technical efficiency scores (Sahin and Ozcan, 2000; Jacob *et al.*, 2006). Similarly, if a hospital is experiencing "economies of scale", which equate to its size possibly affecting its productivity level, then the application of the BCC model may be more appropriate than applying the CCR model.

3.2.3 Bootstrapping DEA

The bootstrap is a method of drawing by replacement from a data sample, which replicates the data generating process of the model and generates estimates that are used for statistical calculation. DEA has certain inherent inefficiency created by noise, formed by the distance from the efficient boundary. Moreover, bootstrapping helps to overcome these efficiencies for bias and to develop the correct confidence intervals, whilst accepting that the data has random noise. In Bootstrapping, the probability of distribution of the inefficiencies in DEA follows the true, but the unknown distribution of data. By taking a sample from the DEA inefficiencies, the researcher is actually taking out data from the population. By taking repeated samples, it is possible to build an empirical sample distribution for all the DEA efficiencies. This sample is then used to develop the confidence intervals for DEA efficiencies (Efron, 1987).

3.2.3.1 The Concept of Bootstrapping

Bootstrapping is used in a number of instances, such as hypothesis testing when it is not possible to form a statistical inference. By using re-sampling with bootstrapping, the assumed randomness of the data is redistributed, and this randomness is seen when variables from the model show deviations from their estimated value calculations. When the variance is higher in the residual data, then it means that the confidence intervals of the bootstrap model will be wider. Accuracy of the bootstrap model is derived from the bias of the process and the variance in the residuals, and these depend on the sample size. Residual variance creates differences in the bootstrapping distribution. What is more, the centre point of the bootstrap distribution curve must be equal to the computed value, and this variance is known as the *bootstrap bias*, caused by the random sampling method. With smaller samples, observations are erratic and the bias increases. In some cases, the bootstrap estimator can also fall to bias, and it will show variance from the true values (Simar & Wilson, 2007).

The steps in using the bootstrapping method are indicated through a series of stages (Simar & Wilson, 2000). Firstly, use DEA and calculate the efficiency scores for the data. The next step is to obtain through replacement from the empirical distribution of the scores from the first step. Indeed, if the distribution is smoothened, it provides better results. The original efficient input levels must be divided by the new or pseudo efficiency score, obtained from the empirical distribution and this step provides the bootstrap results for the new inputs. Subsequently, the following step is to calculate the bootstrapped efficiency scores by applying DEA for the newly obtained inputs with the same outputs. Overall, the previous steps can be repeated along with the bootstrapped scores to test the hypothesis and obtain the statistical inference of the results.

According to Simar and Wilson (2008), in order to construct a set of homogenous bootstraping efficiency estimates $\hat{\eta}_b^*$ for the original DEA efficiency scores $\hat{\eta}_{DEA}$ $\{\hat{\eta}_b^*(x_n, y_n) | b = 1, \dots, B\}$ for an observed point (x_n,y_n), there are eight steps to be implemented as follows:

1. To calculate the DEA efficiency scores $\hat{\eta}_{DEA}$ by using the original data set. Then, for simplicity, these efficiency scores are parameterised by $\hat{\theta}_{DEA} = \frac{1}{\hat{\eta}_{DEA}}$ in order to avoid creating estimated lower bounds for confidence intervals that are negative. The corresponding parameterised bootstrap efficiency estimates $\hat{\eta}_b^*$ is $\hat{\theta}_b^* = \frac{1}{\hat{\eta}_b^*}$.
2. To choose a smoothing parameter, the bandwidth h that is discussed in Silverman (1986) to calculate this bandwidth parameter. In the current study,

$$h = 1.06\, min\, (\hat{\sigma}\,, \hat{R}/1.34)\, n^{-1/5}\ .$$

3. To generate β_1^*,....., β_n^* by drawing with replacement a random sample of efficiency from the constructed set D_{2n} of 2n reflected efficiencies $(2 - \hat{\theta}_n)$ out of the n computed in step 1; D_{2n} =$\{\hat{\theta}_1\ , \ldots\ldots, \hat{\theta}_n \left(2 - \ \hat{\theta}_1\right), \ldots\ \left(2 - \ \hat{\theta}_n\right)\}$. Drawing from the data set of D_{2n} instead of the efficiency computed in step 1 is to permit for the possibility that DEA efficiency has an upper bound of 1.

4. To adjust the sample of efficiencies drawn in step 3 by drawing ε_n^* , independently from the kernel function K (.) and find the values for $\beta_n^{**} = \ \beta_n^* + h\varepsilon_n^*$ for each *n = 1, ..., N*.

5. To calculate the values for β_n^{***} , $\beta_n^{***} \ = \ \bar{\beta}_* + \frac{\beta_n^{**} \ - \bar{\beta}}{(1+h^2\sigma_k^2\sigma_\beta^2)^{1/2}}$,

where: $\overline{\beta^*} \ = \ \sum_{n=1}^{N} \beta_n^* \ / \ n, \ \ \sigma_\beta^2 \ \ = \sum_{n=1}^{N} (\beta_n^* \ - \ \overline{\beta^*} \ )^2 / \, n$

σ_k^2 is the value of the variance seen in the probability density function in the kernel function. Subsequently, the value of θ_n^* is calculated as:

$$\theta_n^* = \begin{cases} 2 - \ \beta_n^{***} & , \forall \ \beta_n^{***} \ < 1 \\ \beta_n^{***} & otherwise \end{cases}$$

6. The bootstrap sample is created as: $X_n^* = \{(x_n^*, y_n) \mid n = 1, \ldots\ldots N\}$,

where: $x_n^* = \theta_n^* \hat{\theta}_n^{-1} x_n$.

7. To complete the set of the bootstrap DEA efficiency estimate $\widehat{\theta_n^*}(x_n, y_n)$ for the original sample observations with the reference set of X_n^*.

8. The steps 3-7 are repeated B times, which is at least 2000 times to derive the bootstrap set estimate of $\{\widehat{\theta_b^*}$ (x, y) | b = 1, ...,B}.

The bootstrap bias is estimated for the original DEA estimator as follows:

$$\widehat{BIAS}_B\big(\hat{\theta}_{DEA}(x,y)\big) = B^{-1} \sum_{b=1}^{B} \hat{\theta}_{DEA,b}^* - \hat{\theta}_{DEA}(x,y) \qquad (3.9)$$

B is the number of instances that the process was carried out, $\hat{\theta}_{DEA,b}^*$, which provides the bootstrap DEA scores, and $\hat{\theta}_{DEA}$ is the DEA score. For this equation, the biased corrector estimator $\theta(x,y)$ is the unknown true efficiency of $\hat{\theta}_{DEA}(x,y)$:

$$\begin{aligned}\hat{\hat{\theta}}_{DEA}(x,y) &= \hat{\theta}_{DEA}(x,y) - \widehat{BIAS}_B\big(\hat{\theta}_{DEA}(x,y)\big) \\ &= 2\hat{\theta}_{DEA}(x,y) - B^{-1} \sum_{b=1}^{B} \hat{\theta}_{DEA,b}^* \qquad (3.10)\end{aligned}$$

Efron and Tibshirani (1993); Simar and Wilson (2008) argue that this bias correction can introduce extra noise. Therefore, the sample variance of the bootstrap value must be recalculated as:

$$\hat{\sigma}^2 = B^{-1} \sum_{b=1}^{B} [\hat{\theta}_{DEA,b}^* - B^{-1} \sum_{b=1}^{B} \hat{\theta}_{DEA,b}^*]^2 \qquad (3.11)$$

It may be required to avoid the bias from the above equation, unless:

$$\frac{|\widehat{BIAS}_B(\hat{\theta}_{DEA}(x,y))|}{\hat{\sigma}} > \frac{1}{\sqrt{3}} \qquad (3.12)$$

According to Daraio & Simar (2007) and Simar and Wilson (2008), in comparison to the original DEA values, the estimates for bias corrected values (bootstrap DEA values) must be preferred in consideration when the bias is more advanced than the standard deviation (σ).

3.2.3.2 Studies using DEA and Bootstrapping Approaches

A number of researchers have used DEA with bootstrapping methods to analyse the performance and efficiency of hospitals and the healthcare sector organisations. Staat (2006) has researched the performance and efficiency of German hospitals by using the DEA-bootstrapping procedure. The process was applied to two data sets of hospitals, and all hospitals had comparable quality and range of services. Furthermore, this helped to overcome the earlier issues of DEA efficiency analysis with regression analysis.

Bernet *et al*. (2008) examined data from two geopolitical regions of Ukraine to compare polyclinics in Ukraine in order to analyse whether the inflexibility of Soviet system of planned economies developed lower economic efficiency in eastern regions, and the DEA with bootstrapping methods was used in the evaluation. Assaf and Matawie (2010) used the DEA bootstrapping approach to analyse the efficiency of health care foodservice operations in the USA. The process helped to derive the bias from estimates and the confidence intervals of DEA efficiency score, as well as to resolve the co-relation problem of DEA efficiency scores is the second stage anlysis. Halkos and Tzeremes (2011) examined the Greek public healthcare delivery efficiency by using data envelopment analysis and the bootstrap method. The efficiency levels of the hospitals were analysed by using convex and non-convex models with bootstrap techniques, and overall the analysis helped to find the misallocation of healthcare resources among the Greek regions.

In other similar studies, Kounetas and Papathanassopoulos (2013) used different input–output combinations to identify factors that influence the Greek hospital performance. Invariably, they used the DEA bootstrapping method to evaluate the productive efficiency of different hospitals in the data set.

The bootstrapping DEA method is an advanced methodology to overcome the disadvantage associated with the standard DEA, which is due to the deterministic nature. However, there are just a few health care applications for such approaches, as mentioned previously in Chapter One. Therefore, the present study applies the above methodology for the empirical analysis of HTI care in Chapter Six.

3.3 DEA based Malmquist Productivity Index

Productivity and efficiency of an organisation are interrelated. However, efficiency is static, as it does not consider the time taken for production, while time is important for productivity. When the productivity measures change, the implication is that there are changes in the efficiency. Therefore, measuring productivity becomes imperative. Index numbers are used to measure changes in productivity for different periods. A popular index is the Malmquist Productivity Index (MPI), which was introduced by Caves *et al*. (1982). They used the proposed idea by Malmquist (1953) that defined the index number as ratios of the distance function. In fact, MPI is sometimes referred to as Total Factor Productivity (TFP), which can evaluate any progression or regression of efficiency over time, as well as any change of frontier technology in terms of progress or regress over time. Following the work of Färe *et al.* (1994), MPI became a standard methodology to evaluate the productivity over time with non-parametric methodology, as well as it being used in a number of studies for DEA analysis of efficiency changes for different organisations, industries and countries.

The concept of productivity is illustrated in Figure 3.4, which presents the production case for an input X and output Y for constant returns to scale. In the figure, technological advancement is shown to have taken place at times t and t+1. The production frontier for t+1 would have moved to the left of the production frontier for period t. Thus, progress is evident for productivity between t and t+1 (Färe *et al*., 1994).

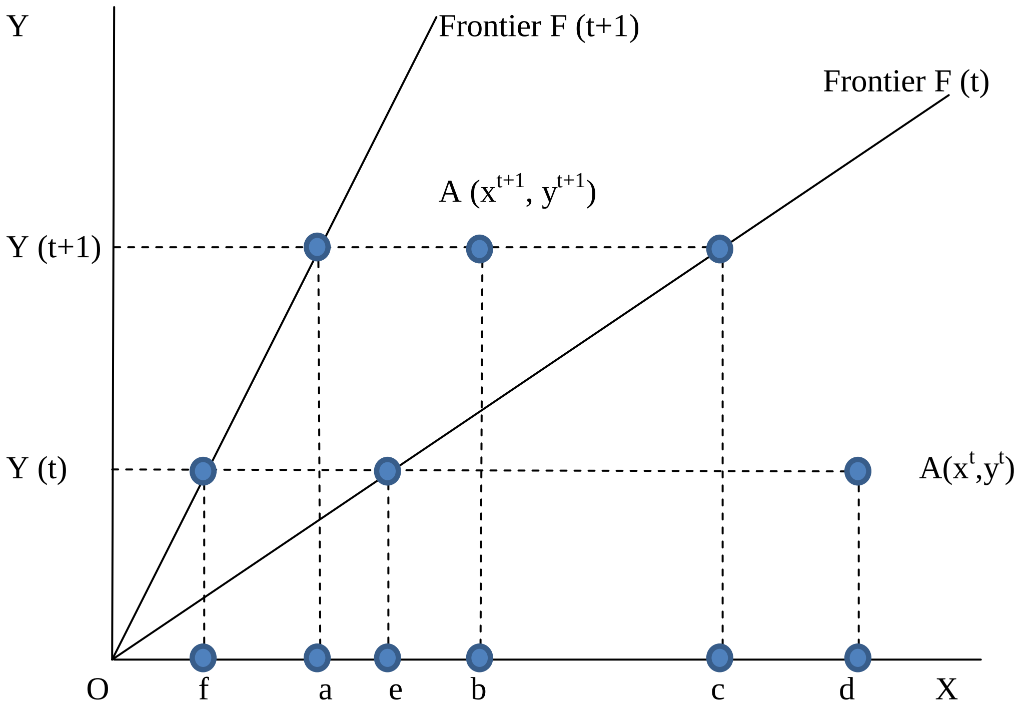

Figure 3.4: The input-based Malmquist productivity index.

Adapted from Färe et al., (1992, p. 91)

Figure 3.4 indicates hospital "A" that operates at points A (x^t,y^t) at time *t*, and A(x^{t+1}, y^{t+1}) during the time *(t+1)*. There are two ways for measuring the efficiency of hospital "A" over time; by referring to the frontier at time *t* F (*t*) or by referring to the frontier at time *(t+1)* F (*t*+1). For the first way, the efficiency of hospital A at point (x^{t+1}, y^{t+1}) is compared to the lower input level that could be reduced with reference to frontier *t*. This can be expressed as $D_n^t(y^{t+1}, x^{t+1})$ or (Oe/Od). Then, the efficiency of hospital "A" at point (x^t,y^t) is compared, as well as the lower of input level could be reduced in reference to frontier *t*, which is the input distance function $D_n^t(yY^t, xX^t)$. Subsequently, the input-MPI to time *t* is:

$$M_n^t = \frac{D_n^t(y^{t+1}, x^{t+1})}{D_n^t(y^t, x^t)} \quad (3.13)$$

The second way to calculate the efficiency over time is by referring to time (*t*+1) following the same construction with period *t*. Then the input-MPI to time *t* +1 is:

$$M_n^{t+1} = \frac{D_n^{t+1}(y^{t+1},x^{t+1})}{D_n^{t+1}(y^t,x^t)} \qquad (3.14)$$

In order to choose from the two ways of measuring productivity over time these periods, Färe *et al*. (1989 ,1994) suggests taking the geometric mean of M_n^t and M_n^{t+1} to define the input-MPI M_n:

$$M_n\ (y^{t+1},x^{t+1}\ ,y^t,x^t) = \ [M_n^t . M_n^{t+1}]^{\frac{1}{2}}$$

$$= \ \left[\frac{D_n^t(y^{t+1},x^{t+1})}{D_n^t(y^t,x^t)} . \frac{D_n^{t+1}(y^{t+1},x^{t+1})}{D_n^{t+1}(y^t,x^t)}\right]^{1/2} \qquad (3.15)$$

where, D_n is the input based distance function and M_n is the geometric mean of two ratios of input distance functions.

According to Färe *et al*. (1989, 1994) the Equation (3.15) can be rewritten as the following equation:

$$\mathrm{M_n}\ (y^{t+1},x^{t+1}\ ,y^t,x^t) = \frac{D_n^{t+1}(y^{t+1},x^{t+1})}{D_n^t(y^t,x^t)}\left[\frac{D_n^t(y^{t+1},x^{t+1})}{D_n^{t+1}(y^{t+1},x^{t+1})} . \frac{D_n^t(y^t,x^t)}{D_n^{t+1}(y^t,x^t)}\right]^{1/2} \qquad (3.16)$$

where:

Efficiency change (EC) = $\frac{D_n^{t+1}(y^{t+1},x^{t+1})}{D_n^t(y^t,x^t)} = \frac{Oa/Ob}{Oe/Od}$

Technological Change =$\left[\frac{D_n^t(y^{t+1},x^{t+1})}{D_n^{t+1}(y^{t+1},x^{t+1})} . \frac{D_n^t(y^t,x^t)}{D_n^{t+1}(y^t,x^t)}\right]^{1/2} = \left[\frac{Oc}{Oa} . \frac{Oe}{Of}\right]^{1/2}$

Therefore, the MPI is used to measure the changes in productivity between two sets of data for different time periods. This MPI is a result from the product of relative change in efficiency that takes place between time t and t+1 (called the catch-up effect), and technology change that takes place between time t and t+1 (called the frontier shift effect). In addition, if M_n is > 1, then the productivity has improved over time, and if M_n <1, then the productivity has reduced, and M_n = 1 indicate a constant productivity. The method to calculate the MPI discussed above and its components with the DEA method is provided below.

According to Fare *et al*. (1984), the first four distance functions must be calculated by using four linear programming DEA approaches for the n DMUs and for time periods of t and t+1. Assuming constant returns to scale and input oriented, the functions are given as:

Distance of nth DMU in time t referring to frontier t is:

$$[D_n^t(y^t, x^t)]^{-1} = \min \eta$$

subject to:

$$\eta x_{n,t} - \lambda X_t \geq 0$$

$$\lambda Y_t - y_{n,t} \geq 0$$

$$\lambda \geq 0 \qquad (3.17)$$

Distance of n^{th} DMU in time t+1 referring to frontier t+1 is:

$$[D_n^{t+1}(y^{t+1}, x^{t+1})]^{-1} = \min \eta$$

subject to:

$$\eta x_{n,t+1} - \lambda X_{t+1} \geq 0$$

$$\lambda Y_{t+1} - y_{n,t+1} \geq 0$$

$$\lambda \geq 0 \qquad (3.18)$$

Distance of n^{th} DMU in time t referring to frontier t+1 is:

$$[D_n^{t+1}(y^t, x^t)]^{-1} = \min \eta$$

subject to:

$$\eta x_{n,t} - \lambda X_{t+1} \geq 0$$

$$\lambda Y_{t+1} - y_{n,t} \geq 0$$

$$\lambda \geq 0 \quad (3.19)$$

Distance of n^{th} DMU in time t+1 referring to frontier t is:

$$[D_n^{t}(y^{t+1}, x^{t+1})]^{-1} = \min \eta$$

subject to:

$$\eta x_{n,t+1} - \lambda X_{t} \geq 0$$

$$\lambda Y_{t} - y_{n,t+1} \geq 0$$

$$\lambda \geq 0 \quad (3.20)$$

where x is the vector of DMU inputs, y is the vector of DMU outputs, and λ is the vector of weights assigned to matrices of inputs X and outputs Y.

An important point is that η and λ have different values for the four equations that have been developed above. In the Equations (3.19) and (3.20), there is no need for η to be less than or equal to 1. This is because, when there is technical progress, the hospital can be placed beyond the production frontier of the previous period, giving a value of η greater than 1 (Fare *et al*., 1984).

In order to allow for VRS in MPI, Fare *et al*. (1984) suggested that the technical efficiency change in the above MPI Equation (3.16) is decomposed further into the Scale Efficiency Change (SEC) and Pure Technical Efficiency Change (PTEC): TE = (SEC) × (PTEC). This can be evaluated by solving Equations (3.17) and (3.18) through using the convexity constant

$\sum_{i=1}^{n} \lambda = 1$. Additionally, distance functions can be calculated relative to variable returns to scale technology. Subsequently, the CRS and VRS estimates are used for scale efficiency computation, along with the change in both pure technical efficiency and scale efficiency. Results from CRS provide the level of change in technical efficiency and the VRS gives the level of pure technical efficiency change. As a result, the scale efficiency change provides the deviation of TEC for CRS and VRS. The formula is given as (Fare *et al.*, 1984):

$$\mathrm{M_n}\,(y^{t+1}, x^{t+1}, y^{t}, x^{t}) =$$

$$\frac{SE_n^{t+1}(y^{t+1},x^{t+1})}{SE_n^{t}(y^{t},x^{t})} \cdot \frac{D_{VRS}^{t+1}(y^{t+1},x^{t+1})}{D_{VRS}^{t}(y^{t},x^{t})} \cdot \left[\frac{D_{CRS}^{t}(y^{t+1},x^{t+1})}{D_{CRS}^{t+1}(y^{t+1},x^{t+1})} \cdot \frac{D_{CRS}^{t}(y^{t},x^{t})}{D_{CRS}^{t+1}(y^{t},x^{t})}\right]^{1/2} \qquad (3.21)$$

where:

$$\text{Scale efficiency change} = \frac{\text{Scale efficiency in period } (t\ +\ 1)}{\text{Scale efficiency in period } (t)}$$

$$= \frac{SE_n^{t+1}(y^{t+1},x^{t+1})}{SE_n^{t}(y^{t},x^{t})}$$

$$\text{Pure Efficiency Change} = \frac{\text{Pure Technical Efficiency in period } (t\ +\ 1)}{\text{Pure Technical Efficiency in period } (t)}$$

$$= \frac{D_{VRS}^{t+1}(y^{t+1},x^{t+1})}{D_{VRS}^{t}(y^{t},x^{t})} \qquad (3.21)$$

The above Equation (3.21) has been criticised by Grifell-Tatjé and Lovell (1995), as they stated that the result provided in this model is biased in the case of non-constant return to scale. Therefore, many alternative decompositions, in terms of VRS based MPI, have been proposed, which have included Ray and Desli (1997) and Grifell-Tatjé and Lovell (1999).

However, Lambert (1999) argued that the exclusion of the scale effect when MPI assumes CRS is the reason of the biased recognition by Grifell-Tatjé and Lovell (1995), and therefore VRS based MPI provide unbiased measurements of productivity change if the scale effect is considered. Grosskopf (2003) agreed that the provided model (Equation 3.12) is the correct methodology and produces an accurate measurement of the productivity change.

A number of researchers have used the Malmquist measurement with DEA to study efficiency in the healthcare sector. De Castro Lobo *et al.*, (2010) studied performance and productivity changes for the Brazilian Federal University Hospitals in the period 2003-2006 by using MPI. Tlotlego *et al*. (2010) used the DEAP software with DEA-based MPI to study the productivity of hospitals in Botswana for the period 2006 to 2008. What is more, MPI, which had been decomposed into efficiency changes, technological changes, as well as pure and scale efficiency, was used by Chowdhury et al. (2011) in the evaluation of service efficiency in hospitals within Ontario during the period of time between 2003 and 2006. In regards to the output orientated MPI, as well as its decompositions, confidence intervals were obtained through bootstrapping techniques.

MPI was used to study the productivity changes for the Veterans Integrated Service Networks (VISN) in Turkey during the period 1994-2004 (Ozcan and Luke, 2011). Chang *et al*. (2011) examined the hospital productivity growth using MPI in Taiwan between 1998 and 2004. Moreover, Sulku (2012) used DEA-based MPI to compare the performances of public hospitals in Turkey, while Ng (2011) studied the sources of inefficiency in Chinese hospitals by using the Malmquist Index computation along with panel data for the period of 2004-2008. De Nicola *et al*. (2012) applied bootstrap to DEA with MPI to study the productivity of the Italian Health System. Thus, it is seen that the DEA method with the Malmquist index is widely used by researchers in healthcare settings to study the productivity and efficiency. The current research uses the input-VRS Malmquist index to measure the change of productivity over the period of study in the empirical analysis in Chapter 6.

3.4 Other Methodological Considerations

3.4.1 Choosing Inputs and Outputs

According to Magnussen (1996), the selection of inputs and outputs for the assessment of hospital efficiency is very important, as it affects not only the results, but also the ability of the technique to provide useful and meaningful information. In Chapter 2, the common approaches were documented for selecting inputs and outputs that were provided in relevant literature.

The selection of inputs and outputs for the DEA application on head trauma care was firstly guided by the theoretical principles of DEA, and subsequently, on prior research associated with other DEA application and head trauma literature. Finally, the selection was finalised based on data availability, and the selected inputs and outputs for the DEA application are presented in Table 3.1.

Inputs	**Outputs**
Average number of doctors seen per patient per year (avg_doc) Average number of consultants seen per patient per year(avg_cons) Total cost (£) per patient per year (totalcost)	Percentage of patients with minor injuries who recovered satisfactorily per year (pctmin) Percentage of patients with moderate injuries who recovered satisfactorily per year (pctmod) Percentage of patients with severe injuries who recovered satisfactorily per year (pctsev) Average of the total period (days) of stay per patient per year (avglos) Average number of surgical operations per patient per year (avtotop) Average number of treatments provided by emergency services per patient per year (avg_treat)

Table 3.1: Selected input and output variables for the DEA application on HTI care.

The selected inputs included the number of personnel working in head trauma hospitals and the capital “total cost”, as these inputs are the most common inputs in DEA literature. The term “doctors” referred to the ED doctors involved in head trauma care, and the term “consultants” referred to the doctors with similar basic training as “doctors”, but with additional specialised training in head trauma care. The two later inputs (avg_doc, avg_cons) are obtained by calculating the number of doctors or consultants for each patient in each year and then taking the average of all patients for each hospital.

Furthermore, “total costs” were also included as a proxy for the capital input, even though the common “capital input” used in efficiency studies is through the number of beds in hospitals, it was decided to incorporate better proxy which is the economic cost measurement for head trauma care, and the “total costs”, as an economic measure, were based on the estimation used by Morris *et al*. (2008). The authors estimated the treatment costs from the perspective of the National Health Service (NHS) in England and Wales, and the estimation was restricted to patients treated with TBI. Indeed, they calculated treatment costs for each patient based on the following components: transportation to the hospital, hospital stay (A&E, critical care, regular ward), and TBI-related surgical procedures.

In the present study, the cost was calculated in the same way, but we excluded TBI-related surgical procedure components due to the limitation of the available data for components of these surgical procedures. Resource use for every component was measured for the average number of TBI patients in each hospital in the current dataset. *Unit costs* were subsequently assigned from external sources to each item (Morris *et al.*, 2008). In Table 3.2, further details on the data used and the methodology applied regarding the assignment of *unit costs* to each cost component are provided. Furthermore, as far as can be evaluated, this is the first study that uses this economic cost methodology in the DEA context.

Cost component	Unit	Unit cost (GBP)	Source and notes
Mode of arrival at hospital:			
Ambulance	Cost per minute	5.50	(Curtis and Netter, 2004: p. 112); cost per minute of emergency ambulance service.
Helicopter	Mean cost per patient journey	1650	London air ambulance website; mean cost per mission (2007).
Hospital stay:			NHS reference costs 2004; mean cost per attender across all A&E healthcare resource groups (2005)
Emergency Department	Mean cost per attender	278	
Regular ward	Mean cost per day	281	
Critical Care Unit	Mean cost per day	1328	

Table 3.2: Unit costs used for DEA analysis
Source: reproduced from Morris, *et al.* (2008)

The y_1- y_3 outputs were selected based on the level of head injury severity and one treatment outcome (i.e. satisfactory treatment, which is good recovery in the GOS). The use of case-mix adjustment, according to the level of injury severity (minor, moderate and severe), has ensured greater comparability between outputs of each hospital and outputs across hospitals. The total period of stay y_4 measures the utilisation of the hospital capacity for hospitalised patients. Therefore, it has been considered as a favourable output of the head trauma hospital. The average number of total operational procedures y_5 and the number of treatments provided by emergency services y_6 are both important indicators of health services provided. Therefore, they were chosen to be outputs for measuring the performance of head trauma hospitals.

Furthermore, a number of the environmental variables, which are “uncontrollable” variables, were also chosen to distinguish the variations of efficiency scores (DEA results) in the second stage analysis. These are shown in Table 3.3 below. These variables were selected due to the fact that they have a potential impact on the outcomes and the costs of head trauma patients.

Enviromental variables
Percentage of patients with GCS ≥ 13 (minor injuries)
Percentage of patients with GCS 9–12 (moderate injuries)
Percentage of patients with GCS < 9 (severe injuries)
Percentage of patients with age > 60
Percentage of patients with age 18-60
Percentage of patients with age <18
Percentage of patients who were male
Percentage of patients who were female
Neurosurgical unit (Yes/No)
Year

Table 3.3: Environmental variables

3.4.2 Input/Output Orientation

In general, the proponents of the “output-oriented” approach highlight the maximisation of outputs with keeping inputs constant, whereas the proponents of the “input-oriented” approach highlight the difficult economic times of our era, where cost savings become a critical factor for hospital efficiency.

In the previous sections, the “input-orientation” and the “output-orientation” were discussed as alternative approaches to both the CCR and BCC models. Overall, the choice of the DEA analyst depends on the nature of the objective function and the constraints, and whether observed inputs or observed outputs are the most well-known controllable variables. Several studies have been conducted using both orientations. Al-Shammani (1999) used an “output-oriented” approach to estimate the technical efficiency of hospitals in Jordan. Similarly, Valdmanis et al. (2004) investigated the capacity of public hospitals in Thailand using an “output-oriented” approach. Comparatively, Zere et al. (2006) and Thanassoulis (2000) used an “input-oriented” approach in order to estimate technical efficiency of hospitals in Namibia and the UK, respectively.

In policy terms, if the management team of a hospital is in a position to observe more inputs than outputs then they should use the “output-oriented” approach. On the contrary, if more outputs are observable, the hospital should apply the “input-oriented” approach for more accurate technical efficiency scores (Sahin and Ozcan, 2000; Jacob *et al*., 2006).

The “input-oriented” DEA framework is used in the empirical analysis of this current study. The reason for choosing this “input-oriented” DEA is to answer the question of how much can be saved in terms of cost and resources for head trauma care. In addition, the input-orientation seems to be more consistent with the nature of head trauma care, in which managers have more control over inputs (resources) than they do over outputs (outcomes and services).

3.4.3 Returns to Scale

The concept of *returns to scale* refers to the change in the output scale of production, when changes in the levels of input have already been implemented. As discussed previously, there are two different types of returns to scale: the Constant Returns to Scale (CRS) and the Variable Returns to Scale (VRS).

Constant Returns to Scale (CRS) refers to the case where a hospital, or more generally a DMU, is experiencing an increase of inputs by a particular factor would lead to a proportionate increase to the produced output. However, Variable Returns to Scale (VRS) refer to the case where the response of output, following an increase of inputs by a specific factor, is not proportionate. There are two situations that may occur: Increasing Returns to Scale (IRS) or Decreasing Returns to Scale (DRS). The former refers to the case where the input organisation is such that it allows the output to increase by a more than proportionate factor, which is more than the factor according to which the inputs have been increased. The opposite is true in relation to DRS, as the output is expected to increase by a lower factor than the one used to increase the inputs.

It is clear that the VRS approach allows the analyst to differentiate between the scale size of hospitals and the different sources of possible inefficiency, and hence, identify and avoid a possible efficiency loss due to the scale of a particular hospital. However, the CRS approach may be more appropriate when the scale size of hospitals is similar.

There are many studies that discus CRS and VRS in hospital settings. Masayuki (2010) revealed the statistically and economically significant *returns to scale* in Japan's hospitals, as it was reported that when the size of hospitals double, their productivity increases by more than 10%. Invariably, this increase was found to be associated with the quality of inpatient care. However, the same study did not find that certain groups of professionals or certain medical specialties were characterised by better *returns to scale* than others. The author concluded that increasing the size of very small hospitals by consolidating them into bigger regional ones may be a plausible way of increasing productivity due to the underlying increasing returns to scale, although there was no information regarding the efficiency aspect. Nonetheless, the study made it clear that hospital consolidation should be carefully monitored in order to avoid the creation of hospitals that are 'too large', in which case decreasing returns to scale could slow-down productivity rates. Evans (1999) discussed similar findings for a group of hospitals in the United States. Unfortunately, certain authors warned about the possible bias associated with the empirical estimation of the impact of *returns to scale* when the sample size is very small (Smith, 1997).

In addition, Ferrier and Valdmanis (1996) estimated the efficiency of 360 rural hospitals in the USA and found the scale efficiency to be 0.893; Hollingsworth and Parkin (2001) used DEA modelling to estimate the scale efficiency of 49 neonatal care units in the UK and found varying *returns to scale;* and Dalmau-Matarrodona and Puig-Junoy (1998) estimated using DEA the efficiency of 94 Spanish acute hospitals in 1990 and found that scale efficiency to be influenced by size and severity of illness.

Most of the authors that have been mentioned adopted the VRS approach to measure efficiency. However, comparisons with the CRS approach were normally conducted. As it should be obvious from discussions, there is no actual guideline as to which approach may be better in measuring hospital efficiency because the decision will always depend on which empirical DEA model will be adopted for the analysis.

In the current study, the empirical DEA application applies the VRS approach, due to the nature of our inputs and outputs that include ratio and percentage data, which make the only appropriate assumption to be VRS (Hollingsworth and Smith, 2003). Hence, if the CRS is applied with inputs and outputs that contain ratio data, there is a possibility of creating output targets that exceed their upper bounds (e.g., 130% survival), which makes this CRS model incorrect. The use of VRS assists to overcome this problem due to the existence of the convexity constraint, which restricts the target values for inputs and outputs to be less than or equal to 1. In addition, this VRS approach was chosen in order to take advantage of the distinguishing factor between the technical efficiencies and the scale efficiencies.

3.5 Sample Selection

The data for this current study were directly obtained from the TARN, who kindly agreed to provide access to relevant databases, as mentioned in Chapter 1. There was no access to individual patients or hospital identifications. The inclusion criteria were simply 93499 patients that were hospitalised for HTI in 185 hospitals that were included in the TARN database for the time-period between 2009 and 2012.

The associated hospitals normally complete a data entry sheet for each patient with information on: age; gender; severity of the injuries; treatment provided at the scene of the accident; en route to hospital or in A&E; and any other care received at the hospital; including diagnostic tests performed; specific treatment provided; and any TBI-related surgical procedures; length of stay (LOS) and discharge status and the year of admission. For patients who arrived at A&E, additional data were utilised that includes the mode of arrival at

A&E; the time from emergency call to arrival at A&E; the time spent in A&E; the number of doctors; specialists and nurses seen in A&E. Furthermore, the dataset includes: the Glasgow Coma Scores (GCS); the Injury Severity Scores (ISS); details relating to patient admission to critical care (ICU, neurocritical unit or HDU); and further details about the LOS in critical care and the total LOS. Finally, data in regards to whether or not the treating hospital had a neurosurgical unit were also available. All of these data were at patient level, while the data that the current research required to compare head trauma care has to be at hospital level. Therefore, the summary data were required at the hospital level, rather than at patient level for the DEA application.

3.6 Conclusion

A comprehensive presentation of the models for DEA, which are addressed and applied in this study, is provided in this chapter. The CCR model, which is associated with CRS, remains the most intuitive model of conducting DEA when hospitals operate with the similar scale of size. However, it is not in a position to account for “scale effects”.

The BCC model offers an improved solution to the linear programming DEA model by acknowledging the “scale effects” as part of the technical efficiency. The comparison between the two models provides insights into the possible loss of efficiency in case the DEA analyst proceeds to the calculation of the technical efficiency of a hospital, while ignoring its size. Unlike the CCR, the BCC model does not provide the same efficiency scores from the “input-oriented” and the “output-oriented” approaches to the linear DEA programming.

In addition, the chapter has presented additional modelling approaches, such as bootstrapping DEA methodology, as well as the DEA-MPI. Moreover, the current chapter provides some additional methodological considerations. In particular, the time for when it may be more appropriate to apply the “input-orientation” or the “output-orientation” in the DEA has been discussed. Subsequently, the chapter has presented the chosen inputs and outputs, together with the environmental variables for the empirical DEA application to head trauma care. The penultimate section was dedicated to a detailed explanation of *returns to scale* in measuring hospital efficiency. Finally, the selection of the data sample has been explained, and the way of calculations for the available data in order to obtain the selected inputs and outputs for the empirical part of the current study.

CHAPTER FOUR: DATA ENVELOPMENT ANALYSIS WITH MISSING DATA

4.1 Introduction

A common problem in health care studies relates to how to analyse incomplete or missing data. DEA applications in health care do not generally consider this problem, as DEA is a non-parametric approach, which means that each relevant information source to inputs and outputs is important when producing consistent results. Subsequently, any missing from this information could affect the results of DEA. No matter how sophisticated the recommended technical solutions are in reducing the negative impact of missing data, it is impossible to avoid this problem in empirical studies. In the current study, an approach based on multiple imputations using chained equations (MICE) is proposed in order to replace missing data for data envelopment analysis.

This chapter is structured into specific sections of detail. Section 2 consists of a background and literature review of DEA, missing data in DEA and multiple imputation approaches. Section 3 presents some experimental results of MICE and the effects upon DEA efficiency scores associated with different rates of missing data. Section 4 presents a designed experiment to demonstrate the proposed method by using the actual data with artificially induced absent data. Finally, Section 5 discusses the results and presents a summary and conclusion.

4.2 Background

This section introduces DEA models and consists of a literature review of current techniques to replace missing points in DEA. It also presents an introduction to multiple imputation.

4.3 Methods for Dealing with Missing Data in DEA

DEA modelling is a linear programming technique, which assumes complete data availability for all inputs and outputs that are involved within the process. However, in practice, this is not normally feasible. On the contrary, missing data appears to be the considered the norm, rather than the exception. For this reason, the research needs to consider how to allow for missing data before proceeding with the DEA modelling. One approach is to estimate, or impute, all input or output values that are missing. Moreover, the degree of accuracy associated with such estimation also determines the influence that missing data has on the calculations of technical efficiency scores.

A simple way, and the standard approach, for countering the problem of missing data is the exclusion of all DMUs associated with missing values (Kuosmanen, 2002). This particular approach also affects the efficiency scores of the remaining DMUs, due to the fact that the DEA is very sensitive to different sample sizes and, therefore, it does not provide an actual solution to the problem. Additionally, Kao and Liu (2000) proposed a fuzzy set approach to handle missing inputs and outputs. Hence, each missing value of a DMU in input or output is signified by a triangular fuzzy number formed from the values of other DMUs present in that specific input or output. Following this, the efficiencies are calculated by using a fuzzy DEA model.

Another approach is through the coding of missing data by using dummy values, which has been proposed by Kuosmanen (2002), such as zeros for missing outputs and a large number of missing inputs. Weight restrictions should be applied within this dummy replacement DEA approach in order to minimise the influence of the missing points. Likewise, a similar approach to a fuzzy DEA approach is to estimate an interval range for each missing value with the view to identify the best missing value within the interval range (Smirlis and Despotis, 2002; Smirlis *et al*., 2006). Overall, the bounds of these intervals are obtained by different estimation approaches, such as statistical or experimental techniques.

There are certain methods that can be used to deal with missing data that is presented within the DEA, such as using average values for replacing missing data. However, such an approach can lead to inaccurate calculations of efficiency scores due to the fact that multiple missing values of data are replaced with a single static value. Moreover, Aksezer and Benneyan (2010) proposed multiple imputations through the use of a multivariate normal assumption, in order to replace missing values in the matrix of inputs and outputs, and compared this approach with other approaches for replacing missing data, including bootstrapping and smart dummy variable replacement. That specific study found that multiple imputation forms a satisfactory estimation procedure for such missing values in the DEA context, when compared with other methods.

Finally, Ben-Arieh and Gullipalli (2012) have proposed using the fuzzy clustering concepts to deal with missing values in DEA. The current paper recommends an optimal completion strategy (OCS) within a modified fuzzy c-means algorithm in order to calculate the missing values, while still taking the sample size and initial values into account.

4.4 Multiple Imputation

Multiple imputation (MI) is a statistical technique used for tackling missing data problems (Rubin, 1987). This method has become increasingly popular, as indicated by the applications in many statistical software packages (Harel and Zhou, 2007). In general, the idea of MI is to predict a group of plausible values for relevant absent data, which is structured by using the distribution of the missing data conditional on the observed data. These groups of completed data (imputed data sets) are subsequently analysed on an individual basis through an identical process, which is completed in order to provide estimates of parameters that are combined to establish the final estimates, as shown in Figure 4.1.

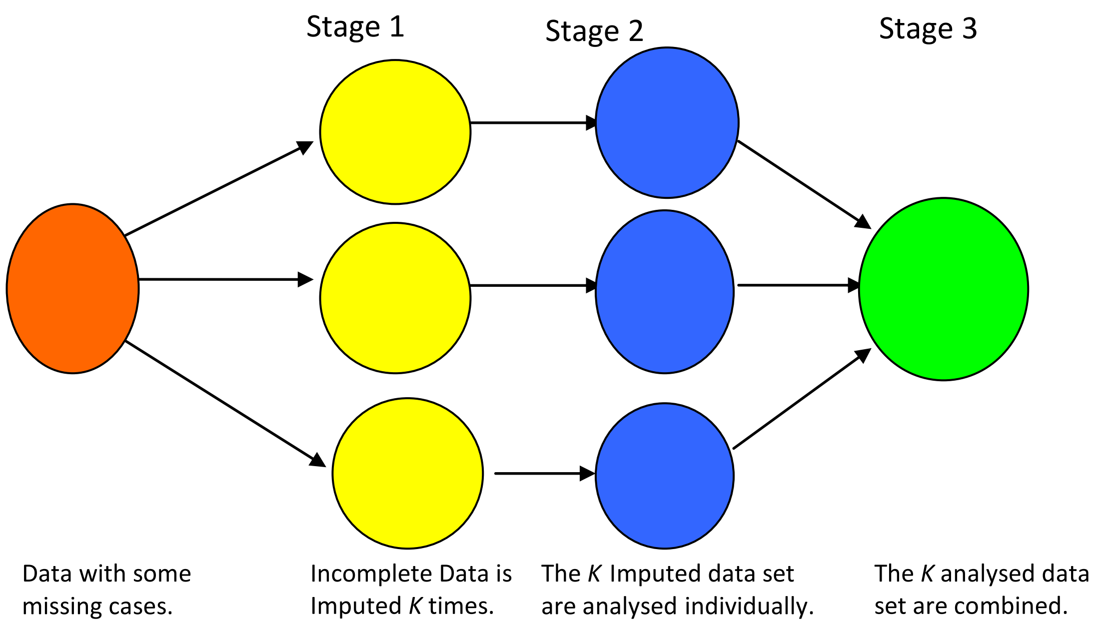

Figure 4.1: Multiple imputation process

According to White *et al*. (2011) MI can be explained formally through the following three stages:

1- The generation of multiple imputed data sets by random draws from a distribution of missing data and observed data is the first stage. This is to say, K independent simulated data sets (K >3) replace the missing data through random draws that derive from the posterior predictive distribution of the absent data conditional on the observed data. More precisely, for a variable with missing values z, the construction of an imputation model is based on the type of variables (e.g. continuous, binary), which regress this particular variable z on all other completed variables $x_1, x_2, x_3, \ldots, x_s$ among individuals with the observed values of z in order to estimate $\hat{\beta}$ (regression parameters) and V (covariance matrix). Then β^* is randomly drawn, k times, from the posterior distribution of $\hat{\beta}$ and V. Subsequently, β^* and appropriate probability distribution are used in order to draw the posterior predictive distribution of z, which subsequently produces K imputation sets of the variable z.

2- The analysis of multiple imputed data sets is the second stage. Thus, every individual imputed data set is analysed separately in order to obtain the estimates of interest.

3- The combination of estimates from multiple imputed data sets is the final stage. This stage is to gather the estimates from the K imputation data sets in order to provide a single overall estimated set using asymptotic theory in a Bayesian framework. More precisely, let $\hat{\eta}_k$ and $\hat{v}_k$ become the estimate of interest and the corresponding variance respectively. In order to have an overall estimate, the mean of the individual imputed set of values is calculated as follows:

$$\hat{\eta} = \frac{1}{K}\sum_{k=1}^{K}\hat{\eta}_k \qquad (4.1)$$

The variance of $\hat{\eta}$ is calculated as the sum of the average of variances from each imputed set (the within-imputation variance), and the between-imputation variance.

$$\mathrm{var}(\widehat{\eta}) = \frac{1}{K}\sum_{k=1}^{K}\hat{v}_k + \frac{K+1}{K}\left[\frac{1}{K-1}\sum_{k=1}^{K}(\hat{\eta}_k - \hat{\eta})^2\right] \qquad (4.2)$$

4.4.1 Specification of the Imputation Model

The next phase in multiple imputation is specification of the imputation model. Two distinct approaches are used: the multivariate normal model and the chained equations approach.

4.4.1.a. Imputation Using the Multivariate Normal Model

The multivariate normal model (MVN) was introduced by Rubin (1987), as well as Little and Rubin (2002). One of the initial studies, using MVN, was published by Schafer (1997). The main assumption that is required to apply this approach is that all variables present within the imputation model possess a multivariate normal distribution. In this model, in order to obtain imputed data using the estimated multivariate normal distribution, Bayesian framework is used to enable the capability to generate proper imputation (Rubin, 1987). Even though the assumption of multivariate normality is often implausible, such as when binary and categorical variables are present, Schafer (1997) suggested that inference from the multivariate normal imputation appears to be plausible, even if multivariate normality does not hold. Moreover, multivariate normal imputation has been used frequently in situations where data are visibly not defined as multivariate normal (Choi *et al.*, 2008; Seitzman *et al.,* 2008).

4.4.1.b. Imputation Using the Chained Equations Approach

A different technique for imputation is multiple imputation by using chained equations (MICE or ICE), which is known to be one of the best approaches in practice for the formulation of multiple imputation. Indeed, certain researchers have referred to this process through a more details description as fully conditional specification and sequential regression multivariate imputation (White *et al.,* 2011).

The methods of regression are defined for each particular variable which contain different missing values, and this is conditional on alternative variables that are present in the approach through imputation (White *et al.,* 2011). For instance, when the variable x_1 has values missing it becomes regressed upon all different variables (x_2 , x_3. . . , x_s), although this remains restricted to individual variables that present values for x_1. Through the use of simulated draws from posterior predictive distribution of x_1, values that are missing in x_1 are filled. Consequently the next variable's imputation would follow a distinctly similar trend.

In particular, the variable x_2 with missing values becomes regressed upon all different variables (x_1 , x_3. . . , x_s), with using the imputed values of x_1 and restricting to individual variables that present values for x_2. Then, the values that are missing within x_2 are filled by simulated draws from the posterior predictive distribution of $x_{2,}$. Following this, when values are missing for of x_3,...,x_s, the same procedure is applied, which is ultimately referred to as a process by the term "cycle". In order to create results that are stable, the cycle is conducted multiple times, which is commonly completed 10 or 20 times and finally results in generating one specific imputed data set.

In general, the imputation procedures are generated by calculating each conditional distribution using observed cases for the variable under consideration and imputed data for the other variables at that iteration and imputing missing values. The overall process is applied K times to generate K imputed data sets.

4.4.2 Advantages of MICE and Comparison with MVN

To decide which model should be used in the current study, it is necessary to compare the two approaches of MICE and MVN (Lee and Carlin, 2010; and Marchenko, 2011). One advantage of MVN is its theoretical underpinning, while MICE fail to have such a strong theoretical basis. On the other hand, MICE has the advantage of imputing data on a variable by variable basis, while MVN uses a joint modelling approach technique, which relies on a multivariate normal distribution (Schafer, 1997). MICE can also deal with different types of variables, such as ordinal and nominal data, while MVN can only handle normal distribution data. If data are non-normal, MVN needs to transform them to be normally distributed (Schafer, 1997). Furthermore, MICE can include restrictions within a subset of data, whereas MVN imputation cannot accomplish this.

The multivariate normal approach has relatively strong theoretical assumption, although its conditional distributions are necessary to be set as normal. Therefore, univariate regression techniques cannot be applied adequately using, for example, ordered logistic regression for ordinary variables and logistic regression for binary variables (Van Buuren, 2007). In contrast, the chained equations approach can be applied flexibly, as it does not depend on the hypothesis of multivariate normality (Van Buuren *et al*., 1999 and, 2006).

4.5 Adaption of MICE for DEA Applications

Although DEA is a nonparametric technique, which does not hold any assumptions about model parameters for the missing data, it is possible to adapt a parametric method represented by the MICE approach, since this nonparametric technique is conducted at the level of the input and output matrix.

A standard assumption that is required to apply MICE is that the mechanism of missing data should be distinguished as missing at random (MAR). Thus, there is no instance that the probability of missing data from a specific variable can rely on the variable itself, although it can rely on other variables. Nonetheless, as the dataset is grounded due to missing data points, this assumption is not able to be tested.

As mentioned previously, this approach can be applied flexibly for different types of variables (continuous, categorical and binary), and Table 4.1 sets out the models that are used for different types of variables. In the current study, the variables are continuous, so linear regression will be applied as the imputation model. However, there are some continuous variables which remain skewed. White *et al*. (2011) discussed two main ways of dealing with skewed variables, which include predictive mean matching and transformation towards normality. The current research has adopted the latter approach of transformation towards normality for handling evidential skewed continuous variables.

Type of variable	**Model used for imputation**
Continuous variable	Linear regression
Binary variable	Logistic regression
Ordinal variable	Ordinal logistic regression
Nominal variable	Multinomial logistic regression

Table 4.6: Imputation models for different types of variables

One specific study that has applied multiple imputation in a DEA context was undertaken by Aksezer and Benneyan (2010). They studied the efficiencies of hospitals in Turkey and preferred to incorporate the multivariate normal approach to deal with missing data problems. Nevertheless, this multivariate normal approach cannot be used flexibly for non-normal datasets, as was mentioned previously, so an approach has been applied based on multiple imputation by chained equations.

4.6 Methodology

This section presents a simulation study of MICE in DEA using a real data set. Although this data set has incomplete cases, it is beneficial to work with a complete data set in order to investigate the proposed methodology and its accuracy for DEA results. The data are taken with permission from the Trauma Audit Research Network (TARN) database, which is maintained by The University of Manchester. The data set provided for analysis contains information relating to sixty-six hospitals with ten characteristics comprising four inputs and six outputs. Table 4.2 below contains a list of these particular input and output variables.

Such data sets, which do not contain any missing value, offer possibility of obtaining true efficiency scores for the data sample. To replace some observed cases with simulated missing data for experimental simulation analyses, a specific method was followed in the current study. Individual observations comprising 1%, 5%, 10% and 20% of the complete data set were chosen randomly and removed from the data set. These four separate versions of missing data enable the researcher to examine the robustness and sensitivity of the MICE approach. In addition, Aksezer and Benneyan (2010) stated, “experience showed that when the rate of missing data is more than 10%, it is almost impossible to carry out DEA”, which has been theorised to be assessed in this investigation.

For consistency and reliability with the MAR related hypothesis, all inputs and outputs are put into a pool for selection. Consequently, no preference is instilled to any specific input or output and no precedence is provided to the relevance of input sets above outputs, or output sets over inputs. After applying different levels of missing data, MICE is conducted for each problem in different scenarios for the numbers of imputations, in order to investigate the sensitivity of this factor. For broad generality, the scenarios that have been chosen for consideration in current research are 5, 10 and 20 repeated imputations.

Inputs	Outputs
Average number of doctors seen per patient per year (X1)	Percentage of patients with minor injuries who recovered satisfactorily per year(Y1)
Average number of consultants seen per patient per year(X2)	Percentage of patients with moderate injuries who recovered satisfactorily per year(Y2)
Average number of nurses seen per patient per year(X3)	Percentage of patients with severe injuries who recovered satisfactorily per year (Y3)
Total cost (£) per patient per year (X4)	Average of the total period (days) of stay per patient per year (Y4)
	Average number of surgical operations per patient per year (Y5)
	Average number of treatments provided by emergency services per patient per year (Y6)

Table 4.7: List of inputs and outputs

In order to evaluate the effectiveness of the methodology, input oriented VRS-DEA with the complete data is solved first, before this analysis is repeated for the different missing data sets with all the explained scenarios. Subsequently, the efficiency scores (estimated efficiencies) are gathered for all cases and compared with those obtained from the complete set (true efficiencies). To enable such comparisons, different methods have been used in the literature. Aksezer and Benneyan (2010) used linear regression to compare estimated efficiencies with true values obtained from multiple imputation using the MVN assumption and it is agreed that this method is beneficial for comparisons of this nature. This is useful here because both the complete and partial approaches contain errors, which violates the usual assumption for linear regression that the independent variable should be error free. Thus, that assumption is important in order to generate unbiased estimates using this regression approach.

In general, it is common in the DEA literature to use correlation and rank correlation as a comparison measurement for different purposes. We also argue that this method is beneficial for such comparisons. This is to say that when the results of the two techniques have high correlation, this suggests consistent agreement between the results. Contrastingly, high correlation values do not imply that agreement exists between the two methods. Nevertheless, even though the correlation coefficient calculates the strength of the relationship, it could be erroneous to conclude that high correlation corresponds to high levels of agreement. The explanation for this surprising result is that two methods are in agreement when their scatter lies along the line of equality, though high correlation can be achieved if the scatter lies along any straight line that need not pass through the origin. Offset intercept bias does not alter the value of the correlation coefficient in any way.

Therefore, we are going to use mean absolute error (MAE) and root mean square error (RMSE) as a comparison measurement of the estimated efficiency with the true efficiency for all cases. Below are the specifications of both equations of error where the usual formulation is adopted, whereby efficiencies are measured as percentages rather than proportions.
The MAE specification is:

$$\frac{1}{N}\sum_{n=1}^{N}\left|\hat{e}_n - e_n\right| \quad (4.3)$$

In this equation, $\hat{e}_n$ is the estimated efficiency of hospital *n*, e_n is the true efficiency of hospital *n* and *N* is the number of hospitals. The process of calculating MAE is relatively straightforward, as it is necessary to determine the sum of magnitudes (absolute values) that comprise the errors in order to ascertain and understand the 'total error' prior to using the amount of DMUs to divide the total error.
The RMSE specification is:

$$\sqrt{\frac{\sum_{n=1}^{N}(\hat{e}_n - e_n)^2}{N}} \quad (4.4)$$

Similarly to MAE, this measure is straightforward to calculate. Firstly, the differences between the estimated and true efficiencies are evaluated and then squared. Secondly, these errors are summed before dividing the total by the number of DMUs. Finally, the square root is taken.

Scenarios	Description	MAE (%)
5 Imp of 1%	5 imputations of 1% missing	0.097
10 Imp of 1%	10 imputations of 1% missing	0.129
20 Imp of 1%	20 imputations of 1% missing	0.194
5 Imp of 5%	5 imputations of 5% missing	0.794
10 Imp of 5%	10 imputations of 5% missing	0.782
20 Imp of 5%	20 imputations of 5% missing	0.745
5 Imp of 10%	5 imputations of 10% missing	1.305
10 Imp of 10%	10 imputations of 10% missing	1.257
20 Imp of 10%	20 imputations of 10% missing	1.325
5 Imp of 20%	5 imputations of 20% missing	2.013
10 Imp of 20%	10 imputations of 20%missing	2.005
20 Imp of 20%	20 imputations of 20% missing	2.013

Table 4.8: MICE scenarios and MAE

Table 4.3 shows the different scenarios and resulting MAEs. As can be seen from the resulting MAEs, the same percentages of missing data produce relatively similar MAEs. For example, for 5% of missing data, there is little difference among the results for 5, 10 and 20 imputations. However, differing percentages of missing data do lead to different MAEs, although the values are still very small, given that MAE is expressed as a percentage on the scale 0 to 100. Figure 4.2 demonstrates visually how the MICE scenarios and MAE change according to the number of imputations and the percentage of missing data. It clearly shows that there is a monotonic increase in terms of MAE, so that the higher the percentage of missing data, the higher the MAE.

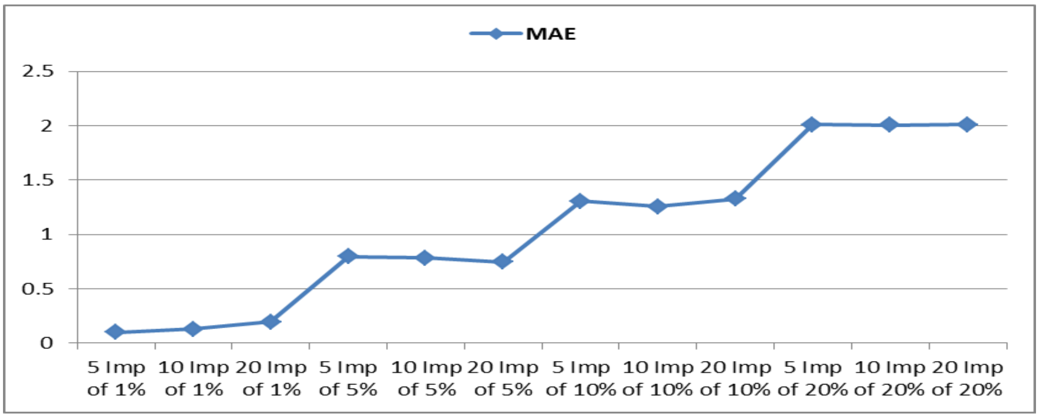

Figure 4.2: MICE scenarios and MAE

Similarly, Table 4.4 shows the different scenarios and resulting RMSE values. It is quite obvious that the same percentage of missing data leads to relatively similar RMAE values. Nonetheless, even though there are differences among them, these are not large differences. For instance, for 5% missing data, the results show that RMSE for 5 imputed datasets is 3.7, whereas for 10 and 20 imputed datasets the RMSEs are both about 3.8.

Scenarios	Description	RMSE (%)
5 Imp of 1%	5 imputations of 1% missing	0.553173
10 Imp of 1%	10 imputations of 1% missing	0.657267
20 Imp of 1%	20 imputations of 1% missing	1.111306
5 Imp of 5%	5 imputations of 5% missing	3.724245
10 Imp of 5%	10 imputations of 5% missing	3.825572
20 Imp of 5%	20 imputations of 5% missing	3.744997
5 Imp of 10%	5 imputations of 10% missing	5.473299
10 Imp of 10%	10 imputations of 10% missing	5.332542
20 Imp of 10%	20 imputations of 10% missing	5.323721
5 Imp of 20%	5 imputations of 20% missing	6.012238
10 Imp of 20%	10 imputations of 20% missing	6.010408
20 Imp of 20%	20 imputations of 20% missing	6.03233

Table 9.4: MICE scenarios and RMSE

It is different when we take into account the differences in percentages of missing data, which lead to different RMSE values. Figure 4.3 demonstrates visually how the MICE scenarios and RMSE change according to the number of imputations and the percentage of missing data. Likewise, as with the results for MAE in Figure 4.2, it can be seen that RMSE increases monotonically when the amount of missing data increases.

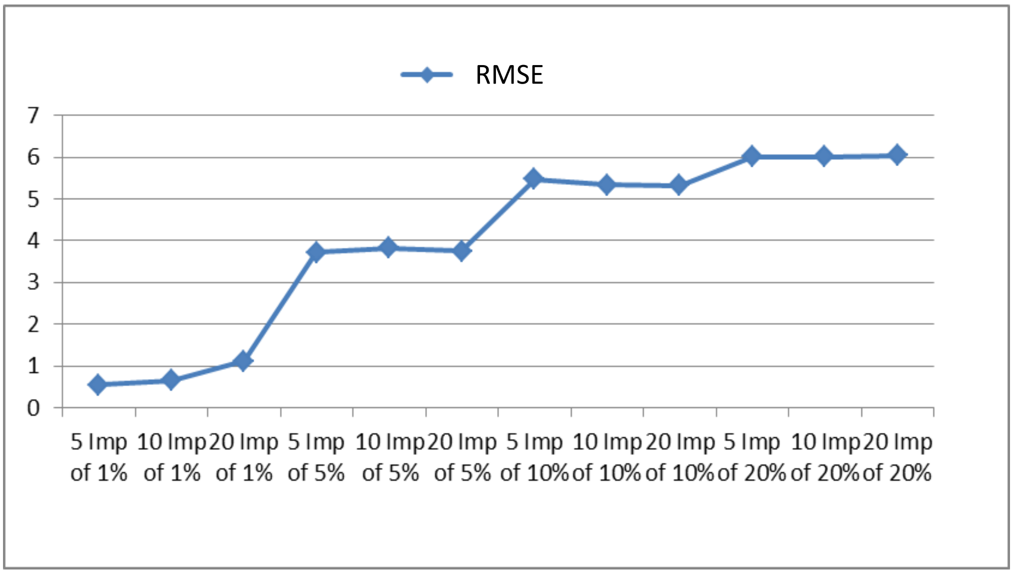

Figure 4.3: MICE scenarios and RMSE

For further comparisons, the Maximum Absolute Error (MAX-AE) is calculated, but only for 5 imputations of the different levels of missing data. Hence, the same 1%, 5%, 10% and 20% missing levels are conducted and nested from the completed data set, and subsequently MICE of 5 imputations is applied. The estimated efficiency scores then compare with the true values by calculating MAX-AE, as shown in Table 4.5. This table shows that there is a five-fold increase in MAX-AE from the 1% and the 20% missing scenarios. Figure 4.4 similarly demonstrates monotonically MAX-AE increase when the level of missing data increases.

Scenarios	**MAX-AE**
1% missing	4.21
5% missing	7.68
10% missing	13.18
20% missing	20.61

Table 4.10: MICE scenarios and MAX-AE

MAX-AE results provide consistent outcomes with both MAE and MSE. Therefore, this simulation study suggests that MICE is an effective approach to estimate the true efficiency when missing inputs or outputs are experienced. However, when the rate of missing data increases, the precision of estimated DEA analysis tends to decrease.

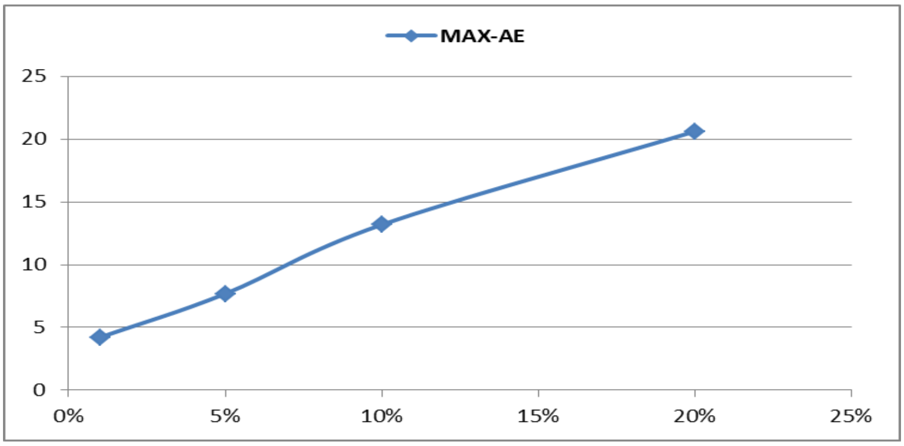

Figure 4.4: MICE scenarios and MAX-AE

4.7 Empirical Analysis: A Case of HTI Hospital Efficiency in 2009

This section is an empirical analysis using the MICE approach in order to estimate the efficiency of 115 HTI hospitals in 2009. Therefore, the purpose of this application section is to illustrate the proposed method of MICE in order to measure head trauma care efficiency using data envelopment analysis under the input oriented VRS assumption. According to Magnussen (1996), the selection of inputs and outputs for the assessment of hospital efficiency is very important, as it affects not only the results, but also the ability of the technique to provide useful and meaningful information. Consequently, the selection of inputs and outputs for this empirical example, as mentioned previously in Chapter 3, is firstly guided by the theoretical principles of DEA and, subsequently, by previous research associated with other DEA applications, as well as the head trauma literature. Finally, the selection is finalised based on the availability of data.

The resulting inputs that are considered are the average number of doctors seen per patient per year (avg_doc); the average number of consultants seen per patient per year (avg_cons); and the total cost (£) per patient per year. Contrastingly, the outputs are the percentage of patients with minor injuries who recovered satisfactorily per year (pctmin); the percentage of patients with moderate injuries who recovered satisfactorily per year (pctmod); the percentage of patients with severe injuries who recovered satisfactorily per year (pctsev); the average of the total period (days) of stay per patient per year (avglos); the average number of total surgical operations per patient per year (avtotop); and the average number of treatments provided by emergency services per patient per year (avg_treat). Overall, the data for this application were directly obtained from the TARN database, and there was no access to individual patient or hospital identifications.

The inclusion criteria for the research were simply 15,786 patients who were hospitalised for traumatic brain injury (TBI) in 115 hospitals included in the TARN database for 2009. In general, a data entry sheet is completed online for each patient by every one of these hospitals to provide information that includes: the age; a patient's gender; the overall injury severity; how treatment is provided, whether that is at the accident scene, en route to the hospital or specifically in the accident and emergency (A&E) unit. Moreover, another part of the information provided relates to other care that is received within the hospital that can include: diagnostic tests, specific treatment such as surgical procedures related to trauma and brain injury, total length of stay (LOS), the status at discharge, as well as the admission date.

Additional data were collected about patients suffering from head trauma in A&E, which included: the mode of transport to A&E, the duration of time between emergency call and A&E admission; the total duration for a patent spent within A&E; and the amount of doctors, specialists and nurses who were present in A&E. Additionally, the set of data includes the Glasgow coma scores (GCS); the injury severity scores (ISS); patient details when admitted to critical care units; together with additional details in regards to the critical care LOS and LOS as a whole. Furthermore, data were also available that related to whether a neurosurgical unit was present within the treating hospital. All these data specifics were at the patient level, while the data that has been needed to compare head trauma care were at the hospital level. Therefore, summary data were required at the hospital level rather than at the patient level for the current DEA application.

Data aggregation by hospital for all the variables was undertaken and summary statistics such as mean, proportion and percentage were derived. These summary data represent the inputs and the outputs that were mentioned above for this empirical study. Furthermore, "total costs per patient" were also calculated as a proxy for the capital input. Despite that the common "capital input" used in efficiency studies is the number of beds at hospitals it was not possible to collect this kind of information due to significant limitations in the availability of data. Therefore, the researcher decided to use the economic cost measurement for head trauma care as a proxy of the capital input. The "total costs", as an economic measure, was based on the estimation from a previous study, as the treatment costs from the stand point of the English and Welsh National Health Service (NHS) were hypothesised, as well as a restriction placed on the estimation to patients who were treated with HTI (Morris *et al.*, 2008). It was calculated through that particular study that each patient's treatment cost was directed from various components. For instance, the mode of transport to the hospital, duration of hospital stay, whether in A&E, critical care, or a regular ward, as well as surgical procedures that were TBI related were all relevant. A brief statistical description of the input and output variables, including mean, standard deviation (SD) and number of missing points, is shown in Table 4.6. It is worth noting that, although the weighted averages and SDs of the variables are more appropriate to allow for hospital size, it has been decided to not calculate them because these statistics are just for explaining the data and are not included in the main analysis.

Variables	Mean	S.D.	Min	Max	Number of missing points
pctmin	3.65	6.14	0.00	26.32	0
pctmod	9.83	15.36	0.00	53.97	0
pctsev	5.04	8.01	0.00	41.09	0
avglos	15.78	7.16	2.12	55.00	0
avtotop	1.83	0.99	1.00	8.00	11
avg_treat	16.81	8.22	1.00	33.00	0
avg_doc	2.07	0.78	0.84	4.20	14
avg_cons	1.17	0.19	1.00	2.33	27
totalcost	4247.87	4241.39	139	18,427.33	0

Table 4.6: Descriptive statistics for input and output data

As shown in Table 4.6, there are missing data in the average number of doctors seen per patient, the average number of consultants seen per patient and the average number of total surgical operations per patient. These missing values are due to poor data collection procedures, which mean that these data specifics meet the MAR condition. Thus, the MICE approach is applied in order to address the problem of missing data and the Stata software version 13 is used. We then evaluate the efficiencies under the input oriented VRS assumption. Overall the imputed values are not very different from those observed, although a comparison of the distribution before and after imputation shows a clear similarity between the two distributions for each of the variables (Figures 4.5.a to 4.5.c).

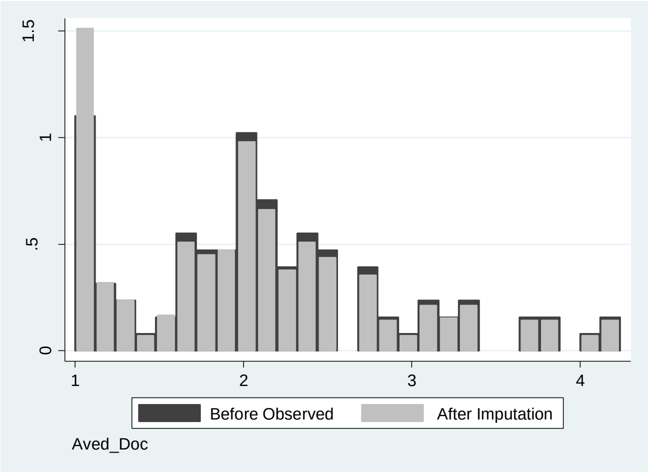

Figure 4.5.a

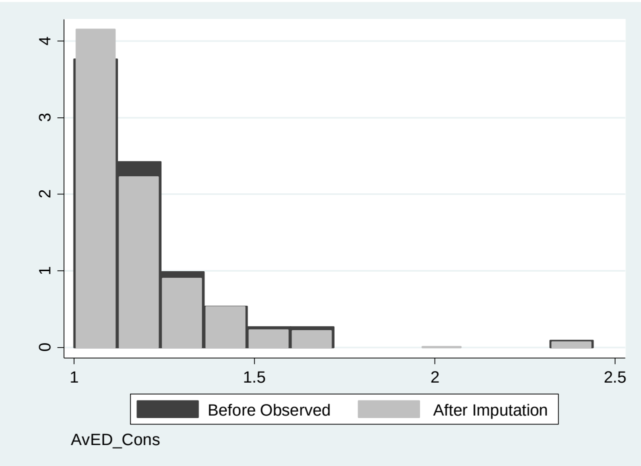

Figure 4.5.b

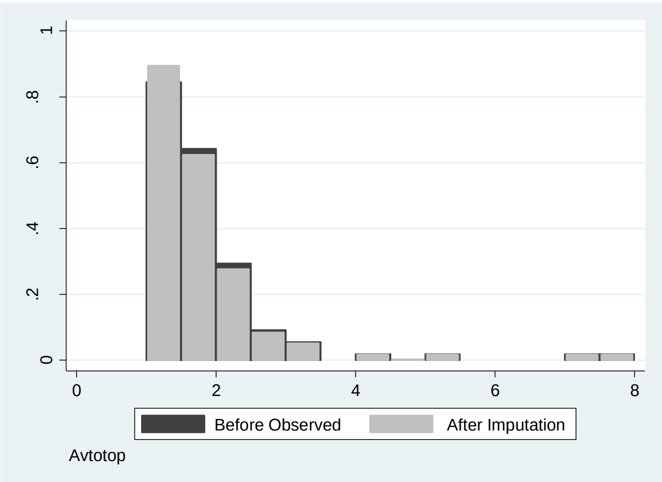

Figure 4.5.c

Figures 4.5.a to 4.5.c: Distributions of variables with missing data before and after imputation

The results of the corresponding DEA frontier analysis are shown in Table 4.7 and provide an overview of the development of the head trauma care sector. The mean technical efficiency, which results from factors such as poor management within the hospital and disadvantageous operating environments other than scale, is about 92 %. This means that there is a possibility of improving average hospital efficiencies by adopting best practices, whereby hospitals can reduce extra inputs by 8% more than they actually reduced from the same level of outputs. However, the potential decrease in inputs from adopting best practices varies among hospitals.

Average	92.13
SD	9.66
Maximum	100
Minimum	56.06
No.of inefficient hospitals	67

Table 4.7: Summary of hospitals' technical efficiencies

The general value of the standard deviations in Table 4.7 tends to be minimal, which means that the average technical efficiency is high. Moreover, the minimum scores of the inefficient hospitals are about 56%. In addition, Table 4.7 demonstrated that 67 of the 115 hospitals are deemed to be operating below 100% relative efficiency. Nonetheless, as 100% relative efficiency is very difficult to achieve and cannot be surpassed, this should not be taken as any form of critical judgment of the performance of these hospitals, but is actually more appropriately an indication of where in the network it might be appropriate to target extra resources in order to make possible improvements.

4.8 Conclusion

The current chapter provides an experimental study of the most frequently utilised methodology of the frontier analysis method, which is Data Envelopment Analysis (DEA), where missing data are frequently encountered. Invariably, the purpose is to find appropriate counter-measures to deal with such situations to ensure the accuracy of results generated.

The research focuses particularly on the healthcare industry and provides a literature review of DEA as a method that is employed within the sector to determine the technical efficiencies of hospitals and health care, and conducts a literature review of approaches for dealing with missing data in DEA. A comprehensive analysis along with these literature reviews is presented to enhance the complete understanding of the matter and describe the notion of multiple imputation. In particular, this current research proposes MICE methodology for applying DEA analysis when some of the necessary inputs or outputs are missing. An experimental study, for a completed real data set of 66 hospitals, is used to simulate the MICE approach for different missing scenarios, in order to investigate its validity as a methodology for replacing such missing values with DEA applications. The results of this experimental study denote that MICE function well and enable an acceptable estimate of true efficiency. In addition, two factors were investigated in order to test for sensitivity, the rate of missing data and the number of imputations. The number of imputations was seen to be an insensitive factor for the results of MICE, whereas the increasing level of absent data leads to decreased accuracy of the results. However, this decrease of accuracy is minimal and still acceptable for practical application.

CHAPTER FIVE: INTEGRATED DEA WITH STRUCTURAL EQUATION MODELLING

5.1 Introduction

Chapter 3 reviewed the literature on hospital efficiency, and it has become clear that DEA is the most popular method in evaluating hospital efficiency. This chapter deals with common issues that are still faced by researchers in hospital efficiency. This issue is how to deal with the environmental factors (uncontrollable factors) in DEA context. Thus, to address this issue, several studies have attempted to answer the question of how to attain the best model in order to estimate and examine the relationship between continuous variables bounded between 0 - 1 (efficiency score) and environmental factors. The majority of the previous studies dealt with these factors using a two stage analysis, with the initial stage evaluating the DMUs efficiency score through the use of DEA Models. Therefore, in the current study, a two stage analysis using SEM has been proposed as a second stage tool to investigate the effects of the environmental factors.

This chapter is organised into various sections. The next section introduces current methods to deal with the environmental factors, proposes a new method to deal with such factors and provides a real example to highlight the advantage of the proposed method. However, this part excluded the hospitals with missing data, due to this specific example including purely hospitals with completed cases. The full dataset that includes hospitals with missing data is included in Chapter 6, as we employed the ICE model to fill the missing data and get the efficiency score for each hospital. Additionally, some conclusions are offered in the final section. Overall, this chapter presents the results of the data analysis methods, which include variables description and SEM using ML and the tobit model. Furthermore, it presents the SEM through the use of robust standard errors. Throughout the study, the statistical software STATA 13 was used to conduct SEM.

5.2 DEA with Environmental Variables

The data envelopment analysis occurred under the assumption that all *observed* inputs and outputs can be controlled. However, in practice this may not necessarily be the case. One common problem reported in the literature has been in relation to the handling of "exogenous", "non-discretionary", "environmental" or "contextual" variables, which determine observed variables that are exogenously-determined and, therefore, "uncontrollable" (Banker and Morey, 1986). Indeed, there are different ways of handling this problem, which related to the one-stage modelling; the two-stage modelling; and the adjusted-values modelling.

The one-stage model includes environmental variables directly in DEA to obtain efficiency scores with an additional restriction in the standard formulation. The first attempt of such a one stage model was Banker and Morey (1986), which remains the most representative model in terms of one stage for handling environmental variables. Another alternative one-stage model was demonstrated by Ruggiero (1996), which may consider as an extension of the model of Banker and Morey (1986), to treat environmental categorical variables, to the situation where these environmental factors are continuous.

Although the one-stage model has the simplicity advantage, there are many problems that have been noticed. Firstly, one needs to know *a priori*, which are the "environmental" variables that may positively or negatively influence the production frontier. In addition to that, the efficient units obtained by this approach are not different from those calculated using conventional approaches in which all variables were controllable. Furthermore, the increase in the number of environmental variables and constraints included in the model, although they facilitate the linear programming problem, may decrease the discrimination power of DEA results. Finally and most importantly, the one-stage models have been criticised due to the fact that environmental factors are not true economic inputs into the production process; instead they only influence technical efficiency. Comparatively, the two-stage modelling applies the DEA by including only controllable variables in the first stage. Therefore, the calculation of the technical efficiency may involve influence from "environmental" variables, which is temporarily ignored.

In the second stage of the analysis, environmental variables are introduced in a regression as independent variables, while the efficiency score, which was obtained from the first stage, is the dependent variable. The aim of this second stage is to explain the differences in efficiency scores that could be caused by environmental factors and not to correct efficiency scores. In addition, although an ordinary least squares (OLS) estimation process may be appropriate choice, some authors recommended the Tobit model (Tobin, 1958) in the second stage, which allows the dependent variable to be treated as a latent variable (McCarty and Yaisawarng, 1993; Hoff, 2007). Thus, the tobit model may provide more consistent and efficiency coefficient estimates because it can take into account the fact that the efficiency score is bounded between 0 and 1. However, there are other options for the choice of regression that have been implemented (Hoff, 2007; Ramalho *et al.*, 2010).

The two-stage approach has the advantage of testing the influence of different environmental variables, which may be helpful in terms of recognising the possible source of inefficiency. However, there is a strong possibility of multicollinearity characterising the set of DEA scores, which may lead to biased and inefficient estimates, and can ultimately be solved by using *bootstrapping* (Simar and Wilson, 2007, 2011a). This is another option to avoid such a problem of treating the DEA scores in the second stage as descriptive measures of the relative technical efficiency of the DMUs, as proposed and supported by McDonald (2009), which will be discussed in detail in the following sections.

Multi-stage modelling is another way to deal with environmental factors, as this approach basically evaluates DEA efficiency by using controllable factors only and then correcting the efficiency scores obtained in further stages in order to account for environmental factors. Subsequently, in the final stage the efficiency scores are corrected by running a DEA model with data adjusted for these environmental variables.

Multi-stage modelling aims to decompose the possible effect of “slacks” associated with the technical inefficiency of DMUs and influence of environmental factors, which has not been included in the first stage. In other words, the idea is for the second-stage to distinguish between the effect of “slacks” associated with the first stage and the impact of such environmental variables which have been included in this stage. The DEA can subsequently be run using the ‘corrected’ variables in order to obtain new efficiency scores.

Different multi-stage models have been proposed in the literature depending on the adhered to approach in order to distinguish between the “slacks” and environmental factors that associated to inferences, such as the semi-parametric model recommended by Fried et al. (1999, 2002) or the non-parametric model proposed by Muñiz (2002). The latter uses input-oriented DEA in the second stage. In this stage, the *slacks* from the first DEA stage are considered as inputs and the environmental factors are considered as outputs. The aim of this stage is to reduce the *slacks*, while taking the value of the environmental variables to be fixed.

Non-parametric methods do not require a specific structural form of the objective equation, and therefore, estimation problems, such as mis-specification error and heteroscedasticity and other issues, which could lead to biased estimates, are avoided. However, it is possible to provide biased results due to the deterministic nature of the method as it uses DEA mode in all stages (Cordero *et al*., 2009). Furthermore, it is unable to identify which environmental factor is the most relevant, and therefore, it is possible that part of the predictive power of the model can be lost, despite the fact that certain environment variables may not be statistically significant.

In addition, in this non-parametric, there is a possibility that efficient DMUs will become inefficient after including environmental effects on the final stage. However, this change cannot be true from the methodological point of view, as discussed in Fried *et al*. (2002) and Cordero *et al*. (2009). Finally, with increasing the number of environmental variables, the discrimination power will be reduced and most DMUs tend to be efficient. This disadvantage shares the one stage model, as has been mentioned previously.

Regarding semi-parametric multi-stage methods aimed at estimating a separate regression involving each “slack” variable for *inputs* or *outputs* (depending on the orientation of DEA in the first stage), and by incorporating environmental factors as independent variables, the estimation process may follow the Tobit model because “slack” variables are censored at zero. This could allow the identification of the statistical significance of environmental factors on the slacks separately. Therefore, this approach would allow adjustment of the original values of variables.

More importantly, this approach would allow the prediction of new *slacks* for each variable that takes into consideration the environmental variables on each unit by using the regression coefficients. Thus, the original values of variables could be corrected using these predicted values by taking the original value of the outputs and subtracting the difference that is present between the most elevated value that is predicted and each units’ predicted value, or by adding it in the case of inputs. Following this, the final DEA is run using these adjusted variables.

The previous approach was described as the four-stage model, which was proposed by Fried *et al*. (1999) with significant improvements in the calculation of the efficiency scores. However, there is a possibility of a bias result through its two-stage counterpart, since the total *slacks* is also predicted by using the information of the whole sample. Indeed, this problem could be treated by using bootstrap to estimate unbiased regressions to predict total slacks, as applied in Cordero *et al*. (2009).

Even though the previous multi-stage models (parametric or non-parametric) appear to be attractive methods, as they distinguish slack results from technical efficiency or from environmental factor, Estelle *et al*. (2010) point out that taking account of these slacks is misguided due to the empirical evidence that there is no additional slack for any benchmark locates in the Farrell projection neighbourhood.

Overall, the two stage approach is the most common form in DEA applications, even though there is no agreement on which is the best method to treat uncontrollable factors in DEA, which explains to managers and policy makers why some DMUs perform better or worse than others, as well as what is the sources of such inefficiencies. In such cases, environmental factors such as ownership types and organisational characteristics, which could also influence DMUs' technical efficiency, need to be taken into account.

5.3 The Proposed Method

As was discussed in the previous section, the two stage model is the most common approach for dealing with environmental factors in DEA literature, which use regression in the second stage. In this chapter we propose a two stage analysis in order to deal with such environmental factors in DEA; a DEA is used to measure hospital efficiency while, SEM, which is a statistical technique for testing and estimating causal relations, is used to determine the direct and indirect effect of the environmental variables on efficiencies. Hence, SEM is used in the second stage rather than standard regression as the nature of the summary data for this study. In particular, most of our environmental factors result from the patient level, such as age, gender and GCS.

Despite the fact that these factors are summarised in order to be in a hospital level, there is a possibility of a casual relationship between these environmental factors and between these factors and efficiencies. For example, gender or age of patient (environmental factor) could affect Glasgow Coma Score GCS for patients (environmental factor), which consequently affects the recovery of the patient or the efficiency of the hospital. Thus, SEM enables a possibility to estimate and test the direct effect of gender on efficiency, as well as the indirect effect of gender on efficiencies through GCS, in order to obtain the total effect of patient gender on efficiencies by combining the direct and indirect effects. Therefore, SEM is proposed through this research, which is the first study to combine SEM with DEA in order to treat uncontrollable factors.

In addition to the previous reason for choosing this method in the current research, SEM has some advantages over the regression. Initially, it is a very flexible and comprehensive approach, which permits latent variables as well as multi-dependent variables. Secondly, it has the ability to deal with complex data, including missing data, non-normal data and time series with auto-correlated error. Moreover, variables in SEM could be independent and dependent, whereas variables in standard regression are either independent or dependent. Unlike multivariate regression, SEM has the ability to solve the equations of the model construct relationships simultaneously. Finally, a graphical presentation provides a convenient approach and powerful picture to explain a very complex relationship in SEM.

For illustrative purposes, this methodology has been used to investigate the effect of environmental factors on the performance of 256 BTI hospitals. DEA scores provide important information for the performance of hospitals, while SEM exposed additional and valuable details that have not been identified from previous studies.

5.3.1 Introduction of Structural Equation Models

One specific statistical multivariate technique, which is very proficient, is through Structural Equation Modeling (SEM), as it functions through various methods of analysis. Hence, the researcher becomes capable of measuring the effects that are both direct and indirect by creating a performance of test models that exist with multiple dependent variables, whilst implementing different equations of regression at the same time. SEM is considered as a graphical model that is formed through econometrics, even though, due its historical development in the area of genetics, it has advanced with an introduction into sociology, which was referred to as *path analysis*. In fact, SEM contrasts from the single-linear regression models used for fitting the relationship between two groups of variables. In other words, SEM examines and confirms the causal relationships between the *exogenous* and *endogenous* variables, and they are termed as causal models for correlational data, (Fox, 1984). In SEM, it is possible for a variable to be a predictor (such as environmental variables) in a specific equation, whereas it would be a response in another equation. Additionally, variables can influence one-another, either directly or through another variable (indirect effect) (See Figure 1). Invariably, endogenous variables are defined as variables, whose values are predicted by other variables (for example, Y_1, Y_2, and Y_3 in Figure 1). Therefore, the remaining variables are called exogenous variables. The SEM shown in Figure 1 can be written by a linear model of the form:

$$Y = BY + \Gamma X + \varepsilon \qquad (5.1)$$

The vectors Y, X and **ε** consist of endogenous variables, exogenous variables and disturbance terms, respectively. The parameter matrix B represents the structural coefficients relating to the endogenous variables, whilst Γ relates to the exogenous variables with endogenous variables.

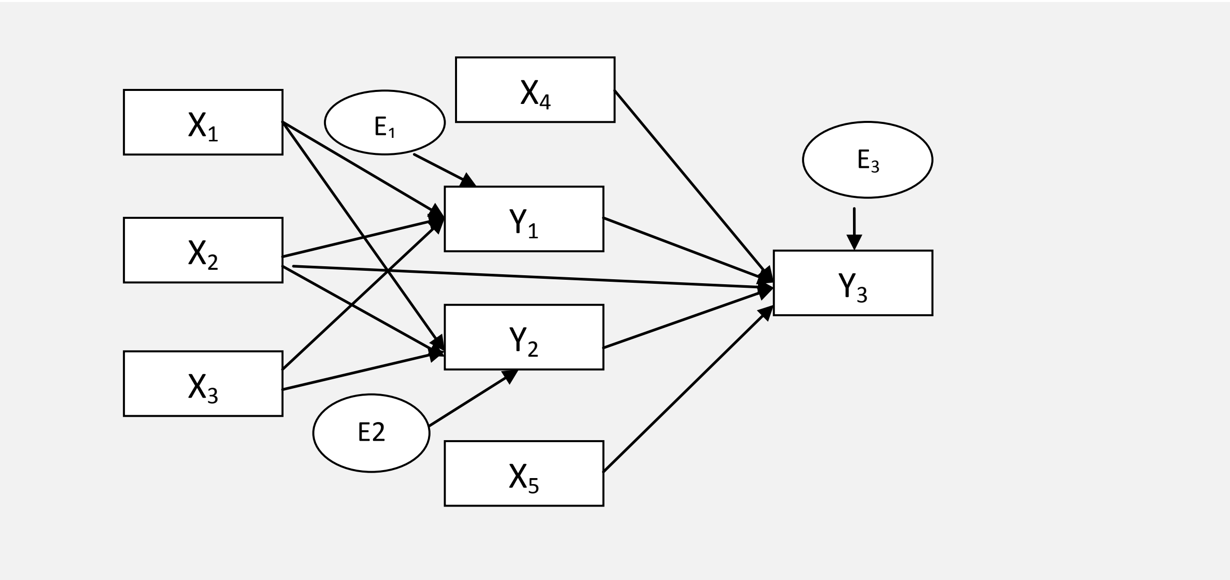

Figure 5.1: Example of path diagram for SEM

5.3.2 Direct, Indirect and Total Effect

In SEM, there are three types of effects: direct, indirect and total effects. The total effect measures the effect of X by external intervention on Y. The direct effect is defined as the effect of X on Y without any intervention (mediation) of any other variable, such as the direct arrow from X_2 to Y_2. On the other hand, the indirect effect involves one or more intervening variables which mediate the effect, such as the effect of X_3 on Y_3 through Y_2. In Statistics, the indirect effect is defined as the difference between direct and total effect.

5.3.3 DEA with SEM Methodology

In the current study, the two stages methodology is used to deal with environmental factors. In the first stage, the DEA model is applied with only controllable variables. In the second stage, SEM is conducted with efficiency scores (obtained from first stage) and environmental factors. Hence, in the second stage of this study, the researcher aims to study the simultaneous relationships among a set of environmental predictors, as well as these environmental factors with the efficiency score response obtained at the DEA first stage, in order to determine the sources of inefficiencies.

Structural equation models (SEM) will enable the possibility to examine those relationships using Multi-equation regression. Thus, SEM investigates the direct effect of the environmental (independent variables) on the efficiency scores (dependent variable), as well as the indirect effect of the environmental variables on efficiency scores through other environmental variables (dependent and independent variables). Even though there are multi dependent variables in SEM model (efficiency scores and the environmental mediators), the main interesting dependent variable is efficiency scores, which is limited variable between 0 and 1. The other dependent variable in our SEM model is continuous, which fits liner regression. Therefore, the study has focused on how model efficiency scores are variables in SEM.

It has been exhibited that in order to carry out the second DEA analysis, there are two main approaches for the interpretation of such an efficiency score variable in the second stage, as discussed in Macdonald (2009). The first and most common approach is to consider this efficiency score as an observed variable of DMUs efficiency. This is to show that efficiency scores are considered as descriptive measures of the efficiency score of the unit sample. Consequently, the frontier can be treated as an (within sample) observed frontier. Hence, in stage two, the efficiency scores can be viewed as other dependent variables in regression methodology, and therefore, standard inference of parameter estimation for the second stage is valid.

A second approach for interpretation is that the efficiency score is an estimated variable of 'true' efficiency scores relative to a 'true' construct. Given this interpretation, standard estimation of second stage is inconsistent and inference is invalid because of the uncertainty due to sampling variation, as well as the dependency of DEA scores on each other, which violates the assumption of within sample independence in regression analysis. Therefore, the second stage of DEA analysis should take these issues into account in order to get consistent estimations, such as methodology proposed by Simar and Wilson (2007), as well as Banker and Natarajan (2008) methodology. In the current study, the first interpretation framework is applied, and hence, the important point relates to choosing a suitable model for the DEA scores, which is a continuous limited dependent variable.

The most common and natural approach to investigate the relationship between DEA scores and environmental variables is the tobit regression, which is convenient with a censored or a corner solution dependent variables, of which DEA scores consider as the second type. A corner solution variable is "continuous and limited from above or below or both and takes on the value of one or both of the boundaries with a positive probability" (Hoff, 2007: p. 426). An alternative approach for modelling DEA scores against environmental variables is linear specification model estimated by ML or OLS. This linear specification model has been supported by both papers of Hoff (2007) and Macdonald (2009) who both concluded in their simulation studies that linear regression is sufficient and a consistent estimator in second stage DEA modelling, which has the advantage of the simplicity and familiarity compared with others. In addition, Banker and Natarajan (2008a) provide proof that linear regression estimated by (OLS) or (ML) in the two stage yields consistent estimators. Therefore, in this study, Tobit and linear specifications that use ML are both applied for modelling DEA scores as the dependent variable in SEM analysis.

5.4 Tobit Regression

The tobit model was first developed in Tobin's pioneering work (1958). This kind of regression fits DEA scores well, as these scores are limited and fail in corner solution as mentioned previously. The corresponding assumption of the tobit model is that the DEA scores are normally distributed in terms of the population, whilst the sample distribution of the scores is for mix distributions. However, the distribution of DEA scores is not normally distributed, and usually is skewed. In order to solve this problem, Chillingerian (1995) proposed that taking the reciprocal of the efficiency scores can help to normalise the DEA distribution. In addition to this, for convenient computational purposes, Greene (1993) suggested the use of a censoring point at zero. Hence, the DEA efficiency scores are transformed into inefficiency scores and leave a censoring point concentrated at zero by taking the reciprocal of DEA efficiency score minus one, that is:

$$\text{Inefficiency scores} = \left(\frac{1}{\text{Technical efficiency scores}}\right) - 1 \qquad (5.2)$$

With this transformation, the best performing DMUs will have the inefficiency score of 0. The inefficient DMUs which have scores less than 1 will have a positive inefficiency value. The transformation will bound the DEA score in one direction and censor the distribution at zero value.

The tobit model may be described by the following equation:

$$y_n^* = \beta x_n + \varepsilon_n \quad , n = 1, \ldots\ldots, N$$
$$y_n = \begin{cases} y_n^* & if\ 0 \leq y_n^* \leq 1 \\ 1 & if\ y_n^* > 1 \\ 0 & if\ y_n^* < 0 \end{cases} \qquad (5.3)$$

where:

y_n^* latent dependent variable.

β estimated coefficients.

x_n environmental variables.

ε_n normally, identically and independently distributed error, $\varepsilon_n \sim N(0,\sigma^2)$

y_n observed inefficiency scores.

The combination between DEA and tobit specification in SEM, as described above, is likely to be informative in the current study. The linear model is an alternative specification in order to model DEA scores in SEM which could be expressed by:

$$y_n = \beta x_n + \varepsilon_n \quad , n = 1, \ldots\ldots, N, \qquad (5.4)$$

β is estimated by OLS or ML.

5.5 Example Empirical Study: DEA with SEM: A Case of HTI Hospital Efficiency

5.5.1 Variables Description

Due to the presence of missing data, this example has included only 256 HTI hospitals that have the full cases. In order to evaluate the efficiency of BTI hospitals, DEA has been conducted with 3 inputs and 6 outputs, which have been described previously in details in chapter 3. These inputs are the average number of doctors seen per patient (avg_doc), the average number of consultants seen per patient (avg_cons) and the total cost per patient (totalcost), whereas the outputs are the percentage of patients with minor injuries who recovered satisfactorily (pctmin), the percentage of patients with moderate injuries who recovered satisfactorily (pctmod), the percentage of patients with severe injuries who recovered satisfactorily (pctsev), the average of the total period of stay per patient (avglos), the average number of total surgical operations per patient (avtotop) and the average number of treatments provided by emergency services per patient (avg_treat). For the investigation of the environmental factors affecting efficiencies, SEM has been applied with seven environmental variables (See Table 5.1). Furthermore, hospitals efficiency variable, which is main interest, is measured by the efficiency score (endogenous variable).

Variable	**Code**
Percentage of patients with GCS ≥ 13 (minor injuries)	pctgcs13
Percentage of patients with GCS 9–12 (moderate injuries),	pctgcs912
Percentage of patients with GCS < 9 (severe injuries)	pctgcs9
Percentage of patients with age 18-60	pctage18-60
Percentage of patients with age > 60	pctage60
Percentage of patients with age <18	pctage18
Percentage of patients who were male	Pctmale
Percentage of patients who were female	pctfemale
Neurosurgical unit (Yes/No)	Neuro
Year	Yr

Table 5.1: Environmental variables

5.5.2 Stage 1: DEA Analysis

In this section DEA has been employed with the inputs and outputs described in the previous section. A brief descriptive statistical overview of these selected variables including mean and standard deviation (SD), is exhibited in Table 5.2. As mentioned previously, although the weighted averages and SDs of the variables are more appropriate to allow for hospital size, it has been decided to not calculate them because these statistics are just for explaining the data and are not included in the main analysis .

Variables	**Mean**	**SD**	**Min**	**Max**
AvED_Cons	1.08	0.2	1	2
AvED_Doc	2.14	0.92	1	7
TotalCost	2337.71	2781.1	240.09	18206
AvED_Treat	18.9	4.18	2.34	29
AvgLOS	14.2	4.08	2.12	41.05
AvTotOp	1.61	0.68	1	5.44
PctMin	8.93	8.28	0.01	33
PctMod	19.45	16.42	0.01	65
PctSev	9.08	9.34	0.01	42

Table 5.2: Descriptive statistics of the input and output variables

The efficiency of HTI hospitals are computed and reported in Table 5.3 using an input oriented DEA model with variable returns to scale assumption, as outlined in Chapter 3. The overall average efficiency of 96.93% indicates that, in general, the HTI hospitals could reduce on average 3% from inputs with the same level of outputs.

Average	96.93
SD	8.37
Maximum	100
Minimum	50
No. of inefficient hospitals	44

Table 5.3: Summary of hospitals' technical efficiencies

5.5.3 Stage 2: Structural Equation Models (SEM) Analysis

SEM was integrated into DEA in order to investigate the effect of environmental variables (Shown in Table 4) on the efficiencies.

Variable	Type	Mean	Std. Dev.	Min	Max
pctgcs912	Numerical	0.859069	0.938745	0	7
pctgcs9	Numerical	1.306999	1.626312	0	15
pctage60	Numerical	41.2224	13.14749	0	74
Pctfemale	Numerical	40.27038	8.476944	18.91892	65
pctage18	Numerical	9.757757	14.43053	0	100
Neuro	Binary			0	1
Yr	Categorical			2009	2012

Table 5.4: Descriptive statistics of the environmental variables

In particular, SEM was used to examine the relationships between the exogenous variables of interest using the equations shown below.

$$pctgcs9 = \beta_0 + \beta_1\, pctfemale + \beta_2\, pctage60 + \beta_3\, pctage18 + e_1 \qquad (5.5)$$

$$pctgcs912 = \alpha_0 + \alpha_1\, pctfemale + \alpha_2\, pctage60 + \alpha_3\, pctage18 + e_2 \qquad (5.6)$$

$$Efficiency = \gamma_0 + \gamma_1 pctgcs9 + \gamma_2\, pctgcs912 + \gamma_3\, pctfemale + \gamma_4\, pctage60 + \gamma_5\, pctage18 + \gamma_6\, neuro + \gamma_7\, yr + e_3 \qquad (5.7)$$

The analysis investigated the effect of:

I) Age and gender on percentage of moderate injured patients using Equation(5.5)

II) Age and gender of percentage of sever injured patients using Equation (5.6)

III) Age, gender, years, severity of injury and Neurosurgical unit on efficiency score, using Equation (5.7).

In addition, structural equation statistical techniques offer the means to study both direct and indirect effects of variables. Hence, the research was directed to examine the indirect effect of age and gender on the efficiency scores through the percentage of severity of patients as mediator variables.

Two SEM models were built with different specification to modelling the DEA scores against the environmental variables. The first approach used the Tobit model, as it has been adopted as the natural ‘choice’ for modelling DEA scores in the second stage estimation. The second approach uses a linear model estimated by ML as an alternative method for modelling DEA scores against environmental influences. For the later model the p-values are calculated using heteroskedastic-consistent standard errors in order to be robust to heteroskedasticity and the distribution of the disturbances. Banker and Natarajan (2008: P.48), in their abstract, state that “Conditions are identified under which a two-stage procedure consisting of DEA followed by ordinary least squares (OLS) regression analysis yields consistent estimators of the impact of contextual variables. Conditions are also identified under which DEA in the first stage followed by ML estimation (MLE) in the second stage yields consistent estimators of the impact of contextual variables. This requires the contextual variables to be independent of the input variables.” Even though this study does not treat DEA scores obtained from the first stage as an estimate of 'true' scores, it is worth checking correlations in order to ensure that the contextual variables are independent of the input variables. Table 5.5 displaysthe correlation coefficients between the inputs used in the first-stage DEA efficiency analysis and environmental variables. The results suggest that there is no strong correlation between these variables, and thus ML estimation (MLE) is consistent.

	aved_doc	aved_cos	Totalcot
pctage18	0.07	-0.01	0.01
Neuro	0.3	0.06	0.32
Yr	-0.09	-0.27	-0.52
pctgcs912	0.14	-0.02	0.05
pctgcs9	0.24	0.09	0.09
pctage60	-0.37	-0.08	-0.3
Pctfemale	-0.38	-0.14	-0.31

Table 5.5: Correlation between environmental variables and DEA inputs

One useful way of representing the structural relation of the underlying model was through the paths diagram. Figure 2 shows the Equations (5.5), (5.6) and (5.7) using the paths diagram of the structural equation model (SEM), and it is evident that all the paths were in one direction where one variable predicts another variable. Additionally, there is no path, which ultimately indicates no direct relationship between the variables.

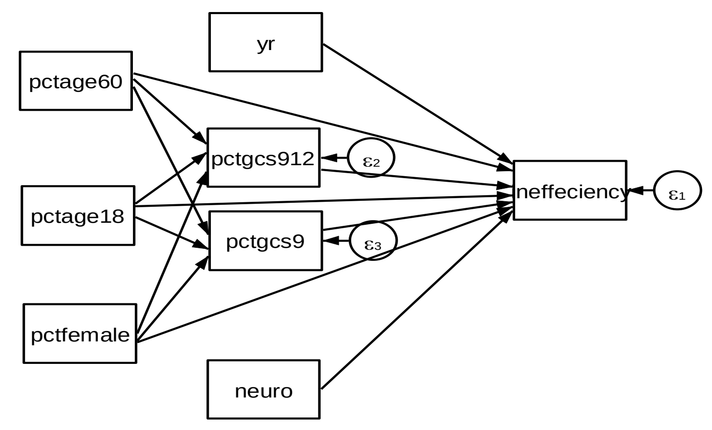

Figure 5.2: Path diagram for SEM

5.6 Results and Discussion

The first aim is to analyse more than one dependent variable at a time using the three equations of SEM, which uses a linear specification to model the ineffecincy scores, and GSEM which uses a tobit specification to model the ineffecincy scores. Then we use SEM to find the indirect and total effects. Table 5.6 shows the results of SEM using ML in terms of the ordinary and the ordinary model when the p-values are calculated using heteroskedastic-consistent standard errors, and it shows also GSEM using the ML Tobit model for efficiency score as censored. Notice for the models of percentage of severity patients that the estimated parameters (coefficients and standard errors), resulting from using GSEM and SEM, were the same since the dependent variables were not treated as censored variables. For the GSEM, the only censored variable of interest was efficiency score.

5.6.1 Influence of Demographic Variables on Severity Patient Variables

According to Table 5.6, the use of the linear model and linearity allowing for heteroskedasticity estimations resulted in a significant negative effect of age> 60 compared with < 18-60 years on severe injuries (p-value< 0.001 and 0.037, respectively), namely this group of age was likely to have a lower percentage of severe injuries compared with the ages between 18-60 years old. Moreover, there was significant negative effect of age<18 compared with the ages between 18-60 years on the severe injuries (p-value= 0.004 and 0.005, respectively). Indeed, the resulting p-values for the two methods of estimation were slightly different.

Regarding the moderate injuries, using the same methods, there was a negative effect of age<18 compared with the ages between 18-60 years on this group of injuries (p-value= 0.061 and .007, respectively) However, this effect was unimportant and would be ignored since the effect was not significant using both procedures. Similar to severe injuries, age >60 had a negative effect, although it was not significant. The impact of gender was positive, as females are likely to have fewer percentages of moderate injuries than males. Nevertheless, invariably, there is no difference between the resulting large p-values from both procedures.

5.6.2 Influence of the Severity of Injures on Efficiency Score

Table 6 lists marginal effects and p-values for Tobit, ML linear model and ML liner allowing for heteroskedasticity. The results show that a positive influence exists of the two severity types of injuries on the efficiency score. However, it was found that the effect was not significant. Note that, although the coefficients of the Tobit and ML linear models are slightly different, the key inferences are the same (See Table 5.6).

5.6.3 Influence of Demographic Variables on Efficiency Score

According to Table 6, there were slight differences in the values of estimated parameters through the use of the Tobit and ML linear model, and this resulted in different p-values of significant effect. The efficiency of hospitals was likely to be low through the measurement of age>60 years compared with age 18-60 years. The efficiency was positively affected by the percentages of females compared with males. In terms of significant influence, there was no any significant impact of any demographic variable on the efficiency score.

Structural model			Tobit		ML liner Allowing for Heterosked-asticity		ML liner	
			β	p-value	B	p-value	β	p-value
patients with GCS < 9	←	Female	.029	.067	.029	.181	.029	.067
	←	Age >60 years	-.046	<.001 *	-.046	.037	-.046	<.001 *
	←	Age <18	-.0234	.004	-.0234	.005	-.0234	.004
	←	Constant	2.26	<.001	2.26	.006	2.26	.008
patients with GCS 9-12	←	Female	.0017	.857	.0017	.875	.0017	.846
	←	Age >60 years	-.0071	.305	-.0071	.281	-.0071	.305
	←	Age <18	-.0090	.061	-.0090	.007	-.0090	.061
	←	constant	1.176	<.001	1.176	<.0001	1.176	<.001
inefficiency	←	patients with GCS < 9	-.0016	0.959	.0000639	0.983	.0000639	0.990
	←	patients with GCS < 9-12	-.01099	0.835	-.0022	0.720	-.0022	0.798
	←	Female	-.01033	0.185	-.00170	0.123	-.0017	0.210
	←	Age >60 years	.0074	0.203	.00097	0.226	.00097	0.336
	←	Age <18	.00110	0.794	.00003	0.922	.00003	0.963
	←	Year	-.3027	<.001 *	-.035	<.001 *	-.035	<.001 *
	←	Neurosurgical unit in treating hospital	.0615	0.622	.0116	0.663	.0116	0.619
	←	Constant	608.169	<.001	70.62	<.001	70.619	<.001

Table 5.6: SEM for inefficiency score using ML estimation

5.6.4 Influence of Neurosurgical Unit in Treating Hospitals on Efficiency Score

Treatment in a neurosurgical centre has an adverse effect on efficiency. However, even though this was not expected, this effect was not significant as shown by all estimation procedures.

5.6.5 Influence of Years on Efficiency Score

The efficiency appeared to be higher during recent years when compared with previous years, as the influence was very highly significant, as shown by the three estimation procedures (p-value<.001).

5.6.6 Direct, Indirect and Total Effect

In this study, The SEM was used to find the direct effect, indirect effect and total effect of gender (percentage of females) and age categories (percentage of age >60 years and percentage of age <18 years) on the efficiency score. According to Table 7, through the use of the three procedures, there was no significant direct effect of gender and age on efficiency, and the same result is observed for the indirect effect. Likewise, the total effect (direct and indirect effect) of the gender and age on efficiency was not significant.

Effect	**Structural model**			**Tobit procedure**		**ML liner Allowing for Heterosked-asticity**		**ML liner**	
				β	**p-value**	**B**	**p-value**	**B**	**p-value**
Direct effects	**Inefficiency**	←	Female	-.01033	0.185	-.00170	0.123	-.0017	0.210
		←	Age >60 years	.0074	0.203	.00097	0.226	.00097	0.336
		←	Age <18 years	.00110	0.794	.00003	0.922	.00003	0.963
Indirect effects	**Inefficiency**	←	Female	-0.000067	0.943	-0.0000018	0.985	-0.0000018	0.990
		←	Age >60 years	0.000156	0.918	.0000126	0.935	.0000126	0.958
		←	Age <18 years	0.0001381	0.874	.0000181	0.854	.0000181	0.896
Total effects	**Efficiency**	←	Female	-0.0103984	0.181	-.0017043	0.126	-.0017043	0.209
		←	Age >60 years	0.0075493	0.178	.0009827	0.233	.0009827	0.315
		←	Age <18 years	0.0012438	0.763	-.0000132	0.967	-.0000132	0.984

Table 5.7: Direct, indirect and total effect of gender and age variables on efficiency

Overall, in the current study, the p-values resulting from the ML linear model that used ordinary and permitted heteroskedasticity procedures were very close, which indicated that using ML ordinary standard error of estimates for constructing SEM were appropriate.

5.7 Conclusion

In general, it has been concluded that DEA is a managerial tool for evaluating hospital efficiency and productivity. This chapter introduces a framework that combined DEA with SEM. While DEA analysis has provided valuable information, SEM results have provided additional findings that were not identified in the previous studies. For example, unlike previous second stage analysis studies in DEA that focused only on the direct effect of environmental factors on the efficiency scores, the current study used SEM to further investigate any indirect effect and the total effect of these uncontrollable factors on the efficiencies. Obviously this additional information is more useful and informative than the previous studies.

Despite the fact that this study used two SEM models specifications in order to incorporate environmental variables with DEA score, the key inferences (that only the year variable was significant and the other variables not significant) are the same for the Tobit model and OLS, as well as the marginal effects for the significant variables are similar. These results support what McDonald (2009: p. 794) states that "there is some evidence that in limited dependent variable and choice situations, although the parameter estimates of alternative methods differ, the main inferences and marginal effects are often similar (see, for example, Greene, 2008: pp. 781-3 for binary choice models, pp. 873-4 for limited dependent models and p. 876 for heteroskedasticity in limited dependent models)".

There are a number of additional topics, although for practical importance to those using SEM analysis, they are beyond the scope of the current study’s analysis. One of these includes the use of a two-part model (two equation model) that explains efficiency scores separately. The first one explains the reason that some DMUs are efficient while others are not (y=1if it is efficient otherwise Y=0) and, the second details the relative efficiency of inefficient units. Another topic is to treat DEA scores obtained from the first stage, as an estimated dependent variable of the true efficiencies in the second stage. Under this framework, the estimated results may be inconsistent and standard inference is less valid.

Therefore, it must to be taken into account how the variables in the first and second stage are correlated, as well as the choice of the convenient regression. In this context, the approach by both Simar and Wilson (2007) and Banker and Natarajan (2008) could be implemented in order to adapt SEM with DEA analysis in the second stage. Indeed, these topics could be areas for future development in DEA/SEM.

CHAPTER SIX: EMPIRICAL STUDY: DATA DESCRIPTION AND ANALYSIS

6.1 Introduction

The current chapter presents a new application of DEA in order to measure head trauma injury (HTI) care efficiency in the UK, as the performance of HTI care within 114 hospitals in the UK, over the course of 4 years (2009-2012), have been evaluated through this chapter to minimize possible associated costs in future. This empirical analysis has been motivated and justified by the proven lack of previous studies that have aimed at measuring the performance of HTI care in order to reduce its associated costly expenditure.

A new methodology for treating missing data in DEA was developed in the previous chapter, as SEM methodology was adopted in DEA in order to investigate the role of environmental factors on efficiency scores. These two proposed methods are conducted in this chapter as an application study for this research, with the evaluation of HTI care efficiency initially conducted through the use of the DEA model. Subsequently, the Malmquist productivity index (MI) is analysed in order to measure performance of HTI hospitals over time (i.e. productivity change) and decompose any change into the efficiency and frontier shift effects.

The structure of this chapter is discerned between sections. Section 2 describes the data, while Section 3 presents the MICE methodology results. Section 4 presents the first stage of the (DEA) empirical results, while Section 5 conveys the Malmquist productivity index results. Following this, Section 6 presents the second stage of the (SEM) empirical results, whilst the final section ascertains some conclusions from this practical study. All of these analyses implemented by the computer program PIM-DEA, which was developed by Aston University and Stata software versions 12 and 13.

6.2 Data Description

For the purpose of measuring HTI care efficiency, relevant inputs and outputs have been chosen, as previously discussed in Section 3.5, Table 3.1. In total, 3 inputs have been chosen: the average number of doctors per patient per year (avg_doc); the average number of consultants per patient per year (avg_cons); and the total cost per patient per year (totalcost). Comparatively, there are 6 outputs: the percentage of patients with minor injuries who recovered satisfactorily per year (pctmin); the percentage of patients with moderate injuries who recovered satisfactorily per year (pctmod); the percentage of patients with severe injuries who recovered satisfactorily per year (pctsev); the average of the total period of stay per patient per year (avglos); the average number of total surgical operations per patient per year (avtotop); and the average number of treatments provided by emergency services per patient per year (avd_treat). Overall, the total data for this application were obtained directly from the TARN database, as previously mentioned in Section 1.4, as there was no access to individual patient details or hospital identifications. The inclusion criteria simply derived from a large sample of 93,499 patients, who had been hospitalised for trauma brain injury (TBI) in 185 hospitals, and had been included in the TARN database for the time-period between 2009 and 2012.

Within the associated hospitals, it was common practice to complete a data entry sheet for each patient with the documentation of information regarding: age, gender, severity of the injuries, treatment provided at the scene of the accident, en route to hospital or in A&E Moreover, any other form of administered care received at the hospital was documented, including: diagnostic tests performed, specific treatment provided, and any TBI-related surgical procedures, length of stay (LOS) and discharge status and the year of admission. For patients who arrived at A&E, additional data were utilised, which included: the mode of arrival at A&E, the time from emergency call to arrival at A&E, the time spent in A&E, and the number of doctors, specialists and nurses seen in A&E. Furthermore, the data set includes the Glasgow Coma Scores (GCS), the Injury Severity Scores (ISS), details about patient admission to critical care (ICU, neurocritical unit or HDU), and further details relating to the LOS in critical care and the total LOS. Finally, data about whether or not the related treating hospital had a neurosurgical unit, were also available.

All of the retrieved data were formulated at patient level, while the data that were required to compare head trauma care had to be at hospital level. Therefore, summary data were required at the hospital level rather than at the patient level for the current DEA application. Data aggregation by hospital and by year for all the variables was undertaken, as well as summary statistics were derived, such as: mean, proportion and percentage. Likewise, the summary data represent the inputs and the outputs that were chosen for the empirical part of the current study, as discussed in Chapter 3. The whole procedure was undertaken using Stata software version 12. Indeed, as an illustration, if one wishes to create the percentage of GCS > 13 for any stipulated year within each hospital, then the following code is applied:

```
keep if Yr==2009
generate  GCS13=ED_GCS_1>=13
by SiteID: egen pctGCS13=mean(GCS13*100)
label variable pctGCS13  "% GCS>=13"
```

The procedure was repeated for all the variables and subsequently a dataset based on the summary statistics was created, which contains multiple readings per hospital for each summary measure. To remove all the duplicated data and keep only one record per hospital, a procedure was devised to create a flag as a binary variable, equal to 1 if it is the first observation of a given hospital and 0 if it is a duplicate. The syntax is as follows:

```
egen pickone=tag(SiteID)
keep if pickone==1
```

Two issues materialised when the dataset was created, which are missing data and an unbalanced dataset (some hospitals do not have data for all the years). Thus, only the hospitals that recorded information for the full period of 4 years have been included in the research, in order to evaluate the change of these hospitals' efficiencies over the period of study. Moreover, the missing data have been handled using the ICE approach, as discussed in Chapter 4.

6.3 Missing Data Replacement: Imputation by Chained Equations

In the current research study, it has been proposed that the imputation by chained equations (ICE) approach is used to fill in for any missing data with DEA analysis, while the working dataset in the application contains several variables with missing values. Over the 4 year period, 456 records are presented that represent summary data for 114 hospitals (following the exclusion of hospitals without complete records for all 4 years). In order to conduct DEA analysis for each year, it was decided to implement the imputation separately for each year, as was recommended by White et al. (2011). In fact, there are 3 variables containing missing data that are displayed in Tables 6.1a and 6.1b, which demonstrate the amount of missing data and the pattern of absence respectively through the use of the 4 years of data. These missing data are due to poor collection procedures, which fail to adhere to MAR conditions. Thus, the MICE approach with 5 imputations is applied in order to address the detrimental issue of missing data, using Stata software version 13.

Variables	observed values	missing values	variable label	% missing
avtotop	441	15	Average total number of operations per patient	3.40
avg_doc	438	18	Average number of doctors per patient	3.95
avg_cons	414	42	Average number of consultants per patient	9.21

Table 6.1a: Percentage of missing data

pattern			# missing variables	frequency
AvTotOp	AvED_Doc	AvED_Cons		
+	+	+	0	409
+	+	.	1	20
+	.	.	2	12
.	.	.	3	6
.	+	+	1	5
.	+	.	2	4
+ complete **. incomplete**				

Table 6.1b: Pattern of missing data

One of the hypotheses for the imputation, for continuous variables, states that the variables must be normally distributed, and a q-plot to check for normality was used, which was carried out using the Stata command: *qnorm*. Figures 6.1a to 6.1c demonstrate the q-plots for all variables, and it is clear that none of them are normally distributed, as identified by departures from the 45^{o} line in the plots.

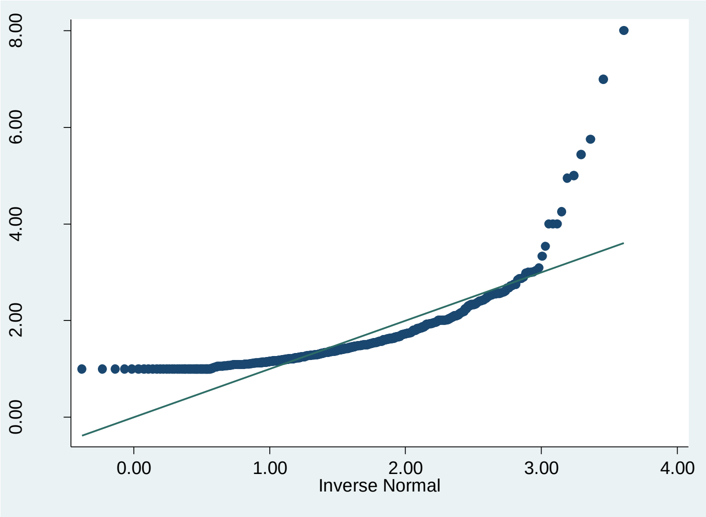

Figure 6.1a

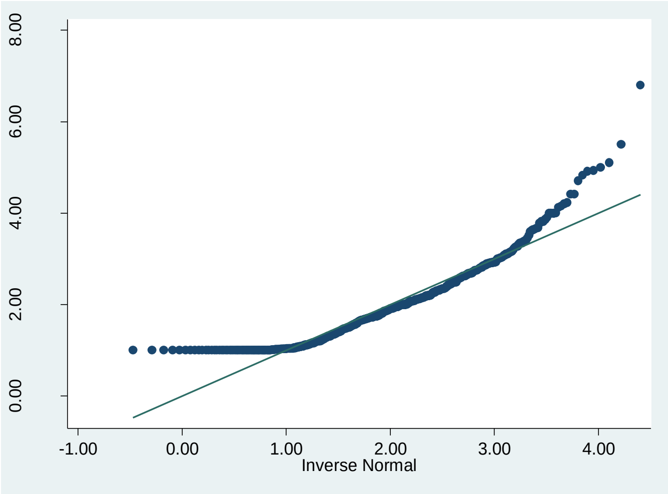

Figure 6.1b

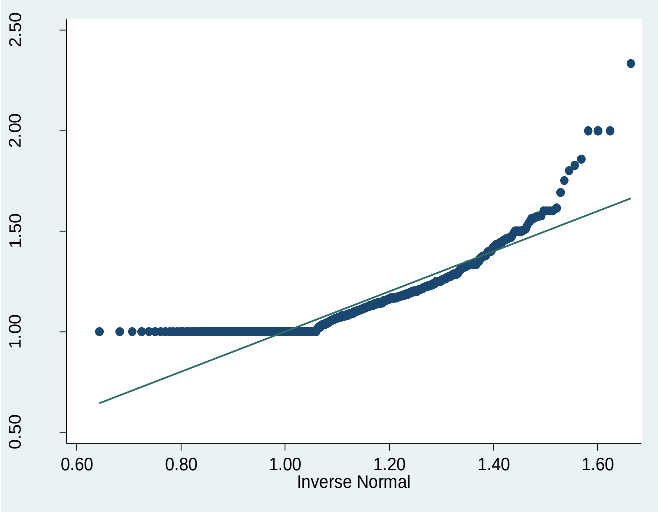

Figure 6.1c

Figures 6.1a to 6.1c: Normal q-q plots of the variables with missing values

To overcome the problem of non-normality, a procedure to normalize the variables was undertaken by using a transformation towards normality approach, as discussed in Chapter 4.4. This procedure exists in Stata under the name *nscore*[4]. Once the variables are normalised and the imputation procedure is carried out, the variables are back-transformed to their original scales using the command *invnscore*. This method assures that the imputed values stay within the ranges of the corresponding original observed data.

The imputation procedure was carried out separately for each year, as explained previously, which was comprised of the three incomplete variables, as well as other complete input and output variables. Figures 6.2a to 6.2c identify the distributions of the observed and imputed values for each of these three variables during the year 2009.

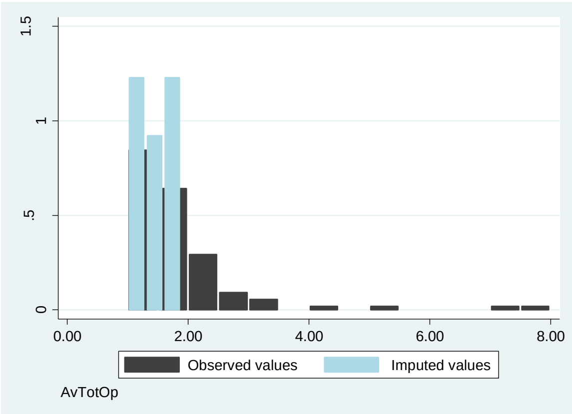

Figure 6.2a

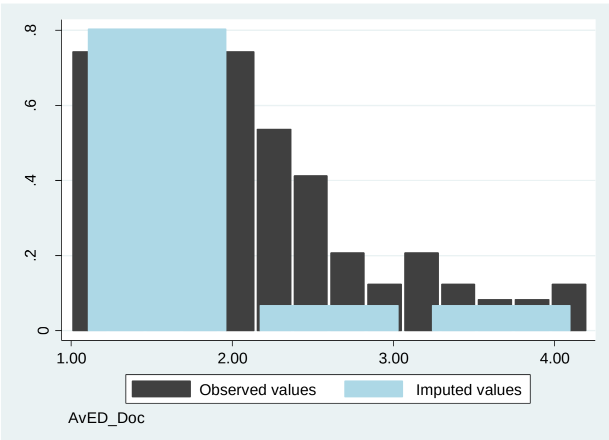

Figure 6.2b

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[4] http://personalpages.manchester.ac.uk/staff/mark.lunt/mi_guide.pdf accessed April 2013

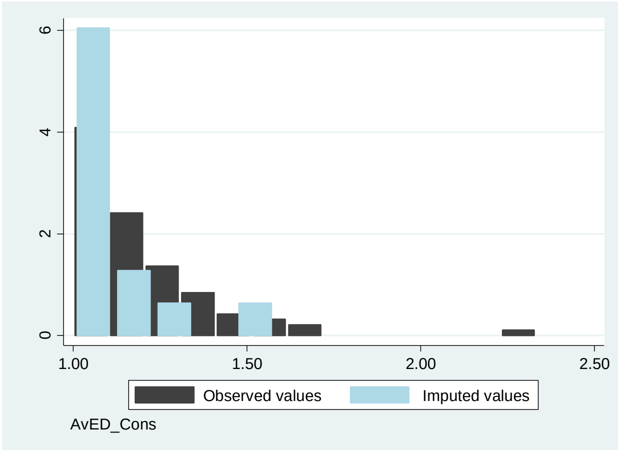

Figure 6.2c

Figures 6.2a to 6.2c: Histograms of observed and imputed values for variables with missing data

Overall, the imputed values are not substantially contrasting to those observed, although a comparison of the distribution pre- and post-imputation shows a clear similarity between the two distributions for each of the variables (Figures 6.3a to 6.3g).

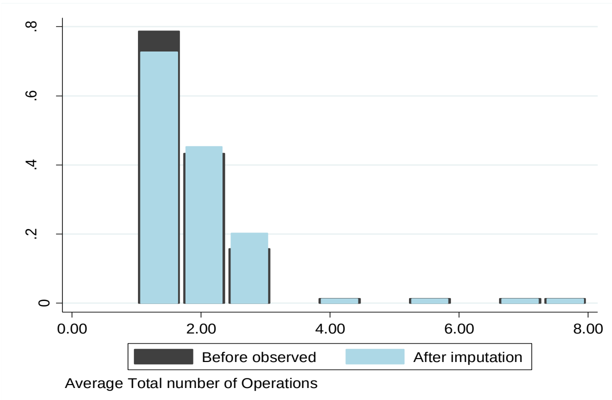

Figure 6.3a

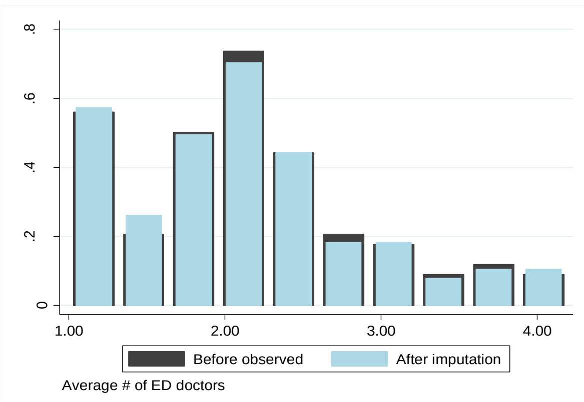

Figure 6.3b

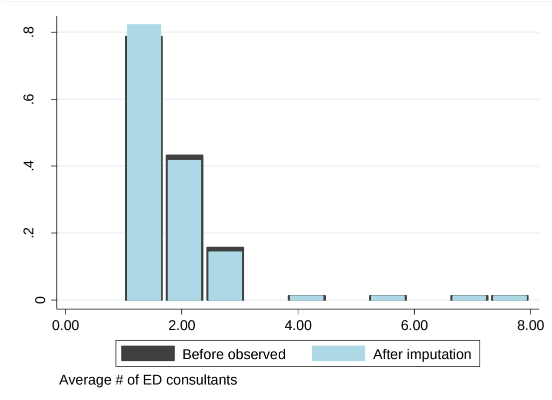

Figure 6.3c

Figures 6.3a to 6.3c: Distributions of variables with missing data before and after imputation (2009)

Similar graphs and tables were produced for the years 2010, 2011 and 2012, which have the results displayed in Appendix A, and to conclude, four datasets containing completed data were created. Brief descriptive statistical analyses of the input and output variables for these four completed years of data are presented in Table 6.2, which demonstrates that the data set consists of 3 inputs and 6 outputs, with a variation in these variables over the study period. It is worth mentioning that again, although the weighted averages and SDs of the variables are more appropriate to allow for hospital size, it has been decided to not calculate them because these statistics are just for explaining the data and are not included in the main analysis. The maximum observed values for the number of doctors, which is one of the inputs, for the years 2009, 2010, 2011 and 2012 respectively, are set at about 4, 5 ,7 and 5 doctors, whereas the minimum observed value is 1 doctor for all years, with an average of about 2 doctors and standard deviations 0.79, 0.77, 0.86 and 0.94 respectively. Moreover, similar summary statistics are presented for the other variables. For instance, considering the percentage of patients with moderate injuries who recovered satisfactorily (pctMod); the maximum observed values of this output variable in the years 2009, 2010, 2011 and 2012 are 100%, 56%, 58% and 65% respectively, and the minimum observed value is set at no patients for all the years, with averages of 10, 12, 18 and 21 patients and standard deviations 17.25, 14,21, 16.16 and 17.80 respectively.

	Outputs						Inputs		
Year/2009	pctMin	pctMod	pctSev	AvgLOS	AvTotOp	Avg_Treat	Avg_Doc	Avg_Cons	TotalCOST
Mean	3.42	10.01	4.62	18.51	2.02	15.94	2.11	1.20	4039.93
SD	6.01	17.25	7.87	33.56	1.14	8.67	0.79	0.20	4083.55
Min	0.01	0.01	0.01	1.00	1.00	1.00	1.00	1.00	278.00
Max	26.32	100.00	41.09	365.00	8.00	33.00	4.20	2.33	18427.33
Year/2010									
Mean	5.58	11.89	6.20	15.11	1.71	17.46	2.02	1.17	60980.49
SD	6.97	14.21	8.13	4.99	0.73	6.80	0.77	0.18	68914.40
Min	0.01	0.01	0.01	1.00	1.00	1.00	1.00	1.00	556.00
Max	34.21	56.25	42.86	36.48	5.75	36.00	4.82	2.00	469717.83
Year/2011									
Mean	8.20	18.11	9.12	17.35	1.60	18.64	2.02	1.15	1669.12
SD	7.97	16.16	10.26	33.79	0.51	4.99	0.86	0.14	1524.85
Min	0.01	0.01	0.01	4.00	1.00	1.83	1.00	1.00	278.00
Max	33.33	57.81	52.62	373.00	4.26	30.00	6.80	1.58	8223.56
Year/2012									
Mean	9.87	20.92	10.44	12.82	1.52	18.86	2.07	1.15	1468.01
SD	8.95	17.80	10.65	4.29	0.56	4.74	0.94	0.15	1525.03
Min	0.01	0.01	0.01	1.50	1.00	1.57	1.00	1.00	278.00
Max	44.00	64.58	46.23	35.37	4.95	29.83	5.11	1.60	8501.63

Table 6.2: Descriptive statistics on input and output data

The ranges between extreme values for most of the inputs and outputs suggest large variation between the largest and the smallest hospitals. Therefore, since DEA models are sensitive to observations, we anticipate finding significant levels of variation in the efficiencies. Furthermore, it is worth noting that the outputs of the sample hospitals have increased over the period under consideration, as shown in Table 6.2. This suggests a possible increase in productivity, which may be the result of progress in technical efficiency or technological change, which will be examined in the next section.

6.4 DEA Efficiency Results

This section determines the efficiencies of 114 head trauma hospitals in different years (2009, 2010, 2011 and 2012), in terms of their ability to provide outputs with minimum input utilization, using the DEA-BCC model. The results of the corresponding DEA frontier analysis provide an overview of the development of the head trauma care sector.

Consequently, such results may indicate how the efficiency scores of the obtained samples by hospitals changed during the period under consideration, and how different hospitals operate relatively to others. As the BCC model assumes a variable return to scale, the average variable-returns-to-scale efficiency for the total sample hospitals by year is provided. As described in Chapter 3, the linear programs involved are solved using the computer program PIM-DEA developed by Aston University.

Prior to reporting the results of the current study, certain points are required to be mentioned and explained in order to make their interpretation clear. Firstly, it should be made clear that the current study has measured the performance of individual hospitals. The measurement criteria are relative to the best practice frontier which is formed entirely from our observations relating to this particular sample of hospitals. In other words, there were no preordained standards for measurements prior to these observations, which means that these measures are relative and not absolute. Secondly, this method compares a given hospital to the other hospitals that are similar to it in terms of inputs and outputs, which means that the study compares similar issues and not contrasting or different issues. Thirdly, this method does not impose structure on technology through a pre-specified functional form, as it reveals and reduces possible specification errors. It also allows the comparison of technologies by hospital type. Finally, the quality of the current study depends on the quality of the data, as when there are biases in the measurement of the variables, these will be reflected in the efficiency measures. In other words, systematic biases will affect the efficiency measures. Ultimately, this problem is significant and essential in this context, as the non-parametric approach used in this study does not clearly include an error term of measurement to allow for sampling error. Therefore, bootstrapping DEA analysis has been conducted to overcome such measurement error issues, as full comprehension into the aforementioned points helps in understanding the measures.

6.4.1 Pure Technical Efficiency

Through the use of the input oriented DEA-BCC method, the efficiency scores of individual hospitals in the sample are calculated relatively on the basis of individual frontiers, which are constructed from "best practice" hospitals for each year of the 4-year period under consideration. The VRS assumption is used due to CRS not being appropriate in forms of technology where ratio data exist (Hollingsworth and Smith, 2003; Cook et al., 2014).

Furthermore, an input-oriented model has been chosen due to the attempt to reduce the costs associated with head trauma care.

In order to summarize the results, the average efficiency scores of all the hospitals, corresponding standard deviations, minimum efficiency values and numbers of efficient hospitals identified for each year are presented in Table 6.3 and Table B in the Appendix. Efficient hospitals have efficiency scores of 1, corresponding to 100% in the tables, while inefficient hospitals relative to the rest of the observations that year mark scores less than 1.

	Mean (%)	SD (%)	Minimum	Number. of efficient hospitals
2009	90.74	10.52	46.65	41
2010	90.52	10.23	53.85	45
2011	92.62	9.00	63.64	51
2012	92.99	9.13	63.19	60
Average	91.72	9.72		

Table 6.3: Annual average pure technical efficiency scores

The annual mean pure technical efficiency, which results from factors such as poor management within the hospital and disadvantageous operating environments other than scale, had been 90.74% in 2009, 90.52% in 2010, 92.62% in 2011 and 92.99% in 2012. Hence, there is a possibility of improving average hospital efficiencies by adopting best practices, whereby hospitals can reduce extra inputs by 9.26% (2009), 9.48% (2010), 7.38% (2011) and 7.00% (2012) than they actually reduced from the same level of outputs. However, the potential decrease in inputs from adopting the best practices varies among hospitals.

The general values of the standard deviations in Table 6.3 tend to decrease when the average efficiencies increase. Moreover, the minimum scores of the inefficient hospitals range between 46.65% (2009) to 63.64% (2011). In addition, Table 6.3 demonstrates that the amount of efficient hospitals increased over the study period from 41 hospitals in 2009 to 60 hospitals in 2012. Consequently, a general overview of average efficiency indicates a slight steady increase over the study period.

Table 6.4 provides the frequency distribution of the pure technical efficiencies of the hospitals for the entire period. The distribution of pure technical efficiency is also depicted in Figure 6.4 below.

	2009		2010		2011		2012	
Eff_Groups	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent
41-50 (%)	1	0.88	0	0.00	0	0.00	0	0.00
51-60 (%)	0	0.00	2	1.75	0	0.00	0	0.00
61-70 (%)	6	5.26	2	1.75	3	2.63	3	2.63
71-80 (%)	11	9.65	11	9.65	9	7.89	9	7.89
81-90 (%)	27	23.68	42	36.84	32	28.07	28	24.56
91-99 (%)	28	24.56	12	10.53	17	14.91	14	12.28
100 (%)	41	35.96	45	39.47	53	46.49	60	52.63

Table 6.4: Distribution of level of pure technical efficiency (%)

The frequency distribution indicates that at least 99% of observations had efficiency scores of more than 50% and that only one observation had an efficiency score less than 50%, which was in 2009. The observations were increasingly distributed at higher efficiency score ranges in the subsequent years. The percentage of observations with efficiency scores higher than 90% accounted for 60.52% in 2009 and increased to about 65% in 2012. Similarly, the number of technically efficient observations increased over time from 36% in 2009 to 53% in 2012.

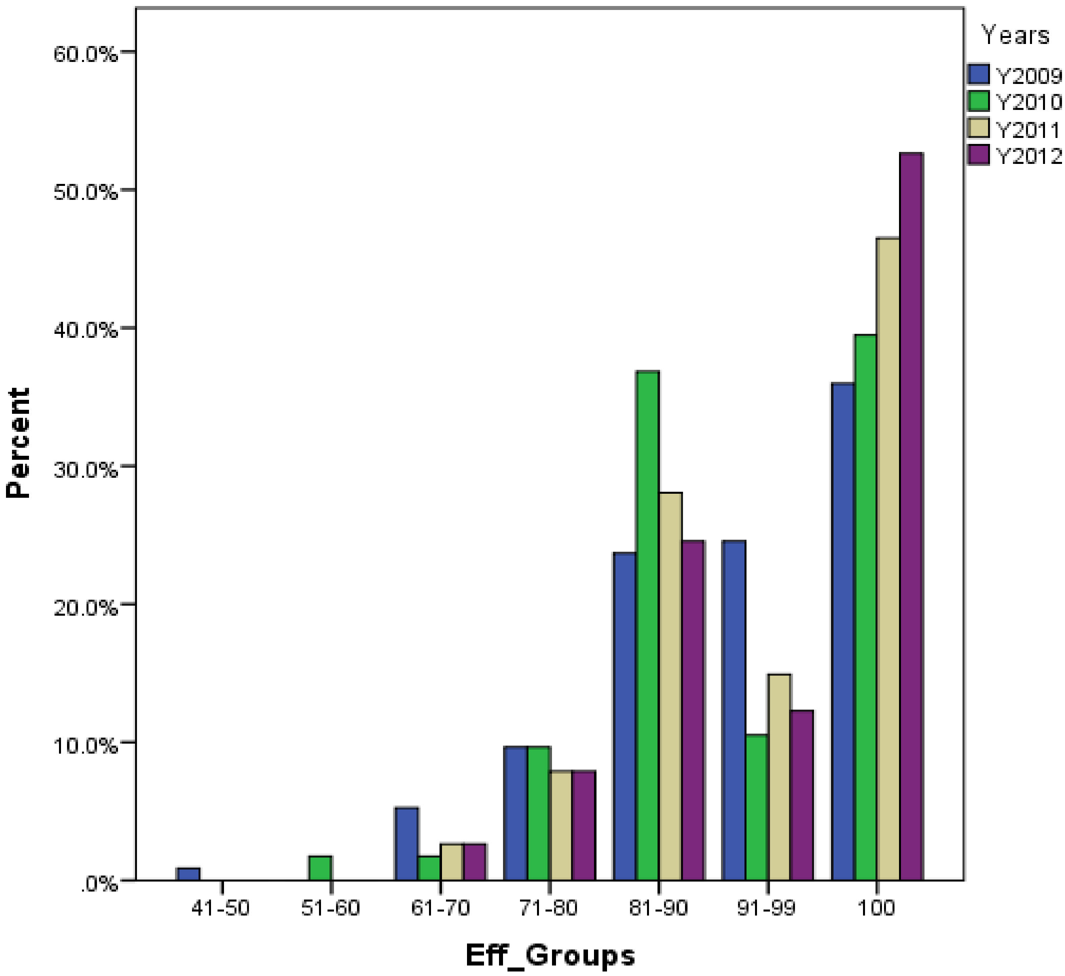

Figure 6.4: Distribution of pure technical efficiency scores (2009-2012)

6.4.2 Reference (Peer) Groups

For each inefficient hospital, DEA identifies a group of corresponding, perfect hospitals, which are collectively called the peer group or reference group and are efficient if evaluated with the optimal system of weights of an inefficient hospital. This set is made up of hospitals, which are characterized by operating methods similar to the inefficient one being examined, and represents a realistic term of comparison that the hospital should aim to emulate in order to improve its performance. Through the current research, Table 6.5 shows that out of the 114 head trauma hospitals and 456 observations over the study period 2009-2012, 85 hospitals appeared to be fully efficient, which means that their efficiency scores are equal to 100%. These hospitals in each year together define the best practice frontier, and thus form the reference set.

Hospital	2009	2010	2011	2012	Total
HOSPITAL_10			1	8	9
HOSPITAL_115	1				1
HOSPITAL_8	7				7
HOSPITAL_80	4	2	4	13	23
HOSPITAL_81			7		7
HOSPITAL_86			1		1
HOSPITAL_87				2	2
HOSPITAL_9	12	2	11	15	40
HOSPITAL_119				0	0
HOSPITAL_91	26	11	14	3	54
HOSPITAL_95	16	79	0	1	96
HOSPITAL_12				1	1
HOSPITAL_120	32	1		1	34
HOSPITAL_121	3	0			3
HOSPITAL_122		1	2	1	4
HOSPITAL_124	5	78	10	4	97
HOSPITAL_125	3	1		1	5
HOSPITAL_128	5	0	2		7
HOSPITAL_129		0	60	1	61
HOSPITAL_13		2	2		4
HOSPITAL_130	11	0	31	11	53
HOSPITAL_132	8	1			9
HOSPITAL_133			17	36	53
HOSPITAL_136	21	1	25	12	59
HOSPITAL_138		63		0	63
HOSPITAL_145		1		1	2
HOSPITAL_146			1	1	2
HOSPITAL_104	0				0
HOSPITAL_147			0	3	3
HOSPITAL_148		0		8	8
HOSPITAL_150	1	1	27		29
HOSPITAL_152		2		0	2
HOSPITAL_153	1	1	3	12	17
HOSPITAL_157		24	2		26
HOSPITAL_158			0	8	8
HOSPITAL_16		1	1		2
HOSPITAL_160	1				1
HOSPITAL_161		0	0	0	0
HOSPITAL_105			0	0	0
HOSPITAL_162	3	2	1	2	8
HOSPITAL_163	1				1
HOSPITAL_164	3		1	1	5
HOSPITAL_165				16	16
HOSPITAL_166			34	3	37
HOSPITAL_169	0	0		0	0
HOSPITAL_17		1			1

Hospital	2009	2010	2011	2012	Total
HOSPITAL_171		0	0	0	0
HOSPITAL_172	4	1	0	0	5
HOSPITAL_107			1	1	2
HOSPITAL_175	68	2	20	22	112
HOSPITAL_178				2	2
HOSPITAL_179				1	1
HOSPITAL_2			1	5	6
HOSPITAL_24		0	0	15	15
HOSPITAL_108	1	7	3	40	51
HOSPITAL_27				11	11
HOSPITAL_3		1	1	1	3
HOSPITAL_31	0	5			5
HOSPITAL_32	2		0	0	2
HOSPITAL_34				1	1
HOSPITAL_36			2		2
HOSPITAL_11				3	3
HOSPITAL_42			1	1	2
HOSPITAL_44	7	2	5	0	14
HOSPITAL_45	1	0	0	6	7
HOSPITAL_46				3	3
HOSPITAL_47		0			0
HOSPITAL_5			2	1	3
HOSPITAL_50			1	3	4
HOSPITAL_51		31	41	12	84
HOSPITAL_110	0			1	1
HOSPITAL_52		0	1		1
HOSPITAL_53	0			1	1
HOSPITAL_54	0				0
HOSPITAL_59	5				5
HOSPITAL_6	4	7	8	11	30
HOSPITAL_62	1	0	0	0	1
HOSPITAL_63		0	0	3	3
HOSPITAL_111	11	1			12
HOSPITAL_64	0		1		1
HOSPITAL_67				2	2
HOSPITAL_7	36	37		32	105
HOSPITAL_71	0		1	12	13
HOSPITAL_74	26		0		26
HOSPITAL_75	3	2	9		14
Number / year	41	45	51	60	

Table 6.5: Reference groups of hospitals over the study period

In DEA terminology, these hospitals are referred to as peers, as mentioned previously, and set an example of good operating practice for inefficient hospitals to emulate. Furthermore, it is worth mentioning that the hospital, which is considered to be generally in the efficient frontier for inefficient hospitals, is called the global leader. Indeed, by counting how many times each hospital is considered to be in the peer group, we notice that HOSPITAL_175 is the most efficient, as this hospital appears 112 times to be part of the peer group over the total study period. Consequently, the performance of this hospital is better on average in all dimensions of efficiencies in comparison to the other efficient sample hospitals. On the other hand, comparing the number of peers over the study period shows that the number has mostly slightly increased over the study period, from 41 hospitals in the year 2009 to 60 hospitals in the year 2012. Therefore, there is no reason to believe that one year is atypical regarding hospital performance.

6.5 Targets

Once inefficiencies have been identified, appropriate measures may be taken to improve the performance of inefficient hospitals. DEA results will not only help managers to measure their performance and determine best practice in head trauma care, but also provide the direction and magnitude for each inefficient hospital in order to be efficient. Since the most efficient hospital has operated in an environment similar to the others, it follows that inefficient hospitals could improve their performances by choosing the same policies and managerial structures of their respective peer (reference) hospitals. The input targets for inefficient hospitals are the average number of doctors, the average number of consultants and the total cost that will enable the hospitals to have the same ratios of outputs to inputs incurred by the most efficient hospitals. It is feasible to calculate these input target values by using the similar CRS target Equation (3.5), in Chapter 3 as follows:

$$\hat{x}_{in} = \sum_{n \in R_n} x_{in} \, \lambda_n^* \quad ; \; i = 1,2,\ldots\ldots,I \qquad (6.1)$$

This is shown as $x_{in}$are the input variables for hospital *n*, $\hat{x}_{in}$ are targets for input variables for hospital *n*, *n=1,….,N* indexes the hospitals and *i* indexes the inputs of hospital *n*.

As can be seen from the above formulation, the feasible target for the improvement of every input is achieved by summing up the products of the weights λ_n^* and respective inputs x_{in}. In order to illustrate the possibility of improved performance, the target level is computed for each inefficient hospital as a ratio of the difference between observed and target input to the observed input level, (observed–target) /observed.

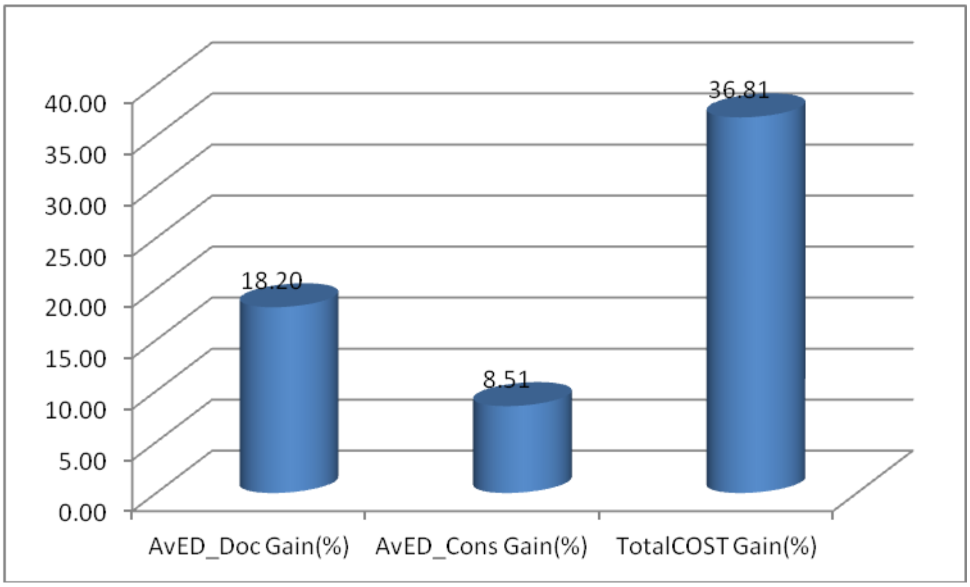

Figure 6.5: Average target level of the input variable over the study period

The average target level for each input variable over the study period (2009-2012) is presented in Figure 6.5. This figure shows that, in order to improve their performance, head trauma care managers need to provide high priority to the total cost and the average number of doctors, while at the same time reducing the average number of consultants. Unlike the efficient hospitals, the inefficient hospitals' managers should reduce the total cost by 36.8% to make their hospitals efficient. Moreover, they need to decrease their average number of doctors by about 18% simultaneously, and their average number of consultants by 8.5%. Clearly, these actions would be wholly inadvisable for implementation and largely counter-productive in practice, as they would have a massively negative effect upon the health of local residents. Hence, these observations should be interpreted merely as an indication of comparative weaknesses, rather than as proposals for change, and should certainly not be used as evidence or recommendations for major policy development.

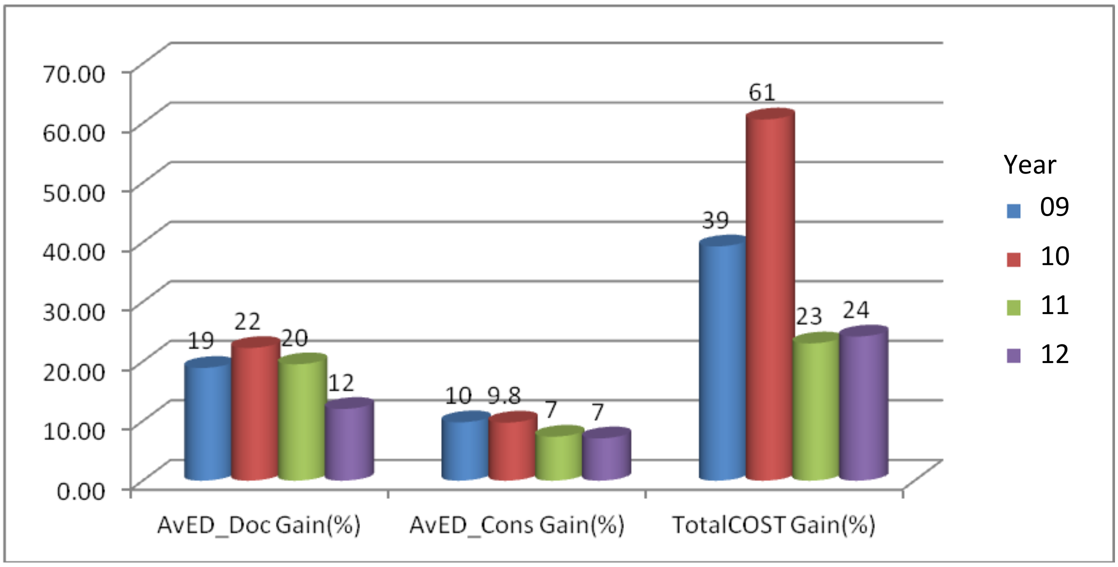

Figure 6.6: Average target level of the input variable over study period (2010-2012)

Comparing the head trauma hospitals over time (2009-2012), Figure 6.6 shows that hospital managers are more oriented toward decreasing the average number of doctors and total cost, and less oriented toward reducing the average number of consultants. Nonetheless, even though most hospitals are more concerned with total cost and less concerned with the average number of consultants, the magnitude of this concern varies over the study period. For example, the average target level of total cost in 2009 was about 39%. Subsequently, it increased to 60% in 2010 and decreased sharply until it fell to 23% in 2011. On the other hand, the average target level of the average number of consultants ranged between 7% (2012) and approximately 10 % (2009).

6.6 Improvements

Following the calculations of the hospital efficiencies, it is of interest to know the improvement targets for inefficient hospitals, as they required to find out the most feasible ways to catch up. It is always good to learn from efficient reference sets with the same or similar input–output mixes. The peer group provides inefficient hospitals with a feasible manner to emulate their efficient peers, and learn from their practices. In order to evaluate better the inefficient hospitals, the current research derives the improvement figures for each hospital, which are derived as the ratio of observed to target outputs and the ratio of target to observed inputs. The efficiency measures obtained are converted to percentages and appear in

Table 6.6 for HOSPITAL-31 and Table C for the other hospitals (See Appendix), where the actual, target, improvement and peer group target are presented for each inefficient hospital.

	I/O	Actual	Target	Improvement %	Peers	Lambdas
HOSPITAL_13 (77.56%)	AvED_Doc	1.77	1.37	-22.60%		
	AvED_Cons	1.33	1.03	-22.56%	HOSPITAL_120	0.01
	TotalCost	2772.51	2150.48	-22.44%	HOSPITAL_175	0.43
	pctMin	6.15	9.6	56.10%	HOSPITAL_80	0.07
	pctMod	15.38	34.87	126.72%	HOSPITAL_9	0.11
	pctSev	13.85	13.85	0.00%	HOSPITAL_91	0.30
	AvgLOS	19.78	19.78	0.00%	HOSPITAL_95	0.07
	AvTotOp	1.88	1.88	0.00%		
	AvED_Treat	8.94	19.98	123.49%		

Table 6.6: Improvement level for inefficient HOSPITAL- 13 (2009)

It is imperative to note that the negative values for the improvements mean that these variables should be reduced, whereas the positive values mean that these outputs should be increased. For example, HOSPITAL_13 has 77.56% technical efficiency, which means that this inefficient hospital has over employed inputs and under produced outputs. Moreover, HOSPITAL_120, HOSPITAL_175, HOSPITAL_80 HOSPITAL_9, HOSPITAL_91 and HOSPITAL_95 are peers of HOSPITAL_13. Through scaling these peers by 0.01, 0.43, 0.07, 0.11, 0.30 and 0.07 respectively, the combination of scaled-input levels of HOSPITAL_120, HOSPITAL_175, HOSPITAL_80 HOSPITAL_9, HOSPITAL_91 and HOSPITAL_95 offer the same output level as HOSPITAL_13, although it uses only 77.56% of the inputs used by HOSPITAL_13. This underlies and explains the efficiency rating of HOSPITAL_13 at 77.56%. HOSPITAL_120, HOSPITAL_175, HOSPITAL_80 HOSPITAL_9, HOSPITAL_91 and HOSPITAL_95 are thus regarded as the efficient benchmarks (peers) for this HOSPITAL_13 in 2009. Likewise, the same scenario can be used for other inefficient hospitals. Consequently, inefficient hospital managers are required to study their efficient peers' practices and set up targets in relation to the combination of input and output levels of their efficient benchmarks.

6.7 Analysis of Robustness and Stability of Efficiency Scores Over Time

As noted previously in Chapter 4, the DEA efficiency results are sensitive to outliers and measurement errors. Therefore, this stage analyses the robustness of the 114 efficiency scores over the study period by the use of the bootstrap DEA of Simar and Wilson (1998, 2000, 2007) as shown in Table 6.7 and Appendix Table D. Table 6.7 presents summary results of the bootstrapping DEA and the original DEA for each year.

	Original DEA Scores			Bootstrapping DEA Scores				Confidence Interval 5%	
Year	Mean	S.Dev.	Min	Mean	Bias	S.Dev.	Min	LB	UB
2009	90.73	10.33	46.65	89.79	0.94	10.98	44.06	87.61	90.76
2010	90.52	10.23	53.85	89.95	0.57	10.66	52.56	88.29	90.54
2011	92.62	9.00	63.64	92.20	0.43	9.31	63.59	91.00	92.64
2012	93.00	9.13	63.19	92.52	0.48	9.53	61.89	91.00	93.01
Average	91.72	9.67	56.83	91.12	0.61	10.12	55.53	89.48	91.74

Table 6.7: Annual average bootstrap and original efficiency scores

The main empirical results are distinguished between five separate factors. Firstly, the average estimate of the bootstrap efficiency was 91.72%, which is very close to the average of the original efficiency scores (91.12%). Secondly, the average minimum value of the original DEA efficiency score is 56.83%. However, after applying the bootstrap method and adjusting for bias, the average minimum bootstrap efficiency score is 55.53%. Thirdly, the bias for each year, which is the difference between the original DEA efficiency score and the bootstrap efficiency estimate, is less than 1%. Fourthly, in Table E of the Appendix, none of the efficient hospitals obtained from the original DEA model change to be inefficient hospitals after correcting for bias by the bootstrapping DEA approach. Fifthly, the most important point which should be noted is that the average DEA efficiency scores of hospitals for each year is included in the 95% confidence interval for the bootstrap efficiency score, which emphasises the importance of the confidence interval for measuring the actual efficiency scores of HTI hospitals.

In order to extend this analysis, a Spearman's rank correlation test of the original DEA efficiency score was conducted, as well as the bootstrap efficiency estimate for each year, as shown in Table 6.8. By testing whether the correlations are zero, it becomes the intention to answer the question into the length of time that an inefficient hospital has remained in that state.

	Bootstrap. DEA (2009)	Bootstrap. DEA (2010)	Bootstrap. DEA (2011)	Bootstrap. DEA (2012)
DEA (2009)	0.9961***			
DEA (2010)		0.9954***		
DEA (2011)			0.9988***	
DEA (2012)				0.9995***

Note ***significance at 1%
**significance at 5%
*significance at 10%

Table 6.8: Spearman correlations for efficiency scores over the period of study

The results of the Spearman rank correlations tests show that the rank correlation of efficiency scores between each pair of yearly observations is not less than 0.99, which is a large statistically significant positive value. These results in Table 6.8 and Table 6.9 demonstrate that no significant difference exists between the original DEA efficiency score and the bootstrap efficiency estimate, which indicates that the original DEA efficiency estimates are robust and consistent.

In addition, the current study investigates internal validity and external validity. "Validity of findings may be divided into internal validity – do the methods alter the results? And external validity – are the results applicable more generally?" (Parkin and Hollingsworth, 1997: p.1428) A test of internal validity is designed to compare the results obtained using different selections of inputs and outputs, with the input-VRS-DEA model from the present research run by excluding three output variables. Invariably, these are either the percentage of patients with minor injuries who recovered satisfactorily, the percentage of patients with moderate injuries who recovered satisfactorily and the percentage of patients with severe injuries who recovered satisfactorily. Overall, the justifications for choosing these particular variables to be excluded have been defined as: (i) in order to use this different model and compare it with the original model, which includes all inputs and outputs (See Table 6.9), as a sensitivity analysis to assess the sensitivity of the DEA results to changes in the methods and data used; and (ii) in order to investigate the effect of the ratio data on the robustness of the DEA results. In other words, by excluding these variables, we plan to demonstrate that the other variables have the same denominator and consequently that the DEA results avoid the problem with mixed ratio data and absolute data, as recognized by Emrouznejad & Amin (2009). It is stated within their paper that input and/or output may result in incorrect efficiency scores when using the standard DEA models for the observations containing ratio data.

	Variables	Model 1	Model 2
Inputs	Average number of doctors seen per patient per year (X1)	*	*
	Average number of consultants seen per patient per year (X2)	*	*
	Average number of nurses seen per patient per year (X3)	*	*
	Total cost (£) per patient per year (X4)	*	*
Outputs	Percentage of patients with minor injuries who recovered satisfactorily per year (Y1)	*	
	Percentage of patients with moderate injuries who recovered satisfactorily per year (Y2)	*	
	Percentage of patients with severe injuries who recovered satisfactorily per year (Y3)	*	
	Average of the total period (days) of stay per patient per year (Y4)	*	*
	Average number of surgical operations per patient per year (Y5)	*	*
	Average number of treatments provided by emergency services per patient per year (Y6)	*	*

Table 6.9: Inputs and outputs for Model 1 and Model 2

The summary statistics for the two models are demonstrated in Table 6.10, which constitutes the mean efficiency for Model 1 as 91.71%, while the mean efficiency for Model 2 is 89.52%. Hence, the difference between average efficiencies in these two models is only 2%. The standard deviation of efficiency estimates from the two models is also close (about 10%). The minimum efficiency scores for both models are similar, at about 57%. Likewise, as shown in Table 6.10, both methods generally yield relatively high mean efficiencies and very similar characteristics in terms of standard deviations and minimum efficiency scores, which do not vary much over time.

Year	Model 1			Model 2			Difference
	Mean	Std. Dev.	Min.	Mean	Std. Dev.	Min.	
2009	90.73	10.33	46.65	88.76	10.96	46.04	1.97
2010	90.52	10.23	53.85	88.96	10.33	53.85	1.56
2011	92.62	9.00	63.64	89.91	9.47	63.44	2.71
2012	93.00	9.13	63.19	90.47	9.76	63.19	2.53
Average	91.72	9.67	56.83	89.52	10.13	56.63	2.20

Table 6.10: Summary statistics of Model 1 and Model 2

The results of the Spearman's rank correlation coefficient tests for the two models are set out in Table 6.11. The results indicate a very large positive correlation between the two models in each year, as the correlation between both models in each year is greater than 0.7, which suggests internal validity.

	Model 1 (2009)	Model 1 (2010)	Model 1 (2011)	Model 1 (2012)
Model 2 (2009)	0.8129***			
Model 2 (2010)		0.8386***		
Model 2 (2011)			0.7240***	
Model 2 (2012)				0.7947***

Note ***significance at 1%
**significance at 5%
*significance at 10%

Table 6.11: Spearman correlations for efficiency scores of Model 1 and Model 2

For testing the external validity, Parkin and Hollingsworth (1997) adapted Spearman's rank-order correlations in order to determine the stability of the efficiency score estimates over time. Based on this adapted test, the Spearman rank-order correlations of efficiencies were tested between each year, as shown in Table 6.12. This table shows that the rank correlation of efficiency scores between each pair of years is positive and statistically significant, although not always significant. The Spearman coefficients estimated that for most of the years under consideration, the efficiency scores are less than 0.6. Similarly, it is observed that the coefficients decrease in value as time increases. This implies that the change in the relative performance of hospitals between each pair of years is quite stable. From the above discussions into the relation between changes during the period of study, it can be concluded that the changes in efficiency scores are unlikely to be so large between the pairs of annual periods.

	2009	2010	2011	2012
2010	0.4194***	1		
	(0.000)			
2011	0.2206***	0.3919***	1	
	(0.0183)	(0.000)		
2012	0.1067	0.3120***	0.5580***	1
	(0.258)	(0.000)	(0.000)	

Note ***significance at 1%
**significance at 5%
*significance at 10%

Table 6.12: Spearman correlations for efficiency scores over the period of study

For enhanced analysis, whether the efficiencies of the sample hospitals change with the further changes of financial and managerial measures in the hospital system, the non-parametric Friedman's test is undertaken initially. The null hypothesis shows that there is no contrast in the distribution of the technical efficiencies across the four years under consideration. The alternative hypothesis is that at least one subgroup has a significantly different distribution. The results are presented in Table 6.13, and from this table, it is clear that a correlation in the efficiency distributions is evidential during the four years, with Friedman=3.51 set p-value=0.319, hence the null hypothesis is not rejected. Consequently, the Friedman's test results reveal that there is no statistically significant difference in hospital efficiencies during the period of study.

Null Hypothesis	Test Statistic	P- value	Decision
The distribution of efficiency scores is the same across the 4 years under consideration	3.51	0.319	Do not reject the null hypothesis

Table 6.13: Friedman's test of DEA efficiency by year

The above analysis estimates the efficiency of each hospital during the study period, although this is not sufficient for the managers, as the researcher would like to be able to identify what hospitals can do to increase their efficiencies. A simple way to find out what each hospital should do to raise its efficiency would be to go to its reference set of hospitals and analyse their contrasting conduct and implementation. Consequently, in the following section of the current study, the characteristics of benchmark performers are presented, in order to provide beneficial information for the decision makers in less efficient hospitals.

6.8 Characteristics of Hospitals

This section attempts to ascertain the characteristics of extreme performing hospitals, through comparing the efficiencies of different groups' results. Hence, the research is less interested in identifying single winners or losers, as the focus is identified as groups of best and worst performers. The operation type within the hospital that affects the composition of the best and worst performing hospitals is evaluated, which subsequently characterises extreme performers.

6.8.1 Efficiency Across Hospital Operating Type

The relative efficiencies of hospitals with varied types are also of importance and relevance, as mentioned previously, there are hospitals which have neurosurgical units and others that do not. The performance of these two different types of hospital in terms of pure technical efficiency is presented in Table 6.14 and their comparison is illustrated in Figure 6.7.

Year	Non-Neuro. Hospitals (N=90)	Neuro. Hospitals (N=24)	All Hospitals (N=114)
2009	90.88	90.18	90.74
2010	90.69	89.93	90.52
2011	93.73	90.97	92.62
2012	92.89	94.54	92.99
Average	92.05	91.40	91.72

Table 6.14: Annual average pure technical efficiency scores by hospital types

The results demonstrate that the hospitals with no neurocritical unit have experienced an increase in technical efficiency from 2009 (90.88%) to 2012 (92.89%). The average pure technical efficiency of these hospitals during the period of study is about 92%, whereas the average technical efficiency of the neurocritical unit hospitals during the period of study is about 91%.

It can be seen in Figure 6.7 that the neurocritical unit hospitals have experienced a steadily increasing efficiency score over the sample period. In general, the results show that efficiency scores of neurocritical unit hospitals are close to non-neurocritical hospitals over the sample period. Hence, it is suggested that both types of hospitals improved over time, and that the neurocritical unit hospitals are decidedly similar to the non-neurocritical unit hospitals in terms of performance. Subsequently, this will be investigated further in the second stage analysis.

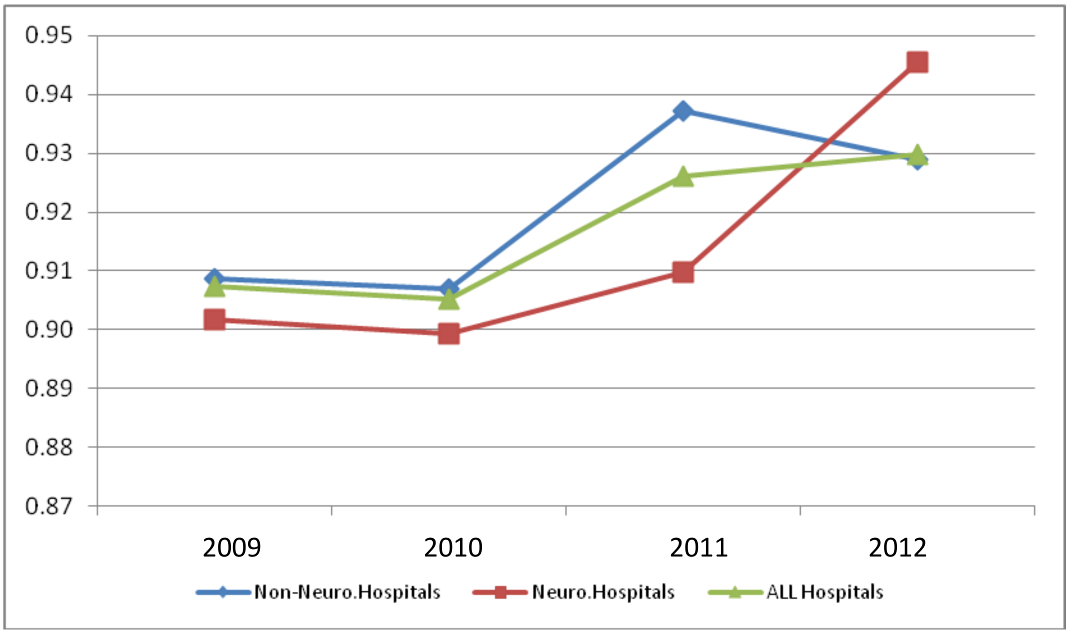

Figure 6.7: Average pure technical efficiency by hospital types

A Mann-Whitney rank sum test is applied in order to compare mean scores of efficiency across different hospital operating styles: neurocritical hospitals and non-neurocritical hospitals. For this test, the efficiency score is considered as a test variable and hospital type is considered as a grouping variable.

Hospital Type	Sample Size	Null Hypothesis	Mean Rank	P-value	Decision
Neuro unit Non-neuro unit	24 90	The distribution of efficiency scores in 2009 is the same across categories of hospital types	1251.5 5303.5	0.3612	Accept the null hypothesis
Neuro unit Non-neuro unit	24 90	The distribution of efficiency scores in 2010 is the same across categories of hospital types	1337 5218	0.7577	Accept the null hypothesis
Neuro unit Non-neuro unit	24 90	The distribution of efficiency scores in 2011 is the same across categories of hospital types	1253 5302	0.3549	Accept the null hypothesis
Neuro unit Non-neuro unit	24 90	The distribution of efficiency scores in 2012 is the same across categories of hospital types	1430.5 5124.5	0.7041	Accept the null hypothesis

Table 6.15: Mann-Whitney test for 2009- 2012 results

The Mann-Whitney test is non-parametric (distribution-free) and is used as an alternative to the independent group t-test in order to test whether the efficiency scores of two samples are equal on average. This is implemented by counting the number of times that efficiency scores from one sample are ranked significantly greater than efficiency scores from another unrelated sample. Moreover, in this test, the ranks of the data are used rather than their values in order to compute the statistic, and the results are shown in Table 6.15. The results of the Mann-Whitney test suggest that no significance difference exists in hospital efficiency performance due to the differences in their operating style, which means that the neurocritical unit hospitals and the non- neurocritical unit hospitals possess similar levels of performance. Hence, the Mann-Whitney test under the null hypothesis demonstrates that two efficiency scores have the same value of median, which are accepted at the 5% level of significance.

6.8.2 Malmquist Productivity Index Results

It has been revealed from the DEA analysis in the previous section that the efficiency of HTI hospitals has been increased during the time of the study. However, this is not to say that the rise in the average efficiency scores between years mean that there is an improvement as far as productivity is concerned. This is because the static DEA does not take into consideration various factors, such as technological improvement. Therefore, although DEA is used to measure efficiency of hospitals over four periods of time, it does not indicate whether changes in productivity are the result of improved management or due to managers' accessibility to technology.

Through the use of the Malmquist productivity indices, a better way to differentiate between changes in terms of technical efficiency and transformation in the efficiency frontier over time. The input-output set, as detailed in Table 6.2, is used as a basis to calculate the indices of total factor productivity change. The productivity change indices are measured by comparing between consecutive pairs of years and reported over the period 2009 to 2012. Furthermore, the changes in total factor productivity indices can be divided into the change in technical efficiency (hospitals getting closer or further away from the frontier) and the change in technology (shift inward or outward of the frontier due to innovation).

The change in technical efficiency is also divided into two components: pure technical efficiency change and scale efficiency scale. Through this process, the values of the Malmquist index or any of its components can be interpreted as follows: values greater than 1 mean progress in HTI care performance; values less than 1 mean the decline of the HTI care performance; values that are equal to 1 equate to no change in the HTI care performance.

6.8.3 Technical Efficiency Change

The level of efficiency change relates to the increased level that individual hospitals are moving away or closer to the efficiency frontier. Thus, this productivity component reveals the hospital performance inside the borders of the production frontier relative to those hospitals performing on the frontier within the period (t) to (t+1). Table 6.16 presents the change in technical efficiency, as well as its decomposition.

Year	Change in scale efficiency (SECH) (1)	Change in pure technical Efficiency (PECH) (2)	Technical efficiency change (EFFCH) (3) = (1) x (2)
2009/2010	0.9901	1.0098	0.9998
2010/2011	1.1641	1.0344	1.2042
2011/2012	1.0167	1.0089	1.0258
Average	1.0570	1.0177	1.0766

Table 6.16: The Average Technical efficiency change and its decomposition

Results reveal that the technical efficiency change was almost 1 in the first year of 2009-2010, which equates to no evidential change. Following this, an improvement occurred in the technical efficiency change in the two subsequent years 2010-2011 and 2011-2012, which indicates that the HTI hospital performance has witnessed overall efficiency progression. The average overall improvement in technical efficiency is 1.0766, which means an increase by 7.66%. Table 6.16 also shows the division of the technical efficiency change components into change in pure technical efficiency and change in scale efficiency.

In addition, the values that are displayed in the third column are the product of those values in the first two columns. Therefore, it can be concluded that the improvement that took place in technical efficiency change is due to the accompanying increases of 1.77% in pure technical efficiency and 5.7% in scale efficiency per year. It can also be concluded that the average technical efficiency change index has not improved in the year 2009-2010, and there has been a the very slight decline in the change of scale efficiency, despite the fact that an increase in the change of pure efficiency is evident. Figure 6.8 reveals the trends for the technical efficiency change and the components of pure technical efficiency change and scale efficiency change.

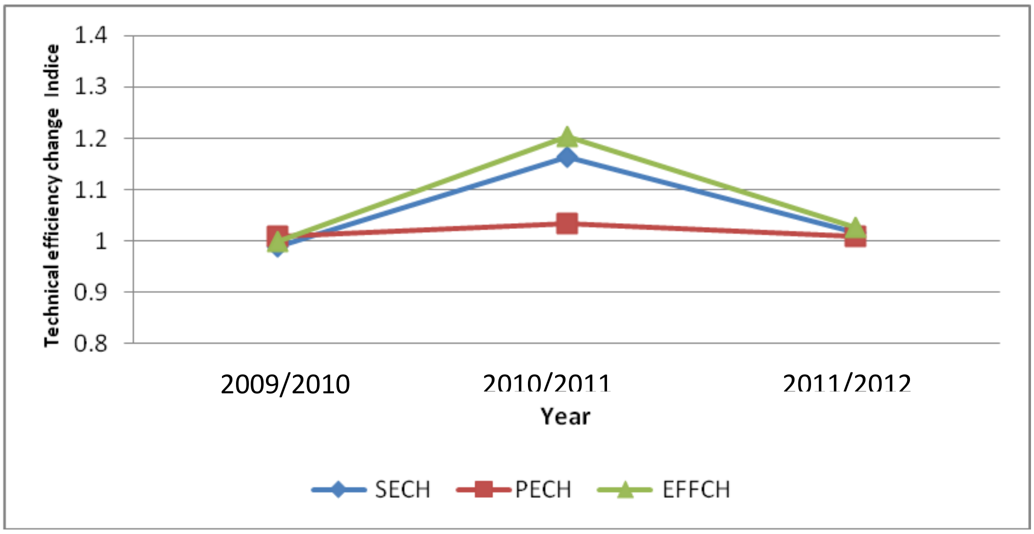

Figure 6.8: Technical efficiency change and its components

The above results are helpful in exhibiting and focusing the annual changes. However, they do not provide a comprehensive picture in regards to the cumulative effects of changes in efficiency. The chained indices are able to provide a useful way to quantify the overall picture of changes for the whole period of the study. For this purpose, the above resulting indices have been changed into cumulative indices by using 2009 as the base year in the computation process of the Malmquist Indices. Table 6.17 and Figure 6.9 indicate what has been discussed above.

Year	Change in scale efficiency (SECH) (1)	Change in pure technical Efficiency (PECH) (2)	Technical efficiency change (EFFCH) (3) = (1) x (2)
2009/2010	0.9900	1.0098	0.9998
2009/2011	1.1627	1.0345	1.2028
2009/2012	1.1492	1.0403	1.1955

Table 6.17: Cumulative decomposition of technical efficiency change

Table 6.17 shows that for the years of 2009-2012, the cumulative index of technical efficiency change is 1.1955, with an overall increase of 19.55% in the productive efficiency of the hospitals. Dividing the cumulative index of technical efficiency change indicates the result that pure technical efficiency has improved by 4.03% within the period of study.

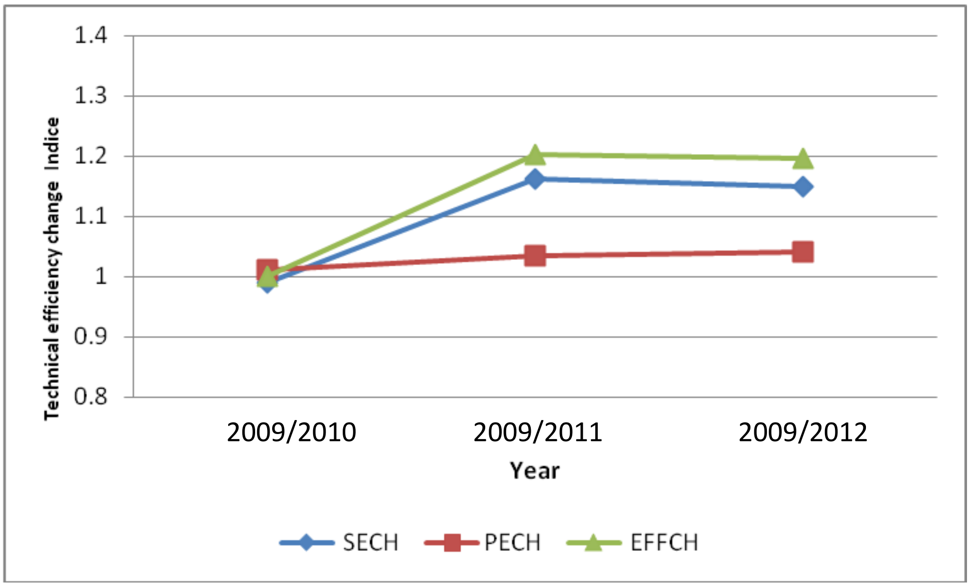

Figure 6.9: Cumulative Technical efficiency change and its components

HTI hospitals have been shown to possess the capacity to feasibly implement the possible efficiency improvements, which has been derived by assuming that all hospitals were 100% efficient in 2009. During the period of the study, it has been found that hospitals had not become more efficient in the sense that they have become closer to the production frontier, as well as functioning improvement in terms of scale efficiency, with an increase of 14.92%.

6.8.4 Technological Change

Through technological change, the efficiency frontier shifts from period (t) to period (t+1) have been defined. Based on this index, the efficient hospital performance in comparison to inefficient hospital performance is shown to changes, which operates inside the production frontier. When the frontier shift variable is greater than 1, it means that the progression of technological changes in the efficient hospital use lower levels of input in the period (t+1) than in the period (t) controlling for output. If the variable of frontier shift is less than 1, then there is evidential regression in the technological change. If the frontier shift variable is 1, this means that there is no technological change, which also identifies the stability of frontier. Burgess and Wilson (1995: p.362) stipulate that the regression of technological change between subsequent years is potential, if some advances in medical treatment and changes in technology take place. These advances can result in hospitals hiring more personnel for patient treatment, which ultimately leads to increases in health care expenditure.

In addition, the substitution effect can also be another possible cause of regression of technological change. One of the functions of the production frontier shifts and the technological change leads hospitals to change their mix of inputs and outputs, even though a relatively small number of technology leading hospitals shift positions in the input-output space. Thus, these leading hospitals shift the frontier outward to only a fraction of the input-output space, which permits the frontier to regress in areas where they do not function.

Table 6.18 reveals the results of the technological change index, which reveals a mixed change patterns in technology. This is due to the production frontier declining in the first years of the study period (2009-2010) and not showing an effect in the final year (2011-2012). However, the production frontier had improved by 4.62% in (2010-2011). Overall, the product of the combined results of these changes is an average of 1.0022, which means that neither improvement nor decline takes place in the technological change. The same table also reveals the cumulative index for the final years of 2009-2012, in terms of technological change, is 0.9909, which means a whole decline in hospital technological change of about 1% for the whole period. These declines indicate that the study hospitals have undertaken some programmes of restructuring during the period of the study.

Year	Technological change (TECHCH)	Year	Cumulative Technological change (TECHCH)
2009/2010	0.9607	2009/2010	0.9607
2010/2011	1.0462	2009/2011	0.9992
2011/2012	0.9996	2009/2012	0.9909
Average	1.0022		

Table 6.18: Technological change and cumulative technological change

6.8.5 Total Factor Productivity

The findings of the productivity changes of the HTI hospitals during the period of 2009-2012 are shown in Table 6.19, which presents a summary of the productivity change results (the Malmquist index), in addition to the technical efficiency change and the components of the technological change. It can be noted here that the numbers which are located in the last column are produced by the numbers in the two previous columns. Table 6.19 reveals that the hospital productivity has increased after it declined during the first two years. More specifically, there is an improvement in productivity in the final two subsequent years (2010-2011) and (2011-2012) following a decrease taking place in the initial year (2009-2010). Generally speaking, the results indicate that HTI hospitals have undergone productivity growth by 7.87% per year in the four years (2009-2012).

Year	Technical efficiency change (EFFCH) (3)	Technological change (TECHCH) (4)	Total factor Productivity change (TFPCH) (5) = (3) x (4)
2009/2010	0.9998	0.9607	0.9582
2010/2011	1.2042	1.0462	1.2537
2011/2012	1.0258	0.99964	1.0244
Average	1.0766	1.0022	1.0786

Table 6.19: Decomposition of Malmquist productivity indices

Figure 6.10 indicates that the total factor of productivity achieved a general upward trend during the study period, despite the fact that it had seen a certain level of decline in the first two years, which was by 0.958 during (2009-2010).

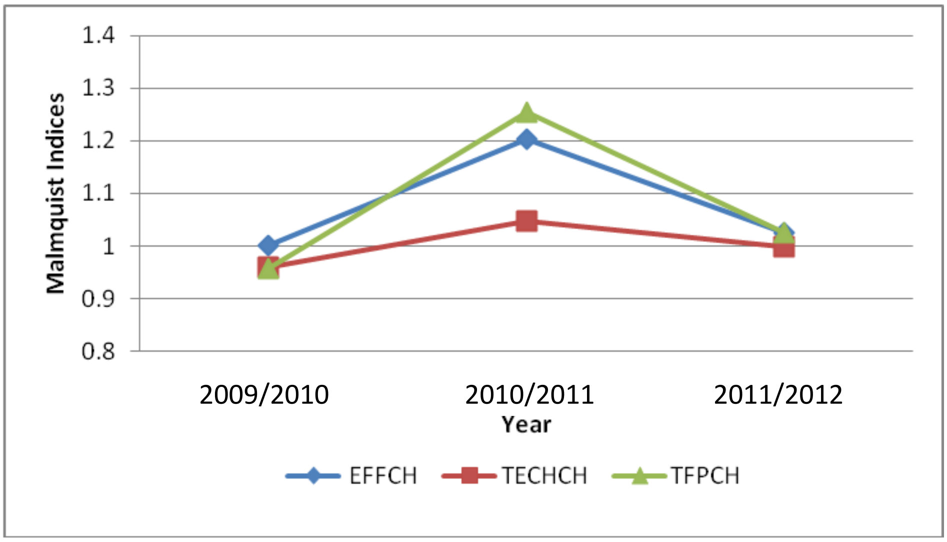

Figure 6.10: Malmquist Indices for HTI hospitals

The increases in productivity and efficiency from one year to another can be explained in terms of the changes in the management and regulation of the health care system during the period of 2009-2012. Cumulative Malmquist indices for the study hospitals for the period

2009-2012 are also calculated and reported in Table 6.20, which are also plotted in Figure 6.11.

Year	Technical efficiency change (EFFCH)	Technological change(TECHCH)	Total factor Productivity change (TFPCH)
2009/2010	0.9998	0.9607	0.9582
2009/2011	1.2028	0.9992	1.2007
2009/2012	1.1955	0.9909	1.1848

Table 6.20: Cumulative Malmquist indices

As far as the cumulative indices are concerned, the most important indices are those which tend to compare the two endpoint years of the study time, 2009 and 2012. Additionally, Table 6.19 reveals the results of the Malmquist total factor productivity change index, which indicates that there has been a productivity growth by 18.5% over the entire period for the study into HTI hospitals. Hence, it is indicated that the hospitals are able, on average, to produce given outputs by using approximately 18.5% less inputs in 2012, as compared to 2009, when the financial and managerial changes in the HTI hospital sector occurred. The results also indicated that the efficiency has improved by up to 19.6%. This suggests that the inefficient hospitals are moving forward in a manner that is closer to the efficient frontier. These results are compatible with the findings of the improvement of technical efficiency discussed in the previous sections. Nevertheless, these results of technological change demonstrate a very slight inward shift of the frontier with a regress of 1% over the whole study period. This can be interpreted as distinguishing that although the inefficient hospitals have achieved, whilst also moving closer to the efficient hospitals in the previous year, they do not possess the ability to slightly provide the same level of health care services by using fewer resources.

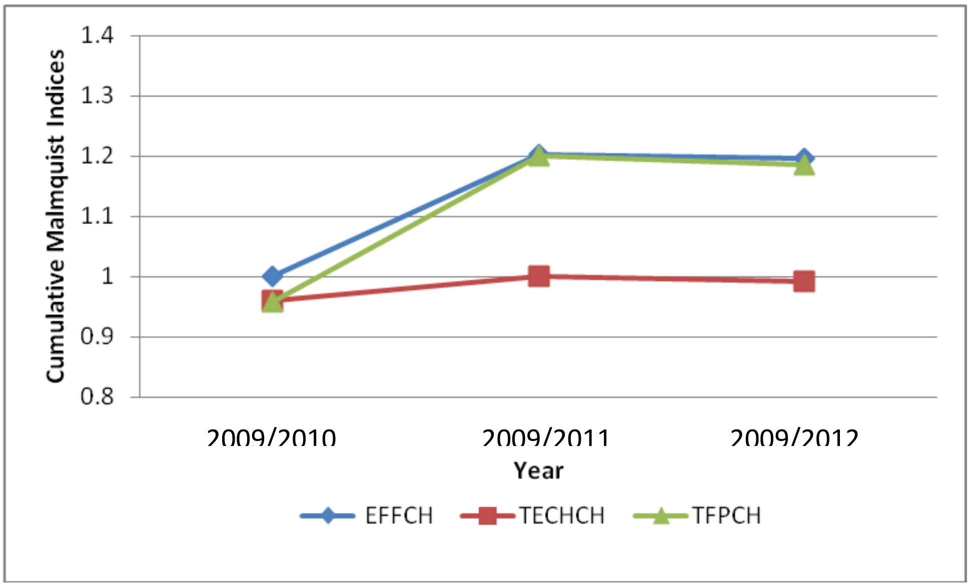

Figure 6.11: Cumulative Malmquist Indices for HTI hospitals

Figure 6.11 graphically explains that the productivity trends have mainly been defined by the change in technical efficiency, rather than the shifts in the efficiency frontier. Besides, the 19.6% increase in productivity must be related to the technical efficiency change. There is a clear upward trend in terms of the technical efficiency improvement, whilst a very slight downward trend is evident in relation to technological change.

The summarisation of the Malmquist indices and all of its components are reported in Table 6.20 below. This also includes the geometric means of all the indices, as well as the cumulative indices for the entire period 2009-2012.

Year	Technological change (TECHCH)	Change in scale efficiency (SECH)	Change in pure technical Efficiency (PECH)	Technical efficiency change (EFFCH)	Total factor Productivity change (TFPCH)
2009/2010	0.9607	0.9901	1.0098	0.9998	0.9582
2010/2011	1.0462	1.1641	1.0344	1.2042	1.2531
2011/2012	0.9996	1.0167	1.0089	1.0258	1.0244
Average	1.0022	1.0570	1.0177	1.0766	1.0786
2009/2012*	0.9909	1.1492	1.0403	1.1955	1.1848

Table 6.21: Malmquist productivity indices and its components

To sum up, the results yielded by the Malmquist productivity indices show that the HTI hospitals generally underwent positive technical efficiency changes during the entire study period. The geometric mean of this technical efficiency change is 1.0766, which creates an improvement of 7.66% to take place each year, which implies that on average the hospitals are getting closer (undergoing efficiency improvement) to the frontier. The geometric mean technological change is 1.0022, pointing to a very slight decrease of 0.22% per year, which is decidedly insignificant and can be ignorable. Thus, it is indicated that the HTI hospitals have, on average, experienced no improvement or decline in technological change during the study period. Therefore, there has been no improvement in terms of the production frontiers to achieve favourable shifts over the whole study period. Hence, the results of progress in technical efficiency change and stability in technological change are shown through the increase in total productivity over time, with an average productivity growth rate of 7.86% per year.

Analysing the Malmquist productivity indices shows that the total factor productivity improved over the period of study. This improvement was attributed to the progress in technical efficiency change during the period study, which is varied from one hospital to another. Therefore, a genuine requirement for further in-depth analysis exists into the determinants that affect variety in the technical efficiency of HTI hospitals, which will be evaluated in the following section.

6.9 Second Stage: SEM Analysis

In the previous sections, the efficiency and productivity of (114) HTI hospitals have been identified through using the DEA methodology and Malmquist productivity index. The results of efficiency revealed that the study hospitals have become more efficient in the study period (2009-2012), and that the increase in the hospital productivity can be explained in terms of the improvement in efficiency. The results also reveal that differences can be found in efficiencies among hospitals, although sources of these differences and variations should be stipulated.

This section is aimed to examine the determinants of efficiency changes during the study period. Previous studies have shown that there can be a number of factors that influence efficiency, which are out of the control of the hospital managers, which are referred to as environmental variables. These environmental variables can include features of hospitals, such as: ownership differences, hospital size, government regulations and location. In the current research, an analysis of some environmental variables is presented in order to determine the factors that influence the HTI hospital efficiency.

The DEA two-stage approach, as discussed in Chapter 5, is used in this analysis, and is the initial stage that uses the traditional inputs and outputs for measuring efficiency in HTI hospitals. Subsequently, the SEM analysis method will be used as a second stage by incorporating environmental variables, as two different techniques are adopted: Tobit censored regression and the ordinary model estimated by ML procedure. Tobit censored regression is considered as a beneficial method for considering censored dependent variables of efficiency, whereas the ordinary model is considered as an alternative to Tobit regression to model the dependent variables of efficiency. In both techniques, the inefficiency scores, which are derived from DEA efficiency scores, are utilised as the dependent variables, while the environmental variables are used as explanatory variables and some of these environmental variables are considered as both dependent variable and explanatory variables. The dependent variables are then regressed against the sets of explanatory variables. Therefore, the results from these two approaches are assumed to answer the question:

Have the efficiency and productivity of the hospitals over the period 2009-2012 been influenced by such environmental variables?

6.9.1 Environmental Variables Description

For the measurement of the environment, seven environmental variables are of interest, five of which are exogenous (year, neuro, pctage60, pctage18, pctfmale), whilst two of them are endogenous (pctgcs13 and pctgcs912) (See Table 6.22). Furthermore, hospitals' efficiency variable, which is the main interest, is measured by the efficiency/efficiency score (endogenous variable), which can be seen in Table 6.22. That represents the descriptive statistics of these environmental factors.

Variable	Code
Percentage of patients with GCS ≥ 13 (minor injuries)	pctgcs13
Percentage of patients with GCS 9–12 (moderate injuries)	pctgcs912
Percentage of patients with GCS < 9 (severe injuries)	pctgcs9
Percentage of patients with age 18-60	pctage18-60
Percentage of patients with age > 60	pctage60
Percentage of patients with age <18	pctage18
Percentage of patients who were male	Pctmale
Percentage of patients who were female	Pctfemale
Neurocritical unit (Yes/No)	neuro
Year	Yr

Table 6.22: Environmental variables

6.9.2 Structural Equation Models

SEM was integrated to DEA in order to investigate the effect of environmental variables (See Table 6.23) in relation to the efficiencies.

Variable-code	Type	Mean	Std. Dev.	Min	Max
pctgcs912	Numerical	1.01	2.64	0.00	50.00
pctgcs9	Numerical	1.44	3.23	0.00	50.00
pctage>60	Numerical	40.32	15.76	0.00	100.00
pctfemale	Numerical	40.47	13.21	0.00	100.00
pctage<18	Numerical	9.58	13.85	0.00	100.00
neuro	Binary			0	1
year	Categorical			2009	2012

Table 6.23: Descriptive statistics of the environmental variables

SEM was used in order to examine and confirm the causal relationships that exist among the exogenous variables. This was implemented by using the equations below:

$$pctgcs9 = \beta_0 + \beta_1\, pctfemale + \beta_2\, pctage60 + \beta_3\, pctage18 + e_1 \qquad (6.2)$$

$$pctgcs912 = \alpha_0 + \alpha_1\, pctfemale + \alpha_2\, pctage60 + \alpha_3\, pctage18 + e_2 \qquad (6.3)$$

$$\begin{aligned} Efficiency = {} & \gamma_0 + \gamma_1\, pctgcs9 + \gamma_2\, pctgcs912 + \gamma_3\, pctfemale + \gamma_4\, pctage60 \\ & + \gamma_5\, pctage18 + \gamma_6\, neuro + \gamma_7\, yr + e_3 \end{aligned} \qquad (6.4)$$

Moreover, structural equation statistical techniques, as explained in chapter 5, can provide the means by which both direct and indirect causal effects of variables can be studied. Therefore, the main concerns have been to examine the role of gender and age in the efficiency scores via the percentage of severity of patients as mediator (causal) variables. Two SEM models were built with different specification in modelling the DEA scores against the environmental variables. The first approach used the Tobit model, as it has been adopted as the natural 'choice' for modelling DEA scores in the evaluation of the second stage.

The second approach incorporated the linear model and was estimated by ML as an alternative method for modelling DEA scores against environmental influences. In addition, although the DEA scores obtained from the previous analysis (section 4) are consistent, the same SEM methodology has been used with bootstrapping DEA scores in order to investigate whether different results will be obtained. For the ordinary linear model estimated by ML, p-values are calculated by using heteroskedastic-consistent standard errors in order to be robust to heteroskedastic and the manner of disturbances distribution.

In their abstract, Banker and Natarajan (2008) state that a variety of conditions are identified under which a two-stage procedure, consisting of DEA followed by ordinary least squares (OLS) regression analysis, produces consistent estimators of the impact of contextual variables. Another group of conditions are also identified, under which DEA in the first stage followed by ML estimation (MLE) in the second stage provides consistent estimators of the impact of contextual variables. This requires that the contextual variables to be independent of the input variables. Nonetheless, even though the current study does not treat DEA scores provided from the first stage as an estimate of 'true' scores, it is useful to check correlations to ensure that the contextual variables are independent of the input variables. Table 6.24 indicates the correlation coefficients between the incorporated inputs.

	aved_doc	aved_cos	totalcot
pctage18	-0.04	0.10	-0.02
Neuro	0.40	0.09	0.42
Yr	-0.02	-0.11	-0.18
pctgcs912	0.02	0.05	0.02
pctgcs9	0.10	0.21	-0.01
pctage60	-0.25	-0.13	-0.05
Pctfemale	-0.25	-0.15	-0.06

Table 6.24: Correlation between environmental variables and DEA inputs

The path diagram is one of the beneficial ways used for representing the structural relation of the underlying model. In Figure 6.12, it is possible to distinguish the equations 1, 2, and 3 where the paths diagram of structural equation model (SEM) were used. The paths were in one direction and one variable predicts the other, whereas in the case where no path is present it means that there is no direct relationship between the variables.

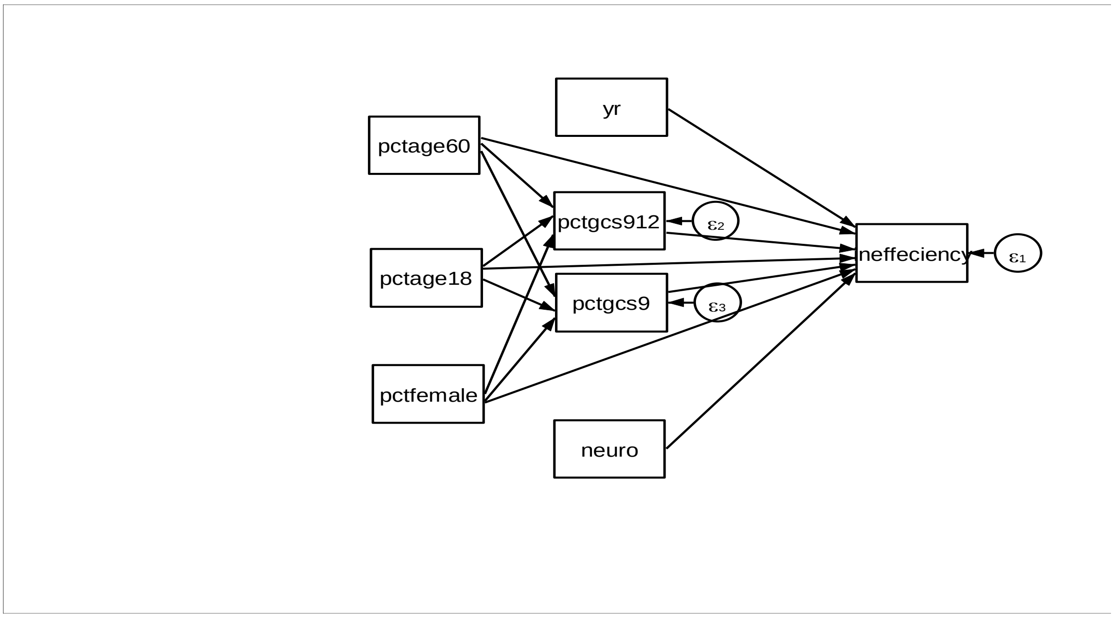

Figure 6.12: Example of path diagram for efficiency variable using SEM

6.9.3 Results of SEM and GSEM Estimates of Inefficiency and Bootstrap-Inefficiency Scores

The analysis was implemented in terms of ordinary and robust producers in order to overcome the issue of non-normality, as the standard error of estimates were approximated using the robust Huber-White variance estimator. Table 6.25 shows the results of SEM using

ML in terms ordinary and robust estimations, and also shows GSEM using ML for the Tobit model for inefficiency score as the *left* censored outcome. Furthermore, notice for the models of percentage of injuries that the estimated parameters (coefficients and p values) resulting from using GSEM and SEM were the same since the dependent variables were not treated as censored variables. Indeed, for the GSEM, the only *left* censored variable of interest was efficiency score.

			GSEM		SEM			
Structural model			**Tobit procedure**		**Ordinary procedure**		**Ordinary Allowing for Heterosked-asticity**	
			B	**p-value**	**β**	**p-value**	**β**	**p-value**
patients with GCS < 9	←	**Female**	-.0217	.115	-.0217	.115	-.022	.327
	←	**Age >60 years**	-.0368	.003	-/0368	.003	-.036	.123
	←	**Age <18**	-.0245	.035	-.0245	.035	-.0245	.211
	←	**Constant**	4.037	<.001	4.037	<.001	4.037	.014
patients with GCS 9-12	←	**Female**	-.005	.695	-.005	.695	-.0045	.643
	←	**Age >60 years**	-.0002	.981	-.0002	.981	-.0002	.961
	←	**Age <18**	-.007	.414	-.007	.414	-.0079	.151
	←	**Constant**	1.274	.006	1.274	.4675	1.275	.014
inefficiency	←	**patients with GCS < 9**	.0043	.226	.0043	.093	.004	.431
	←	**patients with GCS < 9-12**	.0005	.907	.0005	.851	.0005	.850
	←	**Female**	-.0029	.016	-.001	.026	-.001	.030
	←	**Age >60 years**	.0027	.016	.001	.046	.001	.016
	←	**Age <18**	-.0002	.832	-.0001	.916	-.0001	.883
	←	**Year**	-.0293	.004	-.014	.018	-.014	.016
	←	**Neurosurgical unit in treating hospital**	.0310	.279	-.005	.771	-.005	.774
	←	**Constant**	58.95	.004	28.68	.018	28.68	.016

Table 6.25: SEM and GSEM for inefficiency score using ML estimation

6.9.4 Influence of Demographic Variables on Severity of Injured Patients Variables

According to Table 6.25, using the ordinary linear model and linear model allows for heteroskedasticity estimations that result in negatively and significantly affecting age> 60 when compared with ages between 18-60 years on the percentage of severe injuries (p-value= .003), as this age group was likely to present a lower percentage of severe injuries compared with the ages between 18-60 years old.

Structural model			Tobit procedure		Ordinary procedure		Ordinary Allowing for Heterosked-asticity	
			B	p-value	β	p-value	β	p-value
patients with GCS < 9	←	Female	-.0217	.115	-.0217	.115	-.022	.327
	←	Age >60 years	-/0368	.003	-/0368	.003	-.036	.123
	←	Age <18	-.0245	.035	-.0245	.035	-.0245	.211
	←	Constant	4.037	<.001	4.037	<.001	4.037	.014
patients with GCS 9-12	←	Female	-.005	.695	-.005	.695	-.0045	.643
	←	Age >60 years	-.0002	.981	-.0002	.981	-.0002	.961
	←	Age <18	-.007	.414	-.007	.414	-.0079	.151
	←	constant	1.274	.006	1.274	.4675	1.275	.014
Bootstrap-inefficiency	←	patients with GCS < 9	.0046	.230	.0037	.095	.0037	.443
	←	patients with GCS < 9-12	.0003	.945	.0003	.902	.0003	.898
	←	Female	-.0032	.016	-.0015	.026	-.0015	.036
	←	Age >60 years	.0029	.015	.0012	.042	.0012	.015
	←	Age <18	-.0001	.892	.00002	.997	.00002	.996
	←	Year	-.033	.002	-.0170	.008	-.0170	.008
	←	Neurosurgical unit in treating hospital	.0369	.228	.0089	.634	.0089	.636
	←	Constant	67.11	.002	34.33	.008	34.33	.007

Table 6.26: SEM and GSEM for bootstrap-inefficiency score using ML estimation

A significant negative effect was evidential for ages <16 compared with ages between 18-60 years on the percentage of severe injuries (p-value=.035). The same result was observed for the bootstrap-inefficiency score, although minimal differences exist in the values of estimated coefficient (See Table 6.26). However, for both scores, the effect of age groups was not significant in accordance with the ordinary linear enablement for heteroskedasticity. For both inefficiency and bootstrap-inefficiency scores, the impact of gender was positive, as the female is likely to have a less percentage of moderate injuries than males (See Table 6.25 and 6.26). Invariantly, the ordinary and ordinary linear models allow for the heteroskedasticity methods to result in large p-values, which indicate that no significant effects are evident.

6.9.5 Influence of the Severity of Injured Patients on Efficiency

As shown in Tables 6.25 and 6.26, the results from SEM show positive influence of the two types of injuries on the inefficiency and bootstrap inefficiency scores.. However, it was ascertained that these effects were not significant, as this result was also confirmed by the ordinary linear model that enabled the heteroskedasticity method. Additionally, Tables 6.25 and 6.26 stipulate that through GSEM, the coefficients estimated by the Tobit model estimation were slightly different from SEM. Indeed, both GSEM and SEM confirmed that there was no significant impact.

6.9.6 Influence of Demographic Variables on Efficiency

According to SEM, there were slight differences in the values of estimated parameters, as well and using inefficiency and bootstrap-inefficiency scores (See Table 6.25 and 6.26). However, the decision that was made on the basis of p-values of significant effect was the same. The inefficiency of hospitals was likely to be increased through the ages of >60 years, as compared with ages 18-60 years. Similarly, the inefficiency was positively affected by the percentages of females compared with males, and the ordinary linear model allowing for heteroskedasticity agreed with the ordinary method for both inefficiency and bootstrap-inefficiency scores.

GSEM: The values of estimated coefficients using the Tobit model appear to be marginally higher than using the ordinary method (SEM), even though both resulted in the same findings.

6.9.7 Influence of the Neurocritical Unit on Efficiency

According to Tables 6.25 and 6.26, the inefficiency and bootstrap-inefficiency scores seemed to be high, as long as the percentage of the neurocritical unit in treating hospital became higher. However, the influence was not significant, as shown by all the estimation procedures.

6.9.8 Influence of Time (years) on Efficiency

The efficiency and bootstrap- efficiency scores appeared to be higher during recent years, when compared with previous years, and the influence was highly significant, as shown by the three estimation procedures (p-value<0.005). Consequently, this result supports the previous findings of both DEA analysis and Malmqusit Index.

6.9.9 Indirect and Total Effect

In terms of a direct effect, the results provided in Tables 6.27 and 6.28 confirmed that the females, who were above 60 years and less than 18, did not have any indirect impact through intervention variables of patients with GCS. For a total effect, the total influence of gender was -.0014 for inefficiency and -.0015 for bootstrap-inefficiency scores, with both producing significant relevance using ordinary and robust SE. Furthermore, the total influence of age>60 was 0.0010 for inefficiency and 0.0011 for bootstrap-inefficiency scores, where only robust SE resulted in a significant impact. Comparatively, no significant influence was seen for the ages of <18 within both inefficiency and bootstrap-inefficiency scores.

Effect	Structural model			SEM			
				Ordinary procedure		Ordinary Allowing for Heterosked-asticity	
				B	p-value	β	p-value
Indirect effects	Inefficiency	←	Female	-.00008	.248	-.00008	.470
		←	Age >60 years	-.0013	.144	-.0013	.316
		←	Age <18 years	-.00009	.194	-.00009	.291
Total effects	Inefficiency	←	Female	-.0014	.019	-.0014	.037
		←	Age >60 years	.0010	.074	.0010	.019
		←	Age <18 years	-.0001	.780	-.0001	.685

Table 6.27: Indirect and total effect for inefficiency scores

Effect	Structural model			Ordinary procedure		Robust procedure	
				B	p-value	β	p-value
Indirect effects	Efficiency	←	Female	-.00008	.253	-.00008	.643
		←	Age >60 years	-.0001	.145	-.0001	.961
		←	Age <18 years	-.00009	.202	-.00009	.151
Total effects	Efficiency	←	Female	-.0015	.019	-.0015	.045
		←	Age >60 years	.0011	.068	.0011	.018
		←	Age <18 years	-.00009	.868	-.00009	.816

Table 6.28: Indirect and total effect for bootstrap-inefficiency scores

6.10 Conclusion

The aim of this chapter has been to examine the performance of HTI hospitals during the period 2009-2012. As indicated in Chapter 3, the DEA method does not require any prior assumptions in regards to the functional forms, nor any assumptions relating to organisation-specific effects. Therefore, it theoretically avoids imposing a wrong functional form on organisations, which is imperative when analysing hospitals, whose behavioural assumptions are not easily defined. Likewise, its capabilities of accommodating multiple inputs and outputs simultaneously, as well as not requiring input price data, also make the DEA the preferable method for measuring hospital efficiency. Hence, the current research employed the DEA method to measure efficiency, and the Malmquist productivity index to investigate the productivity growth of the HTI hospitals.

The choice of inputs and outputs for this empirical analysis of HTI hospital efficiency assessment was based on the postulated theory, the input- output selection from previous studies, the opinions of TARN managers, and the availability of data. The model specification was subsequently chosen with three measures of inputs and six measures of outputs. The inputs are the average number of doctors per patient, the average number of consultants per patient, and the total cost per patient. Moreover, they are the percentage of patients with minor injuries who recovered satisfactorily, the percentage of patients with moderate injuries who recovered satisfactorily, the percentage of patients with severe injuries who recovered satisfactorily, the average of the total period of stay per patient, the average number of total surgical operations per patient, and the average number of treatments provided by emergency services per patient.

Once the DEA method was used to examine the technical efficiency, it was ascertained that pure technical efficiency relatively increased during the period under consideration, from 90.74% in 2009 to 92.99% in 2012. The improvement analysis demonstrates that inefficient hospital managers' are oriented toward decreasing the average number of doctors and total cost, and less oriented toward reducing the average number of consultants. In addition, HTI hospitals can be equally competitive in relation to pure technical efficiency, as neurosurgical unit hospitals and non- neurosurgical hospitals rank about the same, and no relationship exists between these hospital groups and its efficiency. Hence, there is no reason to believe that hospital performance differs in their ratings from a statistical perspective according to their operating style.

Furthermore, the results of the Malmquist productivity indices showed that the total factor productivity of HTI hospitals increased after a regress in the first pair of years. Overall, the progress of average productivity of 7.87% was mainly due to the technical efficiency improvement of 7.66% per year. The catching-up effect (i. e. improvement in technical efficiency change) was attributable to the positive change in both pure technical efficiency (1.77%) and scale efficiency (5.7%).

Overall, out of the seven environmental factors, three are considered to be important in directly affecting the efficiency of HTI hospitals, which are: the percentage of the age > 60 years old, together with the percentage of female groups and years. Comparatively, the indirect effects of these environmental factors on efficiencies through the 2 groups of the severity of patients was attributed to the percentage of both age groups: the age > 60 years and the age<18 years. However, following the consideration into the total effect of the environmental factors on the hospital efficiencies, only the age > 60 years and the female group demonstrated an important influence.

CHAPTER SEVEN: RESEARCH FINDINGS AND CONCLUSIONS

7.1 Introduction

In the previous chapters, performance measurement approaches have been introduced and the most appropriate procedures have been selected. Despite the fact that DEA has some pitfalls, it is still the most common method used by scholars. The current study uses the DEA approach to appraise the efficiency of HTI care in the UK with the purpose of reducing costs to a minimum. In order to deal with missing data, a new methodology in the DEA context has been suggested, and the majority of the published literature on hospital performance has been reviewed by the study, although challenges remain in certain measurements of hospital performance, such as how to deal with environmental factors. Thus, in order to deal with such factors, SEM has been proposed as an integrated method with the output of DEA, so that the effects of these factors on hospital efficiency can be investigated. Consequently, the current research may be considered to be the first study that has integrated SEM as an exploratory technique with the DEA method to incorporate uncontrollable factors with DEA scores.

Certain conclusions have been exhibited from this chapter, which offer some recommendations to inform and direct future research, and the structure of this chapter is as follows. In Section 7.2, a summary of the research findings are presented; Section 7.3 contains recommendations for managers and discusses policy related implications; Section 7.4 relates to the contributions of the current study to the areas of DEA and health care. Section 7.5 provides some suggestions for future research; study limitations are presented in Section 7.6; and Section 7.7 presents an overall conclusion.

7.2 Overview of the Research Findings

7.2.1 First Stage Results

The data used in the current study represent information collected for a sample of patients who were hospitalised with trauma brain injury (TBI) in any of 114 hospitals during the period of 2009-2012. These data were kindly provided under confidentiality agreements by TARN, in conjunction with the University of Manchester.

The method used to assess the performance of HTI care is the BCC approach, which incorporates 3 inputs and 6 outputs. The input variables in the assessment are the average number of doctors per patient, the average number of consultants per patient, and the total cost per patient. The outputs are the percentage of patients with minor injuries who recovered satisfactorily, the percentage of patients with moderate injuries who recovered satisfactorily, the percentage of patients with severe injuries who recovered satisfactorily, the average of the total period of stay per patient, the average number of total surgical operations per patient, and the average number of treatments provided by emergency services per patient.

Various values were absent, such as the ones related to the average number of doctors per patient, the average number of consultants per patient and the average number of total surgical operations per patient. Ultimately, the MICE approach was one method considered for replacing the missing variables, as comparing the distribution of data pre- and post-imputation demonstrated clear similarities between the distributions for each of the variables. Furthermore, it was noted that all the output variables increased during the study period. However, in regards to the long time period being analyzed, it was expected to be necessary to observe such increasing levels of productivity.

The results obtained from the input VRS-DEA model reveal that the average pure technical efficiency of all HTI hospitals during the study period of time is 91.7%, as based on the selected inputs and outputs. This percentage implies that there are considerable possibilities for increasing the level of technical efficiency by 8.3%. Moreover, the results demonstrate that the mean was relatively stable for the first two years and reached its highest level (93.0%) in 2012. Out of 114 hospitals, the number of efficient hospitals increased from 41 to 60 over this period. The standard deviation of the technical efficiency is negatively correlated with the average technical efficiency over the four years considered. Overall, the minimum score (46.7%) of the inefficient HTI hospitals was in 2009, which improved over the next two years until it reached 63.6% in 2011.

The empirical findings from the current study have answered the uncertainty into whether there is empirical evidence to support the assumption that the costs associated with HTI can be lowered while health care can be improved at the same time. The results have suggested that in order to achieve a high level of hospital performance, head trauma care managers are required to provide the priority to the total cost and the average number of doctors, while simultaneously reducing the average amount of consultants. Similarly, inefficient hospitals' managers should reduce, on average over the study period, the total cost by 36.8% to make their hospitals fully efficient. Managers also need to decrease, on average over the study period, their average number of doctors by about 18.0%, and their average number of consultants by 8.5%. However, the reduction of each input variable varies from one year to another.

In addition, the findings also reveal that the performances of neurosurgical unit hospitals and non-neurosurgical unit hospitals are similar. This was assessed by the Mann-Whitney test, which provides the result that there is no statistically significant correlation between a hospital's characteristics and its efficiency score. The bootstrap DEA method of Simar and Wilson (1998, 2000, 2007) was undertaken in order to investigate the consistency of the DEA results, with the mean of the bootstrap efficiency estimated at 91.7%, which is very close to the mean (91.1%) of the original efficiency score. The point of interest to note is that none of the efficient hospitals identified from the original DEA model change to be inefficient hospitals following correction for bias by the bootstrapping DEA approach. Moreover, the average DEA efficiency scores of hospitals for each year are included in the corresponding 95% confidence interval for the bootstrap efficiency score. Thus, it is confirmed that the original DEA model is robust. Likewise, the Spearman rank correlations between the efficiency scores was also analysed, which was generated by our original DEA model and the bootstrapping DEA model. The observed correlation is a large positive value that is statistically significant at the 5% level.

All these results from the robustness analysis confirm that our DEA model is consistent. To achieve further robustness analysis, the internal validity and external validity were investigated. The internal validity was tested by comparing the results obtained by adopting different selections of inputs and outputs, while the external validity was tested by determining the stability of the efficiency score estimates over a period of time. The Spearman rank correlation of the internal validity analysis results show a large positive correlation between the two models in each year, which confirms internal validity. Similarly, the Spearman rank correlation results of the external validity analysis were positive and statistically significant, although they were not always extensive. Consequently, there is stability of change in the relative performance of HTI hospitals between each pair of years. The Friedman's test result confirms that there is no statistically significant difference in HTI hospital efficiencies over the period of the study. Therefore, this validity analysis reveals that the DEA model was robust and stable during the study period.

7.2.2 Malmquist Productivity Index Finding

Through the use of the Malmquist index approach, results are yielded that reveal how technical efficiency has improved during the study period. Indeed, the sample hospitals in the study have achieved an average increase of 7.7% in technical efficiency per year, totaling 19.6% for the entire period. Moreover, the decomposition of technical efficiency change also reveals that the overall technical efficiency progress was characterised by improvements in scale technical efficiency (5.7% per year and 14.9% for the entire period), rather than that in pure efficiency (1.8% per year and 4.0% for the whole period). The other related finding is that there was no progress or regress in technological change per year. However, it has been noticed that a minimal decline was present in HTI hospitals' technological change that constituted about 1% over the entire period. Overall, the combination of the increase in technical efficiency change and the decline in technological change resulted in a productivity improvement over the study period.

The geometric mean of productivity change was found to be 1.079, corresponding to an increase of 7.86% per year. The cumulative effect of productivity change was 1.185, which reflects an increase of 18.5% during the whole sample period, which indicate that the inefficient hospitals became more technically efficient during the evaluated period. Comparatively, the efficient hospitals became less efficient due to the fact that they could not reduce the inputs that they used to produce a given output at the end of the sample period, as compared to those at the beginning. The regress of the production frontier over the whole sample period is the main reason that gains in productivity are entirely attributed to technical efficiency improvements. Hence, the hospital policies and management procedures have positively affected the hospital efficiency through the reduction of input usage. However, there are some constraints that prevent these policies and procedures from implementing considerable improvements in technology. These constraints include: the lack of financial sources to apply new technologies, the limited knowledge and ability of the staff to apply new medical techniques, and technological developments in HTI hospitals does not receive much attention from the hospital managers.

7.2.3 Second Stage Results

There are differentiations in efficiencies between hospitals, as the results on the relative factors that contribute to the efficiency and productivity of HTI hospitals reveal, with certain hospitals scoring efficiency ratings of less than 50%. Therefore, our initial analysis has been extended in order to explore the factors that contribute to the efficiency of HTI hospitals. Through the review of the empirical DEA literature, it has been shown that the uncontrollable variables that constitute the environmental factors are regulation, market competition, differences in ownership and hospital specific characteristics.

In the current study there are two possible groups of environmental factors. The first relates to the nature of the data, which are a summary of patient-level characteristics, and the second relates to the hospital characteristics that were examined in Chapter 6. In particular, seven environmental variables are of interest: percentage of patients with GCS 9–12 (moderate injuries); percentage of patients with GCS < 9 (severe injuries); percentage of patients with an age > 60; percentage of patients with an age < 18; percentage of patients who were female; whether the hospital has a neurosurgical unit (yes/no); year of admission. Furthermore, regression in the second stage following running DEA in the initial stage was used as a standard methodology for investigating such environmental factors.

Given the nature of the presented data, which are summaries of patient level information, SEM was proposed for the second stage, in order to account for these environmental factors. Two specifications of the efficiency score variable were employed in the SEM model, which were the censored tobit model and multiple linear regression, both of which were fitted using maximum likelihood estimation. For both of these models, the DEA efficiency scores of HTI hospitals were calculated in the first stage, and were subsequently transformed into inefficiency scores that were used as the dependent variable in the model for the second stage, in which the environmental factors were used as explanatory variables.

The results from these two alternate techniques yield some consistent and important findings on the effects of patient characteristics, as well as the hospital characteristics and their impact on hospital efficiency. Three environmental factors out of the seven considered are perceived to be imperative in directly impacting on the HTI hospitals' efficiencies. These are the percentage of patients with an age > 60 years old, the percentage of patients in the female group and the year of admission. However, the indirect effects of these three environmental factors on efficiencies through the two groups of severity of the patients were attributed to the percentage of both age groups, corresponding to age > 60 years and age < 18 years. Invariably, when the total effect of the environmental factors on the hospital efficiencies was considered, only the age > 60 years group and the female group were found to pose a considerable influence.

7.3 Recommendations

Results were accumulated in two stages. The first stage results demonstrate a variety in inefficiencies among the HTI hospitals considered. The second stage results explain these variations, which are related to certain hospital characteristics or patient characteristics. The following section addresses some recommendations for the decision makers and managers to support them in raising the quality of hospital performance.

Some policy-related issues may be derived from the data analysis and findings of the current study, which can be employed to improve the HTI care system and hospital performance in particular. The first issue obtained from the empirical results is that the poor performance of HTI hospitals resulted from the overuse of inputs and a decrease of technological change during the study period. Potential inputs reduction (as the results given by the VRS-DEA model) should be utilised to encourage managers to ascertain more beneficial methods for operating HTI hospitals.

A valuable insight can be obtained by observing the transferring of inputs to outputs in the reference set of the inefficient hospitals, which may also assist managers to benchmark the best practice hospitals. In this case, more sophisticated management methods are needed by HTI hospitals in the improvement of the hospital performance, which can help in relation with two matters. Firstly, it helps reduce the overload that is a consequence of the significantly high occupancy rates (caused by long periods of hospitalisation), and secondly, it may assist in decreasing the wasteful utilisation of inputs.

The findings also indicate that the decline in technological change over the period of the study can be partly explained in terms of the staff's limited skills to appreciate and apply new medical techniques. Hospitals can improve as far as technology is concerned by making improvements in management and in developing their human resources. Therefore, the skills and knowledge of hospital personnel should be improved in order to cope with the changing demands of the age and technology. Invariantly, HTI hospitals should recruit managers with advanced management qualifications and experience, and they should administer management courses for enriching their knowledge and experience, especially those who have medical backgrounds.

Certain hospital managers and policy makers may argue, as a comment on the previous DEA results, that the model is deficient due to particular input and output variables not being included. However, the current research shows that these variables are not easy to include or estimate, as relevant data are not available and there is no logical necessity for including other input and output variables. In addition, increased workload by inefficient hospital managers does not equate to a sufficient reduction of inputs in their marketplace to justify the corresponding hospital outputs. Therefore, the hospital performance will be of poor quality if it has an insufficient reduction of inputs, no matter how hard the managers work.

Another useful outcome from the analysis exhibits that a list of recommendations can be presented to health policy makers. A reasonably pragmatic suggestion is that hospital efficiency should be monitored by using the identified methods on an annual basis, which will help hospitals that steadily become inefficient to take urgent action in order to correct and improve their efficiency. Additionally, a national index of the average of all HTI hospital efficiencies can be generated, which may be utilised to monitor the impact of changes made by regulators in terms of policies and processes for improving hospital efficiency. Information technology should be encouraged in the hospital sector for recording data, including HTI care. Invariably, increasing the accuracy of data records is a beneficial step to health policy makers, as it enables the managers to access a wider range of internal data that can be useful for policy decisions. Hence, by promoting the use of data in administration through a feedback mechanism, supporting the advanced data collection system, and revising the reporting system are all mechanisms that can enhance the development of the information system.

7.4 Contributions of the Study

The main contributions of the current research are as follows:

i. The current research is the first published application of DEA in HTI care, as well as the first study that has used patient level data to determine aggregated hospital level data. This was undertaken due to the shortage of hospital level data by summarising the patient records as ratios, percentages and averages for each hospital. The approach could be generalized to other DEA applications in health care, education and other public services, when the main type of aggregated data required for DEA applications are not available. Moreover, this is the first study to use the economic cost of HTI care calculation proposed by Morris *et al*. (2008) in order to determine an input variable that is a proxy for the costs.

ii. Another theoretical development is shown by the implementation of a new procedure for replacing absent data in the context of DEA, based on multiple imputation methodology. In particular, an approach based on multiple imputations by chained equations (MICE) was adopted in DEA in order to replace any missing values in input and output variables. The MICE approach has been simulated in order to appraise its validity as a method for replacing missing values within DEA applications. This has taken place in an experimental study where data were collected for 66 HTI hospitals. It has been determined from this simulated study that MICE is an effective way for providing an acceptable estimate of true efficiency.

   In order to test sensitivity, two factors have been investigated: the rate of missingness whose level was increasing and leads to decreased accuracy of the results; and the number of imputations, which was considered to be an insensitive factor as the results of MICE show. However, this decrease of accuracy is minimal and the method is still regarded as acceptable for practical applications. The only previous study that adopted the second multiple imputation methodology considered through the present research (imputation using the multivariate normal distribution) is the study by Aksezer & Benneyan (2010). They state that *"experience showed that when the rate of missing data is more than 10%, it is almost impossible to carry out DEA"*. Nevertheless, the current study provides some empirical evidence that DEA can justifiably be applied, even when the rate of missing data is considerably greater than 10%. Thus, it is suggested that the MICE approach could be more consistent than imputation using the multivariate normal distribution, and possibly other methodology, for dealing with missing data. Besides, such absent data analysis is rarely considered in the DEA literature, despite a clear practical need for it.

iii. Another original, and more theoretical, contribution of this thesis is by the combination of DEA and the SEM approach, which has been created in order to test the effect of environmental factors on efficiency scores that estimate using DEA. Unlike standard regression models that appear in the DEA literature for the explanation of uncontrollable variables, the SEM approach can account for not only the direct effects of these uncontrollable factors, but also for the indirect effects of these factors through other environmental factors that affect the DEA efficiency scores. Therefore, the SEM approach models and estimates the total effects which environmental factors have on the efficiencies. The total effect of the environmental factors on efficiencies is the combination of the direct and indirect effects. This information provides a more detailed and potentially more valuable analysis, which has not been included in previous attempts to account for the environmental factors that have been published in the DEA literature.

iv. The impact on an important, real application is another contribution of this study, as the utilisation of the proposed MICE approach in order to replace the missing values of some inputs and outputs are required in the current study's DEA application in HTI care. As a consequence, this is the first real data application for MICE in the DEA context, which considers the missing data issue. This approach could be generalised to other DEA applications when missing data occur. In addition, this is the first substantial application to implement the proposed SEM approach for investigating the effects of environmental factors on DEA efficiency scores. Furthermore, this specific approach could be generalised for other DEA applications when a belief is evidential into certain connections between environmental variables or any belief that there are direct and indirect effects of these environmental factors upon DEA efficiencies.

v. The implementation of the extensive robustness analysis with the empirical DEA study on HTI care, in order to overcome the disadvantage of DEA as being deterministic approach, is also a contribution of this research due to the fact that there are very limited applications of the robustness analysis in the healthcare field as discussed in Chapter1. These extensive robustness analysis included bootstrapping DEA methodology as well as testing for the external and internal validity.

vi. The use of the VRS-Malmquist index in order to measure the change in performance based on annual comparative productivity changes is also a novel development, as well as using 2009 as a base year to define the changes for the whole period of study. Nonetheless, this approach has not been implemented previously in the evaluation of productivity changes of HTI care.

The current study contributes to the literature by providing a better understanding of the efficiency of HTI care by assuming the possibility that the expenditure associated with HTI care can be reduced. As a direct consequence, this in turn helps decision makers by giving them guidelines for future policy decisions.

7.5 The Study's Limitations

The current study contributes to the empirical literature on HTI care performance measurement in the UK, and remains valid for any similar future applications. However, there are some limitations that should be taken into account, which are mostly related to the availability of the data. Firstly, the allocative and economic efficiency are perceived as complements to the analysis of technical efficiency. These help to ensure that efficiency can become the result, when the production is optimal with the least cost. Nevertheless, the measurement of allocative and economic efficiency is not permitted due to the lack of data on input prices, which is an inherent problem. Therefore, the focus of the current study has predominantly been on the technical efficiencies of HTI hospitals.

The second limitation is distinguished by the data needed for the economic cost calculation that were used to get the cost of HTI care input variable were not fully available. In this case, the calculations were necessarily performed by excluding the unavailable data, which is likely to generate different estimates of model parameters and prevent the determination of more accurate estimates of HTI care costs. Indeed, inclusion of unavailable data could lead to different DEA efficiency scores.

Finally, incorporation of specific hospital data in the study's analysis would lead to a deeper understanding of HTI hospital performance and, therefore, enable the decision makers and managers in hospitals to implement better policies and planning in terms of wasteful resource reduction. In particular, the DEA model should include the number of beds, nurses and outcome measures, such as the mortality rate and survival rate. In contrast, the SEM models should include demographic, differences in teaching status and market competition as environmental factors. As a consequence, by including a different data set, such as input variables, output variables, hospitals and time spans, different results of the efficiency scores can be obtained. Specifically for this current study, the availability of the data set is one of the study's limitations in generalising the results of the study. Nevertheless, despite what has been mentioned above, the study results do give an indication of what efficient and inefficient hospitals are, as well as the factors that assist in the identification of efficient hospitals.

7.6 Directions for Future Research

There are several theoretical and empirical issues that may be investigated for further discussion and closer examination, which are stipulated as follows:

i. One of the theoretical issues relates to including the MICE approach in the DEA context in order to deal with missing data. However, even though the current investigation's simulation study of the MICE methodology with different missing scenarios demonstrates that this approach functions sufficiently and provides an acceptable estimate of true efficiency, the simulation study needs to be elaborated upon and explained further. When extended, this MICE methodology can test the sensitivity of other factors, such as extreme inputs and outputs, as well as analyse data sets with more than 20% missing values. Moreover, by using the same simulated data set, a future study could make comparisons between MICE and other current methodologies for dealing with missing data in DEA.

ii. Regarding the considered SEM approach, there are several topics worthy of further investigation and implementation. One of these topics is our novel use of a two-part model that explains the efficiency scores in a separate equation from the initial DEA.

The first equation explains why some DMUs are efficient, while others are not (y=1 if it is efficient and y=0 if it is not). The second equation relates to the relative efficiencies of inefficient units. Similarly, another of these topics is to treat the DEA score, which is generated from the first stage, as an estimated dependent variable representing true efficiencies in the second stage. The estimated results may be inconsistent and standard methods of inference are no longer valid. Consequently, the correlation between the variables in the first and second stages needs to be taken into consideration. The choice of a convenient regression model in the second stage is also an issue that should be considered. In this context, the approaches of Simar and Wilson (2007) and Banker and Natarajan (2008) could be adhered to, in order to combine SEM with DEA in the second stage.

iii. Regarding methodological extensions, it is feasible to compare the results of the DEA model in the present study with those results obtained from other alternative techniques, such as stochastic frontier analysis (SFA). In fact, the use of SFA could yield a different set of efficient data, which might or might not be in agreement with the DEA results from the current study. Hence, this investigation would be helpful to confirm whether analytical methods other than DEA could offer any additional value to the available information on the efficiency results that DEA provides.

DEA does not rank the efficient hospitals, but only identifies them as 100% efficient, which means that additional information would be required to enable comparisons between efficient hospitals. Therefore, the "super efficiency" approach by Andersen & Petersen (1993), which is a statistical method for ranking DMUs in the DEA literature, could be adopted for future research. Similarly, other methodologies in the DMUs ranking field, such as the cross-efficiency approach of Sexton *et al.* (1986), the neutral DEA model of Wang & Chin (2010), and the new super-efficiency DEA method of Li et al. (2015) could be implemented.

iv. The use of more specific inputs and outputs is also worth considering in the process of obtaining results that are more accurate. Among these inputs are the quality of staff (nurse, doctors and specialists) such as their qualifications and experience. Among these outputs are HTI patient survival rate and the associated mortality rate. Another possibility for future research is to employ a larger sample size, as the current analysis is based on a modest data set of only 114 hospitals from within England and Wales. Hence, it would be interesting to investigate this relationship further by incorporating a larger sample of hospitals. A larger sample from the UK, and other samples from different countries, would be useful in attempting to generalise the results of this research. Furthermore, it is possible to propose adding more groups in category comparisons, such as the region (England, Wales and Scotland) and the size of each hospital.

7.7 Concluding Remarks

This research opens up a new way of measuring HTI care efficiency. Although the methodologies developed in this study are specific to the assessment of HTI care performance in the UK, they could be generalised to measure the levels of hospital efficiency in general by selecting suitable inputs and outputs. This study also opens up a new way of incorporating the environmental factors in DEA scores.

Using methods that have not been implemented previously in the assessment of HTI care performance in the UK is one of the main motivations behind the current research. It is hoped that this study will encourage future research on DEA applications using the MICE approach when missing data occurs, as well as on applications of the SEM approach for investigating environmental factors.

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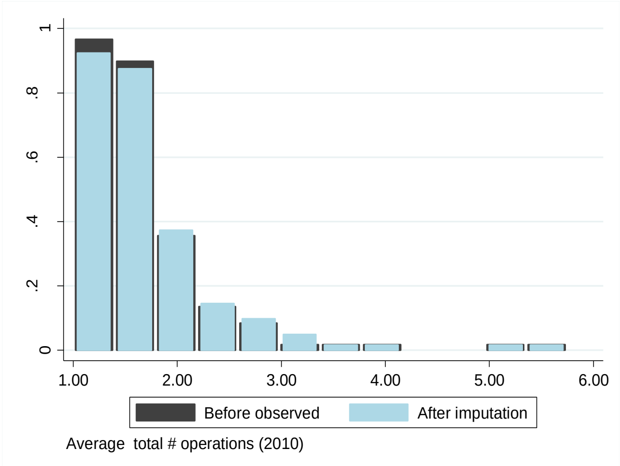
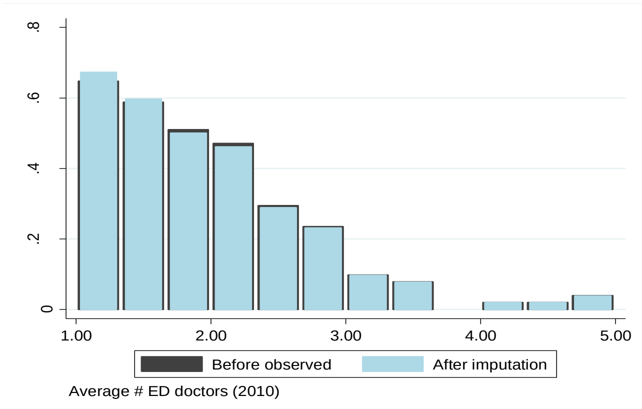
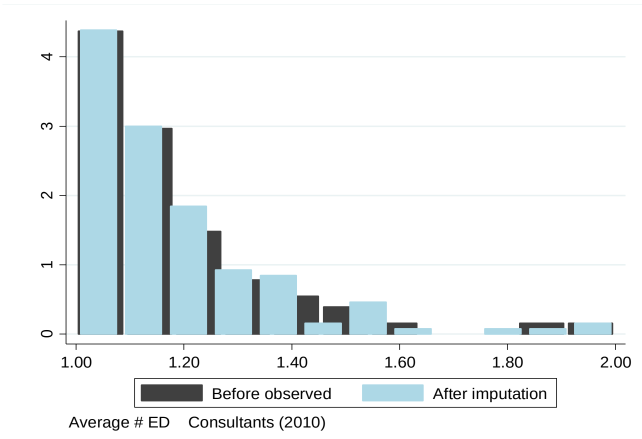
Appendix

Appendix A Distributions of variables with missing data before and after imputation (2010-2012)

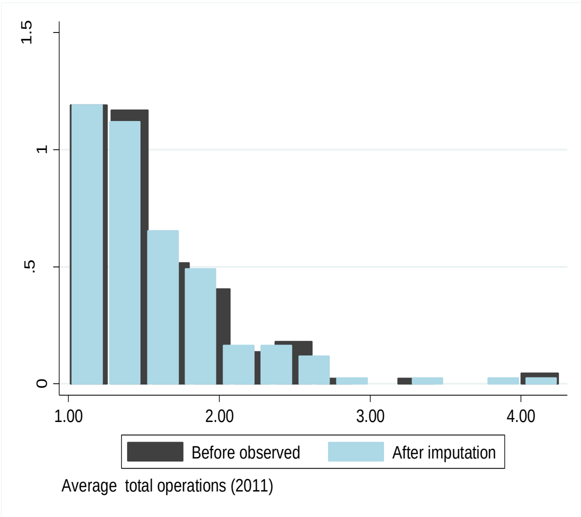
2010

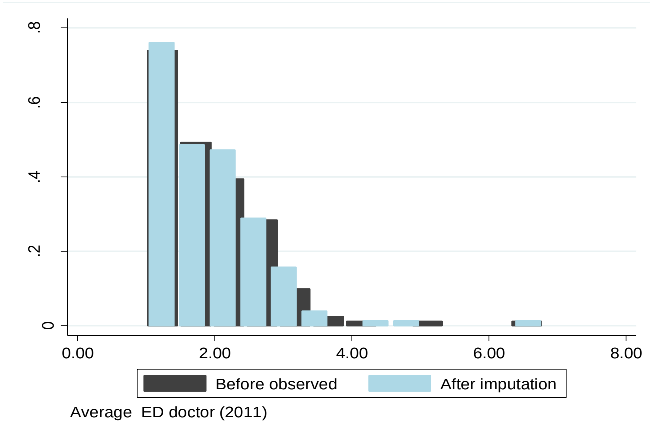


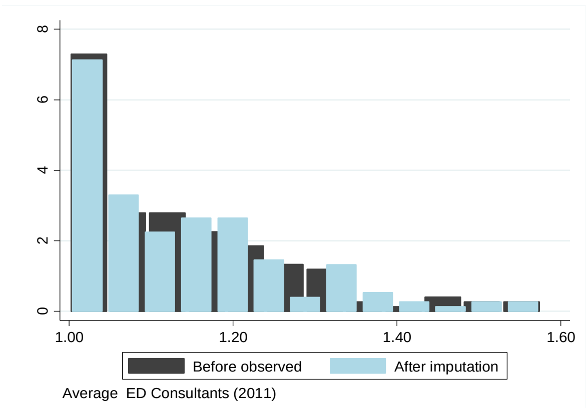




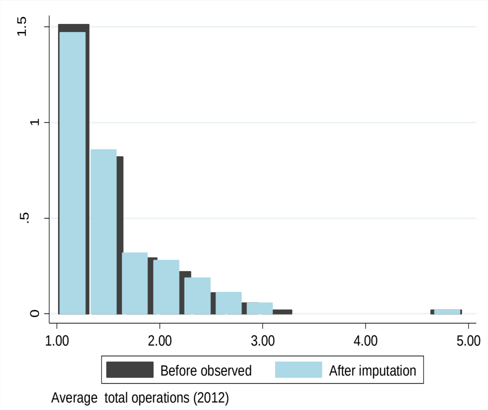
2011


1.5
1
.5
0
1.00
2.00
3.00
4.00
Before observed
After imputation
Average total operations (2011)

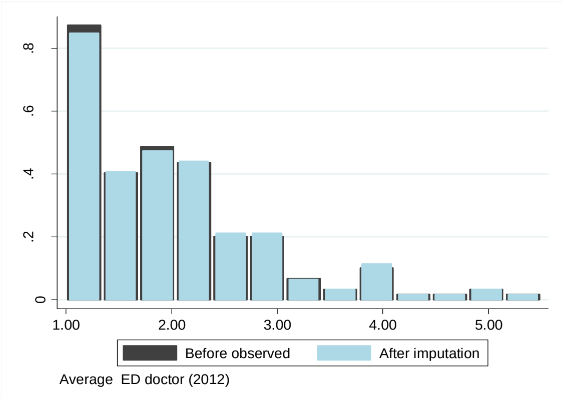

.8
.6
.4
.2
0
0.00
2.00
4.00
6.00
8.00
Before observed
After imputation
Average ED doctor (2011)


8
6
4
2
0
1.00
1.20
1.40
1.60
Before observed
After imputation
Average ED Consultants (2011)

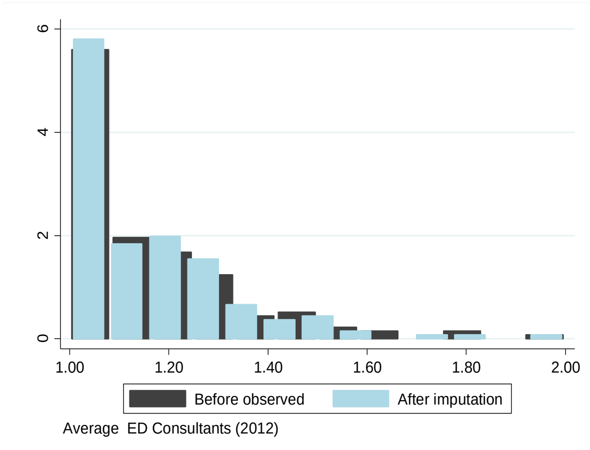
2012



0
.5
1
1.5
1.00
2.00
3.00
4.00
5.00
Before observed
After imputation
Average total operations (2012)



0
.2
.4
.6
.8
1.00
2.00
3.00
4.00
5.00
Before observed
After imputation
Average ED doctor (2012)



0
2
4
6
1.00
1.20
1.40
1.60
1.80
2.00
Before observed
After imputation
Average ED Consultants (2012)

Appendix B Summary of hospital pure technical efficiency

Hospital Code	Efficiency Score				
	2009	2010	2011	2012	Average
HOSPITAL_10	97.64	99.15	100	100	99.20
HOSPITAL_102	65.14	81.13	82.56	68.06	74.22
HOSPITAL_104	100	85.71	70.37	76.4	83.12
HOSPITAL_105	87.19	88.89	100	100	94.02
HOSPITAL_107	90.54	70.37	100	100	90.23
HOSPITAL_108	100	100	100	100	100.00
HOSPITAL_11	86.42	82.72	95.25	100	91.10
HOSPITAL_110	100	98.65	92.91	100	97.89
HOSPITAL_111	100	100	84.19	87.5	92.92
HOSPITAL_115	100	79.45	63.64	85.71	82.20
HOSPITAL_119	96.46	92.31	88.64	100	94.35
HOSPITAL_12	90.78	93.52	87.95	100	93.06
HOSPITAL_120	100	100	98.47	100	99.62
HOSPITAL_121	100	100	95.65	95.83	97.87
HOSPITAL_122	77.56	100	100	100	94.39
HOSPITAL_123	91.45	86.05	86.28	90.99	88.69
HOSPITAL_124	100	100	100	100	100.00
HOSPITAL_125	100	100	71.16	100	92.79
HOSPITAL_128	100	100	100	85.2	96.30
HOSPITAL_129	96.43	100	100	100	99.11
HOSPITAL_13	77.56	100	100	90.08	91.91
HOSPITAL_130	100	100	100	100	100.00
HOSPITAL_132	100	100	99.64	95.5	98.79
HOSPITAL_133	87.8	85.71	100	100	93.38
HOSPITAL_136	100	100	100	100	100.00
HOSPITAL_138	90.91	100	92.93	100	95.96
HOSPITAL_14	86.54	89.71	90.77	95.53	90.64
HOSPITAL_145	46.65	100	82.28	100	82.23
HOSPITAL_146	97.3	87.5	100	100	96.20
HOSPITAL_147	74.96	83.33	100	100	89.57
Hospital Code	Efficiency Score				
	2009	2010	2011	2012	Average
HOSPITAL_150	100	100	100	75.12	93.78
HOSPITAL_152	92.35	100	91.55	100	95.98
HOSPITAL_153	100	100	100	100	100.00
HOSPITAL_157	88.13	100	100	86.36	93.62
HOSPITAL_158	85	73.33	100	100	89.58
HOSPITAL_16	90.33	100	100	84.81	93.79
HOSPITAL_160	100	99.01	98.51	78.89	94.10
HOSPITAL_161	82.27	100	100	100	95.57
HOSPITAL_162	100	100	100	100	100.00
HOSPITAL_163	100	76.19	91.18	78.09	86.37
HOSPITAL_164	100	86.67	100	100	96.67

HOSPITAL_165	81.8	86.96	94.12	100	90.72
HOSPITAL_166	75.39	88.37	100	100	90.94
HOSPITAL_167	77.55	84.29	73.7	68.42	75.99
HOSPITAL_169	100	100	85.71	100	96.43
HOSPITAL_17	92.31	100	87.15	82.77	90.56
HOSPITAL_171	77.56	100	100	100	94.39
HOSPITAL_172	100	100	100	100	100.00
HOSPITAL_175	100	100	100	100	100.00
HOSPITAL_178	85.64	83.35	89.08	100	89.52
HOSPITAL_179	89.13	83.86	87.94	100	90.23
HOSPITAL_19	88.74	90.65	75	84.38	84.69
HOSPITAL_2	96.92	83.68	100	100	95.15
HOSPITAL_20	92.41	88.1	89.49	94.24	91.06
HOSPITAL_21	87.84	85.63	85.85	96.65	88.99
HOSPITAL_22	90.39	94.87	98	94.61	94.47
HOSPITAL_24	87.93	100	100	100	96.98
HOSPITAL_26	80	74.32	84.94	87.24	81.63
HOSPITAL_27	83.33	86.6	88.37	100	89.58
HOSPITAL_29	97.78	85.26	79.81	84.07	86.73
HOSPITAL_3	73.67	100	100	100	93.42
HOSPITAL_30	92.86	85.71	89.39	85.21	88.29
HOSPITAL_31	100	100	86.21	83.19	92.35
HOSPITAL_32	83.75	88.23	100	100	93.00
HOSPITAL_34	93	86.32	96.49	100	93.95
HOSPITAL_36	97.41	85.97	100	94.74	94.53
HOSPITAL_38	65.14	73.95	69.46	85.21	73.44
HOSPITAL_40	85.71	81.32	75.8	80.41	80.81
HOSPITAL_41	90.76	93.62	81.74	71.97	84.52
HOSPITAL_42	77.75	53.85	100	100	82.90
HOSPITAL_44	100	100	100	100	100.00
HOSPITAL_45	100	100	100	100	100.00
HOSPITAL_46	85.41	86.21	99.84	100	92.87
HOSPITAL_47	81.1	100	99.26	93.75	93.53
HOSPITAL_49	77.99	94.44	84.73	80.76	84.48
Hospital Code	Efficiency Score				
	2009	2010	2011	2012	Average
HOSPITAL_50	73.21	73.24	100	100	86.61
HOSPITAL_51	95.45	100	100	100	98.86
HOSPITAL_52	96	100	100	92.86	97.22
HOSPITAL_53	100	71.84	94.7	100	91.64
HOSPITAL_54	100	92.31	78.57	75	86.47
HOSPITAL_55	90.24	76.79	85.08	90.52	85.66
HOSPITAL_58	97.11	82.93	88.72	88.68	89.36
HOSPITAL_59	100	93.94	97.3	93.1	96.09
HOSPITAL_6	100	100	100	100	100.00
HOSPITAL_61	75.01	87.5	90	90	85.63
HOSPITAL_62	100	100	100	100	100.00

HOSPITAL_63	90.63	100	100	100	97.66
HOSPITAL_64	100	81.82	100	77.67	89.87
HOSPITAL_67	88.35	88.89	93.89	100	92.78
HOSPITAL_68	65.81	70.59	70.57	90.01	74.25
HOSPITAL_69	87.33	78.15	86.8	80.5	83.20
HOSPITAL_7	100	100	85.79	100	96.45
HOSPITAL_71	100	81.82	100	100	95.46
HOSPITAL_72	69.81	77.5	86.36	81.25	78.73
HOSPITAL_73	94.36	88.46	81.25	81.41	86.37
HOSPITAL_74	100	89.29	100	88.24	94.38
HOSPITAL_75	100	100	100	97.08	99.27
HOSPITAL_76	83.73	85.42	87.65	88.06	86.22
HOSPITAL_79	88.37	84.78	87.5	76.32	84.24
HOSPITAL_8	97.51	54.74	80	82.37	78.66
HOSPITAL_80	100	100	100	100	100.00
HOSPITAL_81	93.17	89.19	100	90.48	93.21
HOSPITAL_82	87.81	90.48	77.78	87.5	85.89
HOSPITAL_86	88.18	87.73	100	94.35	92.57
HOSPITAL_87	81.82	83.93	85.37	100	87.78
HOSPITAL_89	92.88	85.23	83.46	83.08	86.16
HOSPITAL_9	100	100	100	100	100.00
HOSPITAL_91	100	100	100	100	100.00
HOSPITAL_94	87.81	96.77	84.78	83.33	88.17
HOSPITAL_95	100	100	100	100	100.00
HOSPITAL_97	65.34	66.59	81.6	63.19	69.18
HOSPITAL_99	92.86	85.42	89.74	85	88.26
Average	90.73	90.52	92.62	93.00	91.72

Appendix C: Improvement level for inefficient hospitals (2009-20012)
Year 2009

HOSPITAL	I/O	Actual	Target	Peers(lamda)
unit1 97.64%	pctMin	0	5.22	unit13 (0), unit50 (0.54), unit94 (0.18), unit109(0.28)
	pctMod	0	30.31	
	pctSev	1.46	12.01	
	AvgLOS	18.62	18.62	
	AvTotOp	1.71	1.71	
	AvED_Treat	15.81	15.81	
	AvED_Doc	3.82	1.58	
	AvED_Cons	1.02	1	
	TotalCOST	8451.31	4469.08	
unit2 65.14%	pctMin	1.04	7.05	unit23 (0.05), unit25 (0.02), unit50 (0.8), unit94 (0.02), unit98 (0.11)
	pctMod	0	38.9	
	pctSev	0	7.46	
	AvgLOS	10.15	17.05	
	AvTotOp	1.85	1.85	
	AvED_Treat	22.55	22.55	
	AvED_Doc	2.01	1.31	
	AvED_Cons	1.56	1.02	
	TotalCOST	561.1	365.49	
unit4 92.92%	pctMin	0	0	unit19 (0.3), unit65 (0.16), unit102 (0.54)
	pctMod	0	30.22	
	pctSev	0	0	
	AvgLOS	9	13.05	
	AvTotOp	4.05	4.05	
	AvED_Treat	1	1.46	
	AvED_Doc	2.19	2.03	
	AvED_Cons	1.32	1.22	
	TotalCOST	0	0	
unit5 90.55%	pctMin	13.42	13.42	unit13 (0.02), unit18 (0.14), unit19 (0.09), unit40 (0.02), unit49 (0.02), unit110 (0.71)
	pctMod	41.61	41.61	
	pctSev	24.83	24.83	
	AvgLOS	18.11	18.11	
	AvTotOp	1.75	1.75	
	AvED_Treat	15.42	23.65	
	AvED_Doc	3.78	2.31	
	AvED_Cons	1.21	1.09	
	TotalCOST	6708.2	2497.06	
unit7	pctMin	0	3.66	unit25 (0.45), unit50 (0.35),
	pctMod	0	21.71	

86.42%	pctSev	0	8.25	unit94 (0.2)
	AvgLOS	14.26	15.67	
	AvTotOp	1.93	1.93	
	AvED_Treat	15.05	15.05	
	AvED_Doc	2.21	1.67	
	AvED_Cons	1.16	1	
	TotalCOST	11732.46	1509.78	
unit11	pctMin	0	4.95	unit13 (0.01), unit25 (0.21), unit50 (0.56), unit94 (0.03), unit109 (0.18)
	pctMod	0	27.61	
96.46%	pctSev	0	7.41	
	AvgLOS	21.6	21.6	
	AvTotOp	1.64	1.64	
	AvED_Treat	15.92	16.24	
	AvED_Doc	1.28	1.24	
	AvED_Cons	1.04	1	
	TotalCOST	3121.26	3010.77	
unit12	pctMin	0	2.17	unit9 (0.24), unit13 (0.02), unit50 (0.13), unit94 (0.33), unit98 (0.27)
	pctMod	0	15.14	
90.78%	pctSev	0	10.96	
	AvgLOS	20.85	20.85	
	AvTotOp	2.45	2.45	
	AvED_Treat	23.01	23.01	
	AvED_Doc	2.69	2.44	
	AvED_Cons	1.14	1.04	
	TotalCOST	7310.42	1817.08	
unit15	pctMin	17.93	17.93	unit13 (0.02), unit17 (0.06), unit40 (0.12), unit49 (0.38), unit98 (0.11), unit110 (0.28), unit112 (0.03)
	pctMod	27.72	27.72	
77.57%	pctSev	11.96	12.72	
	AvgLOS	16.45	16.45	
	AvTotOp	1.96	1.96	
	AvED_Treat	21.2	21.2	
	AvED_Doc	2.13	1.65	
	AvED_Cons	1.39	1.08	
	TotalCOST	9746.66	1286.45	
unit16	pctMin	0	3.37	unit9 (0.36), unit13 (0.02), unit50 (0.36), unit94 (0.08), unit98 (0.18)
	pctMod	0	20.09	
91.45%	pctSev	0	7.1	
	AvgLOS	20.53	20.53	
	AvTotOp	1.96	1.96	
	AvED_Treat	25.39	25.39	
	AvED_Doc	2	1.83	
	AvED_Cons	1.12	1.02	
	TotalCOST	1403.2	1274.02	
unit20	pctMin	0	7.14	unit22 (0.18),

96.43%	pctMod	0	39.28	unit50 (0.82)
	pctSev	0	7.14	
	AvgLOS	9.38	14.46	
	AvTotOp	1	1.39	
	AvED_Treat	1	21.36	
	AvED_Doc	1.25	1.14	
	AvED_Cons	1.04	1	
	TotalCOST	278	268.07	
unit21 77.56%	pctMin	6.15	9.6	unit13 (0.01), unit50 (0.43), unit103 (0.07), unit109 (0.11), unit110 (0.3), unit112 (0.07)
	pctMod	15.38	34.87	
	pctSev	13.85	13.85	
	AvgLOS	19.78	19.78	
	AvTotOp	1.88	1.88	
	AvED_Treat	8.94	19.98	
	AvED_Doc	1.77	1.37	
	AvED_Cons	1.33	1.03	
	TotalCOST	2772.51	2150.48	
unit24 87.8%	pctMin	0	10.64	unit50 (0.68), unit110 (0.32)
	pctMod	0.8	44.89	
	pctSev	0	14.27	
	AvgLOS	12.06	15.02	
	AvTotOp	1.23	1.41	
	AvED_Treat	24.63	24.63	
	AvED_Doc	2.53	1.4	
	AvED_Cons	1.14	1	
	TotalCOST	7887.42	630.37	
unit26 90.91%	pctMin	0	8.65	unit25 (0), unit50 (1)
	pctMod	0	47.6	
	pctSev	0	8.65	
	AvgLOS	11.27	16.38	
	AvTotOp	1.48	1.48	
	AvED_Treat	6.61	22.94	
	AvED_Doc	1.63	1.17	
	AvED_Cons	1.1	1	
	TotalCOST	18427.33	284.32	
unit27 86.54%	pctMin	0	1.68	unit25 (0.47), unit50 (0), unit94 (0.53)
	pctMod	0	13.34	
	pctSev	0	13.71	
	AvgLOS	15.26	15.75	
	AvTotOp	2.29	2.29	
	AvED_Treat	11.3	11.3	
	AvED_Doc	3.35	2.49	
	AvED_Cons	1.16	1	
	TotalCOST	8633.78	2565.34	

unit28 46.65%	pctMin	0	9.55	unit50 (0.04), unit94 (0), unit98 (0.14), unit110 (0.63), unit112 (0.2)
	pctMod	0	25.86	
	pctSev	16.67	16.67	
	AvgLOS	3.17	11.32	
	AvTotOp	3	3	
	AvED_Treat	23.67	23.67	
	AvED_Doc	3.67	1.71	
	AvED_Cons	2.33	1.09	
	TotalCOST	3759	968.92	
unit29 97.3%	pctMin	7.05	8.7	unit50 (1)
	pctMod	22.91	47.83	
	pctSev	5.29	8.7	
	AvgLOS	15.22	16.39	
	AvTotOp	1.4	1.47	
	AvED_Treat	22.94	23	
	AvED_Doc	2.12	1.17	
	AvED_Cons	1.03	1	
	TotalCOST	6031.21	278	
unit30 68.44%	pctMin	0	1.87	unit13 (0), unit22 (0.56), unit50 (0.21), unit102 (0.22)
	pctMod	0	10.26	
	pctSev	0	1.87	
	AvgLOS	12	12	
	AvTotOp	1.38	1.68	
	AvED_Treat	12.88	12.88	
	AvED_Doc	2.13	1.19	
	AvED_Cons	1.5	1.03	
	TotalCOST	269.58	184.49	
unit31 91.33%	pctMin	0	0	unit13 (0.03), unit22 (0.21), unit23 (0.02), unit102 (0.5), unit112 (0.24)
	pctMod	0	0	
	pctSev	0	0	
	AvgLOS	27.5	27.5	
	AvTotOp	4.01	4.01	
	AvED_Treat	1	4.41	
	AvED_Doc	1.51	1.38	
	AvED_Cons	1.26	1.15	
	TotalCOST	139	126.95	
unit33 92.35%	pctMin	0	8.09	unit13 (0.01), unit50 (0.93), unit94 (0), unit109 (0.06)
	pctMod	0	44.58	
	pctSev	3.08	8.76	
	AvgLOS	18.91	18.91	
	AvTotOp	1.48	1.48	
	AvED_Treat	21.71	21.71	
	AvED_Doc	1.71	1.18	
	AvED_Cons	1.08	1	
	TotalCOST	1460.75	1064.65	

unit35	pctMin	0	2.08	unit23 (0.62), unit50 (0.24), unit102 (0.14)
	pctMod	0	11.44	
86.31%	pctSev	0	2.08	
	AvgLOS	28	41.11	
	AvTotOp	3	3	
	AvED_Treat	1	6.26	
	AvED_Doc	2.58	1.35	
	AvED_Cons	1.23	1.06	
	TotalCOST	278	239.94	
unit36	pctMin	0	8.7	unit50 (1)
	pctMod	0	47.83	
85%	pctSev	0	8.7	
	AvgLOS	14.98	16.39	
	AvTotOp	1.22	1.47	
	AvED_Treat	22.88	23	
	AvED_Doc	2.44	1.17	
	AvED_Cons	1.18	1	
	TotalCOST	401.61	278	
unit37	pctMin	13.86	13.86	unit18 (0.03), unit49 (0.05), unit103 (0.04), unit110 (0.78), unit112 (0.1)
	pctMod	21.39	33.69	
90.34%	pctSev	22.59	22.59	
	AvgLOS	12.82	12.82	
	AvTotOp	2.02	2.02	
	AvED_Treat	18.38	23.92	
	AvED_Doc	2	1.8	
	AvED_Cons	1.4	1.05	
	TotalCOST	5319.05	1508.57	
unit39	pctMin	0	0	unit22 (0.7), unit85 (0.27), unit112 (0.03)
	pctMod	0	0	
82.27%	pctSev	0	0	
	AvgLOS	16.74	16.74	
	AvTotOp	1.5	1.5	
	AvED_Treat	1.63	11.78	
	AvED_Doc	1.22	1	
	AvED_Cons	1.53	1.11	
	TotalCOST	595.16	239.33	
unit43	pctMin	7.25	7.25	unit50 (0.43), unit86 (0.14), unit94 (0.21), unit110 (0.19), unit112 (0.03)
	pctMod	33.33	33.33	
81.8%	pctSev	13.04	14.2	
	AvgLOS	12	15.95	
	AvTotOp	2.41	2.41	
	AvED_Treat	20.61	20.61	
	AvED_Doc	2.84	2.12	
	AvED_Cons	1.27	1.04	
	TotalCOST	2463.3	1664.21	

unit44 75.39%	pctMin	0	8.26	unit25 (0.05), unit50 (0.95)
	pctMod	0	45.43	
	pctSev	0	8.26	
	AvgLOS	7.43	16.3	
	AvTotOp	1.5	1.5	
	AvED_Treat	1	22.36	
	AvED_Doc	1.84	1.17	
	AvED_Cons	1.33	1	
	TotalCOST	513.71	344.4	
unit45 77.55%	pctMin	0.61	3.03	unit9 (0.34), unit13 (0), unit50 (0.28), unit94 (0.18), unit98 (0.19)
	pctMod	0	18.93	
	pctSev	0	8.92	
	AvgLOS	14.01	14.01	
	AvTotOp	2.11	2.11	
	AvED_Treat	24.76	24.76	
	AvED_Doc	2.94	2.06	
	AvED_Cons	1.32	1.03	
	TotalCOST	1996.41	1548.3	
unit47 92.31%	pctMin	13.59	13.59	unit50 (0.2), unit110 (0.8)
	pctMod	27.72	40.43	
	pctSev	4.35	22.73	
	AvgLOS	12.89	12.95	
	AvTotOp	1.29	1.32	
	AvED_Treat	24.61	27.11	
	AvED_Doc	2.23	1.76	
	AvED_Cons	1.08	1	
	TotalCOST	3293.96	1164.68	
unit48 71.15%	pctMin	0	5.17	unit13 (0.02), unit22 (0.13), unit50 (0.59), unit102 (0.26)
	pctMod	0	28.43	
	pctSev	0	5.17	
	AvgLOS	21.71	21.71	
	AvTotOp	1.33	1.96	
	AvED_Treat	15.71	15.71	
	AvED_Doc	2.33	1.29	
	AvED_Cons	1.45	1.03	
	TotalCOST	278	197.79	
unit51 85.64%	pctMin	0	2.9	unit9 (0.32), unit13 (0.01), unit50 (0.29), unit94 (0.13), unit98 (0.25)
	pctMod	0	17.8	
	pctSev	0	7.51	
	AvgLOS	16.02	16.02	
	AvTotOp	2.18	2.18	
	AvED_Treat	25.65	25.65	
	AvED_Doc	2.3	1.97	

	AvED_Cons	1.21	1.03	
	TotalCOST	5709.91	1345.08	
unit52	pctMin	10.48	10.48	unit23 (0.12), unit50 (0.14), unit72 (0.21), unit98 (0.15), unit110 (0.36), unit112 (0.01)
	pctMod	22.58	28.53	
89.13%	pctSev	1.61	13.36	
	AvgLOS	17	17	
	AvTotOp	2.1	2.1	
	AvED_Treat	21.69	21.69	
	AvED_Doc	2.56	1.68	
	AvED_Cons	1.16	1.03	
	TotalCOST	1188.2	1059.08	
unit53	pctMin	13.58	13.58	unit13 (0.01), unit17 (0.21), unit50 (0.02), unit72 (0.36), unit94 (0.09), unit98 (0.1), unit110 (0.21)
	pctMod	16.36	30.71	
88.74%	pctSev	11.42	14.44	
	AvgLOS	16.53	16.53	
	AvTotOp	1.8	1.8	
	AvED_Treat	20.8	20.8	
	AvED_Doc	2.04	1.81	
	AvED_Cons	1.14	1.01	
	TotalCOST	2418.38	2146.08	
unit54	pctMin	1.79	1.9	unit13 (0.03), unit25 (0.48), unit50 (0.18), unit94 (0.11), unit98 (0.21)
	pctMod	5.66	11.27	
96.92%	pctSev	3.58	4.33	
	AvgLOS	22.95	22.95	
	AvTotOp	2.31	2.31	
	AvED_Treat	17.17	17.17	
	AvED_Doc	1.69	1.64	
	AvED_Cons	1.06	1.03	
	TotalCOST	6936.3	1250.96	
unit55	pctMin	11.3	14.19	unit13 (0.03), unit50 (0), unit103 (0), unit110 (0.96), unit112 (0)
	pctMod	22.59	37.12	
92.41%	pctSev	25.1	25.1	
	AvgLOS	24.42	24.42	
	AvTotOp	1.31	1.31	
	AvED_Treat	18.96	27.08	
	AvED_Doc	2.07	1.91	
	AvED_Cons	1.25	1	
	TotalCOST	3901.44	1336.62	
unit56	pctMin	0	1.07	unit13 (0), unit23 (0.18), unit25 (0.12), unit94 (0.34), unit98 (0.36)
	pctMod	0.67	8.57	
87.84%	pctSev	0.22	8.93	
	AvgLOS	21.08	21.08	
	AvTotOp	3.09	3.09	
	AvED_Treat	17.32	17.32	

	AvED_Doc	2.69	2.36	
	AvED_Cons	1.21	1.06	
	TotalCOST	7364.79	1516.86	
unit57	pctMin	8.33	9.98	unit13 (0.03), unit50 (0.45), unit94 (0.1), unit98 (0.01), unit110 (0.39), unit112 (0.02)
	pctMod	28.33	39.01	
90.39%	pctSev	16.67	16.67	
	AvgLOS	25.62	25.62	
	AvTotOp	1.64	1.64	
	AvED_Treat	23.06	23.06	
	AvED_Doc	1.93	1.74	
	AvED_Cons	1.12	1.01	
	TotalCOST	15295.57	1017.98	
unit58	pctMin	0	2.64	unit13 (0.01), unit25 (0.26), unit50 (0.23), unit94 (0.2), unit109 (0.3)
	pctMod	1.01	16.25	
87.93%	pctSev	1.01	10.03	
	AvgLOS	19.88	19.88	
	AvTotOp	1.87	1.87	
	AvED_Treat	10.03	11.78	
	AvED_Doc	1.85	1.63	
	AvED_Cons	1.14	1	
	TotalCOST	5841.56	5136.3	
unit59	pctMin	0.89	8.7	unit50 (1)
	pctMod	0	47.83	
80%	pctSev	0	8.7	
	AvgLOS	13.46	16.39	
	AvTotOp	1.32	1.47	
	AvED_Treat	17.91	23	
	AvED_Doc	2.2	1.17	
	AvED_Cons	1.25	1	
	TotalCOST	17590.87	278	
unit60	pctMin	0	8.7	unit50 (1)
	pctMod	1.05	47.83	
83.33%	pctSev	1.05	8.7	
	AvgLOS	11.27	16.39	
	AvTotOp	1.25	1.47	
	AvED_Treat	6.93	23	
	AvED_Doc	2.5	1.17	
	AvED_Cons	1.2	1	
	TotalCOST	4723.29	278	
unit61	pctMin	0	8.7	unit50 (1)
	pctMod	0	47.83	
97.78%	pctSev	0	8.7	
	AvgLOS	16.31	16.39	
	AvTotOp	1.17	1.47	
	AvED_Treat	18.32	23	

	AvED_Doc	1.36	1.17	
	AvED_Cons	1.02	1	
	TotalCOST	13283.71	278	
unit62	pctMin	2.64	2.64	unit13 (0.02), unit86 (0.02), unit94 (0.5), unit98 (0.39), unit110 (0.07)
	pctMod	4.88	15.33	
73.67%	pctSev	6.5	14.93	
	AvgLOS	17.97	17.97	
	AvTotOp	2.99	2.99	
	AvED_Treat	21.45	21.45	
	AvED_Doc	4.2	2.86	
	AvED_Cons	1.43	1.06	
	TotalCOST	6894.16	2026.66	
unit63	pctMin	0	8.7	unit50 (1)
	pctMod	0	47.83	
92.86%	pctSev	0	8.7	
	AvgLOS	15.57	16.39	
	AvTotOp	1.26	1.47	
	AvED_Treat	20.2	23	
	AvED_Doc	2.17	1.17	
	AvED_Cons	1.08	1	
	TotalCOST	11157.57	278	
unit66	pctMin	6.35	6.35	unit9 (0.26), unit13 (0), unit50 (0.13), unit94 (0.25), unit98 (0.05), unit110 (0.3)
	pctMod	10.79	24.81	
93%	pctSev	11.11	16.93	
	AvgLOS	15.38	15.38	
	AvTotOp	1.8	1.8	
	AvED_Treat	23.59	23.59	
	AvED_Doc	2.46	2.28	
	AvED_Cons	1.08	1.01	
	TotalCOST	3252.05	1950.55	
unit67	pctMin	0	5.87	unit25 (0.26), unit50 (0.64), unit94 (0.1)
	pctMod	0	33.06	
97.41%	pctSev	0	8.18	
	AvgLOS	15.97	15.97	
	AvTotOp	1.72	1.72	
	AvED_Treat	1.03	18.56	
	AvED_Doc	2	1.42	
	AvED_Cons	1.03	1	
	TotalCOST	11193.57	944.02	
unit68	pctMin	7.9	7.9	unit23 (0.04), unit72 (0.22), unit94 (0.33), unit109 (0.08), unit110 (0.19), unit112 (0.14)
	pctMod	9.73	23.7	
65.14%	pctSev	17.02	17.02	
	AvgLOS	15.83	15.83	
	AvTotOp	2.84	2.84	
	AvED_Treat	12.43	13.57	

	AvED_Doc	3.38	2.2	
	AvED_Cons	1.62	1.05	
	TotalCOST	4760.76	2963.33	
unit69	pctMin	0	8.7	unit50 (1)
	pctMod	0.47	47.83	
85.71%	pctSev	0	8.7	
	AvgLOS	12.51	16.39	
	AvTotOp	1.01	1.47	
	AvED_Treat	6.55	23	
	AvED_Doc	2.26	1.17	
	AvED_Cons	1.17	1	
	TotalCOST	8402.91	278	
unit70	pctMin	2.36	5.46	unit13 (0.01), unit25 (0.06), unit50 (0.48), unit94 (0.42), unit98 (0.04)
	pctMod	4.04	33.31	
90.76%	pctSev	2.36	15.13	
	AvgLOS	18.61	18.61	
	AvTotOp	2.05	2.05	
	AvED_Treat	17.99	17.99	
	AvED_Doc	2.5	2.27	
	AvED_Cons	1.11	1.01	
	TotalCOST	3508.83	1688.32	
unit71	pctMin	10.07	11.39	unit19 (0.03), unit50 (0.09), unit94 (0.13), unit110 (0.69), unit112 (0.05)
	pctMod	37.41	37.41	
77.73%	pctSev	22.3	22.3	
	AvgLOS	10.32	12.88	
	AvTotOp	1.94	1.94	
	AvED_Treat	22.02	23.39	
	AvED_Doc	4.13	2.06	
	AvED_Cons	1.32	1.03	
	TotalCOST	1870.52	1454	
unit74	pctMin	0	4.26	unit9 (0.05), unit13 (0), unit50 (0.38), unit94 (0.3), unit98 (0.26)
	pctMod	0	25.88	
85.41%	pctSev	0.34	11.36	
	AvgLOS	15	15	
	AvTotOp	2.41	2.41	
	AvED_Treat	22.62	22.62	
	AvED_Doc	3.11	2.18	
	AvED_Cons	1.21	1.04	
	TotalCOST	1554.19	1327.48	
unit75	pctMin	0	3.51	unit14 (0.41), unit22 (0.19), unit50 (0.4)
	pctMod	1.82	19.84	
81.1%	pctSev	0	3.51	
	AvgLOS	10.53	12.54	
	AvTotOp	1.47	1.47	

	AvED_Treat	1.58	16.43	
	AvED_Doc	1.33	1.08	
	AvED_Cons	1.23	1	
	TotalCOST	994.67	663.53	
unit76	pctMin	0	4.75	unit25 (0.39), unit50 (0.52), unit94 (0.07), unit98 (0.02)
	pctMod	0	26.69	
77.99%	pctSev	0	6.35	
	AvgLOS	12.64	15.52	
	AvTotOp	1.8	1.8	
	AvED_Treat	17.47	17.47	
	AvED_Doc	1.75	1.36	
	AvED_Cons	1.29	1	
	TotalCOST	4906.89	1012.87	
unit77	pctMin	5.41	6.82	unit23 (0.03), unit25 (0.43), unit50 (0.19), unit110 (0.35), unit112 (0)
	pctMod	18.92	22.54	
92.02%	pctSev	10.81	10.81	
	AvgLOS	10.73	15.2	
	AvTotOp	1.72	1.72	
	AvED_Treat	13.62	18.57	
	AvED_Doc	1.56	1.44	
	AvED_Cons	1.09	1	
	TotalCOST	1341.15	1234.07	
unit78	pctMin	10.89	10.89	unit50 (0.59), unit72 (0.15), unit94 (0.08), unit110 (0.19)
	pctMod	41.58	42.71	
73.21%	pctSev	13.86	13.86	
	AvgLOS	11.22	14.92	
	AvTotOp	1.54	1.54	
	AvED_Treat	18.84	21.87	
	AvED_Doc	2.75	1.57	
	AvED_Cons	1.37	1	
	TotalCOST	2308.75	998.74	
unit79	pctMin	0	0.52	unit13 (0), unit50 (0.06), unit98 (0.85), unit99 (0.08)
	pctMod	0	2.85	
95.45%	pctSev	0	0.52	
	AvgLOS	9	9	
	AvTotOp	2.5	3.43	
	AvED_Treat	31.8	31.8	
	AvED_Doc	2	1.91	
	AvED_Cons	1.17	1.12	
	TotalCOST	6918	433.45	
unit80	pctMin	0	10.14	unit9 (0.01), unit50 (0.74), unit110 (0.25)
	pctMod	0	45.04	
96%	pctSev	0	13.07	
	AvgLOS	11.96	15.28	

	AvTotOp	1.43	1.43	
	AvED_Treat	24.35	24.35	
	AvED_Doc	2.37	1.36	
	AvED_Cons	1.04	1	
	TotalCOST	13956.4	577.66	
unit83	pctMin	0	8.95	unit50 (0.96), unit110 (0.04)
	pctMod	0	47.44	
90.24%	pctSev	0	9.42	
	AvgLOS	16.2	16.21	
	AvTotOp	1.38	1.47	
	AvED_Treat	23.21	23.21	
	AvED_Doc	2.33	1.2	
	AvED_Cons	1.11	1	
	TotalCOST	14522.83	323.76	
unit84	pctMin	0	4.92	unit25 (0.25), unit50 (0.51), unit94 (0.15), unit98 (0.09)
	pctMod	0	28.25	
97.11%	pctSev	0	8.41	
	AvgLOS	9.35	15.1	
	AvTotOp	1.97	1.97	
	AvED_Treat	19.03	19.03	
	AvED_Doc	1.67	1.62	
	AvED_Cons	1.04	1.01	
	TotalCOST	1294.02	1091.31	
unit87	pctMin	0.42	7.68	unit13 (0), unit50 (0.88), unit109 (0.11)
	pctMod	0.42	42.31	
75.01%	pctSev	0	8.77	
	AvgLOS	17.66	17.66	
	AvTotOp	1.42	1.49	
	AvED_Treat	14.78	20.83	
	AvED_Doc	3.22	1.15	
	AvED_Cons	1.33	1	
	TotalCOST	2337.77	1753.61	
unit89	pctMin	0	0	unit13 (0.01), unit22 (0.73), unit42 (0.08), unit85 (0.11), unit109 (0.07)
	pctMod	0	0.05	
90.63%	pctSev	0	0.69	
	AvgLOS	13.33	13.33	
	AvTotOp	1.4	1.4	
	AvED_Treat	13.11	13.11	
	AvED_Doc	1.11	1.01	
	AvED_Cons	1.17	1.06	
	TotalCOST	3536.81	1290.07	
unit91	pctMin	0	6.48	unit25 (0.04),

	pctMod	0	37.33	unit50 (0.67), unit94 (0.21), unit98 (0.07)
88.35%	pctSev	0	11.4	
	AvgLOS	14.85	15.62	
	AvTotOp	1.9	1.9	
	AvED_Treat	20.88	20.88	
	AvED_Doc	2	1.77	
	AvED_Cons	1.14	1.01	
	TotalCOST	5391.27	1014.45	
unit92	pctMin	0	2.67	unit9 (0.21), unit13 (0.04), unit50 (0.28), unit94 (0.09), unit98 (0.38)
	pctMod	2	15.94	
65.81%	pctSev	1	5.78	
	AvgLOS	27.44	27.44	
	AvTotOp	2.42	2.42	
	AvED_Treat	26.03	26.03	
	AvED_Doc	2.92	1.92	
	AvED_Cons	1.6	1.05	
	TotalCOST	1983.17	989.93	
unit93	pctMin	10.78	10.78	unit13 (0.08), unit19 (0.02), unit50 (0.17), unit72 (0.14), unit110 (0.45), unit112 (0.14)
	pctMod	32.34	32.34	
87.33%	pctSev	8.38	15.11	
	AvgLOS	41.05	41.05	
	AvTotOp	2.34	2.34	
	AvED_Treat	19.43	19.43	
	AvED_Doc	3.12	1.66	
	AvED_Cons	1.21	1.06	
	TotalCOST	6116.67	1030.15	
unit96	pctMin	0	8.7	unit50 (1)
	pctMod	0	47.83	
69.81%	pctSev	0	8.7	
	AvgLOS	15.69	16.39	
	AvTotOp	1.36	1.47	
	AvED_Treat	19.45	23	
	AvED_Doc	2.2	1.17	
	AvED_Cons	1.43	1	
	TotalCOST	3151.49	278	
unit97	pctMin	0	2.06	unit13 (0.02), unit22 (0.69), unit50 (0.24), unit102 (0.05)
	pctMod	0	11.31	
94.01%	pctSev	0	2.06	
	AvgLOS	16.02	16.02	
	AvTotOp	1.24	1.24	
	AvED_Treat	2.34	15.11	
	AvED_Doc	1.66	1.1	
	AvED_Cons	1.07	1.01	
	TotalCOST	240.09	225.7	
unit100	pctMin	0	5.33	unit9 (0.35),

83.73%	pctMod	2.6	30.66	unit13 (0), unit50 (0.59), unit94 (0.06)
	pctSev	0.43	8.42	
	AvgLOS	15.58	15.58	
	AvTotOp	1.53	1.53	
	AvED_Treat	24.23	24.23	
	AvED_Doc	2.06	1.59	
	AvED_Cons	1.19	1	
	TotalCOST	2028.28	1169.03	
unit101	pctMin	0	6.14	unit25 (0.29), unit50 (0.71)
	pctMod	0	33.75	
88.37%	pctSev	0	6.14	
	AvgLOS	13.36	15.88	
	AvTotOp	1.63	1.63	
	AvED_Treat	16.19	19.21	
	AvED_Doc	2.08	1.17	
	AvED_Cons	1.13	1	
	TotalCOST	10524.72	668.81	
unit104	pctMin	12.07	12.07	unit17 (0.11), unit50 (0.08), unit94 (0.07), unit98 (0.11), unit110 (0.63)
	pctMod	27.59	33.35	
93.17%	pctSev	4.02	19.97	
	AvgLOS	9.86	12.47	
	AvTotOp	1.67	1.67	
	AvED_Treat	26.47	26.47	
	AvED_Doc	2.04	1.9	
	AvED_Cons	1.09	1.01	
	TotalCOST	4641.43	1571.81	
unit105	pctMin	1.04	2.86	unit42 (0.11), unit50 (0.33), unit98 (0.37), unit99 (0.19)
	pctMod	0	15.73	
87.81%	pctSev	0	2.86	
	AvgLOS	11.55	11.55	
	AvTotOp	1.2	2.56	
	AvED_Treat	27.62	27.62	
	AvED_Doc	1.73	1.52	
	AvED_Cons	1.24	1.09	
	TotalCOST	3123.71	814.57	
unit106	pctMin	13.38	13.38	unit17 (0.63), unit72 (0.1), unit86 (0.17), unit94 (0.02), unit110 (0.07)
	pctMod	26.06	26.23	
88.18%	pctSev	3.52	9.6	
	AvgLOS	14.66	15.26	
	AvTotOp	2.11	2.11	
	AvED_Treat	21.39	21.39	
	AvED_Doc	1.91	1.69	
	AvED_Cons	1.17	1.03	
	TotalCOST	6314.36	3339.76	

unit107 81.82%	pctMin	0	4.72	unit25 (0.46), unit50 (0.54)
	pctMod	0	25.96	
	pctSev	0	4.72	
	AvgLOS	13.66	15.59	
	AvTotOp	1.71	1.71	
	AvED_Treat	8.94	17.11	
	AvED_Doc	1.88	1.17	
	AvED_Cons	1.22	1	
	TotalCOST	5590	885.09	
unit108 92.88%	pctMin	0	5	unit13 (0), unit50 (0.51), unit94 (0.19), unit109 (0.3)
	pctMod	0.23	29.17	
	pctSev	0	12.15	
	AvgLOS	18.98	18.98	
	AvTotOp	1.72	1.72	
	AvED_Treat	15.35	15.35	
	AvED_Doc	2.4	1.6	
	AvED_Cons	1.08	1	
	TotalCOST	5521.73	4750.47	
unit111 87.81%	pctMin	0	5.62	unit25 (0.04), unit50 (0.6), unit94 (0.13), unit98 (0.23)
	pctMod	0.53	31.94	
	pctSev	0.53	8.58	
	AvgLOS	12.13	13.99	
	AvTotOp	2.17	2.17	
	AvED_Treat	23.36	23.36	
	AvED_Doc	1.91	1.68	
	AvED_Cons	1.17	1.03	
	TotalCOST	938.15	742.15	
unit113 65.34%	pctMin	0.73	8.05	unit50 (0.7), unit98 (0.17), unit110 (0.13)
	pctMod	2.19	38.66	
	pctSev	0.73	9.54	
	AvgLOS	12.4	14.1	
	AvTotOp	1.51	1.84	
	AvED_Treat	25.34	25.34	
	AvED_Doc	2.15	1.4	
	AvED_Cons	1.56	1.02	
	TotalCOST	1195.75	423.04	
unit114 92.86%	pctMin	0	5.65	unit9 (0.5), unit50 (0.28), unit110 (0.22)
	pctMod	0	23.08	
	pctSev	0	10.71	
	AvgLOS	11.72	13.82	
	AvTotOp	1.42	1.42	
	AvED_Treat	26.78	26.78	
	AvED_Doc	2.44	1.73	
	AvED_Cons	1.08	1	
	TotalCOST	3470.11	1540.57	

Year 2010

HOSPITAL	I/O	Actual	Target	Peers(lamda)
unit1	pctMin	5.42	5.42	unit17 (0.18), unit26 (0.44), unit35 (0.03), unit94 (0.2), unit112 (0.15)
	pctMod	4.95	12.94	
99.15%	pctSev	8.49	8.49	
	AvgLOS	14.64	14.64	
	AvTotOp	1.54	1.71	
	AvED_Treat	16.82	16.82	
	AvED_Doc	3.35	1.71	
	AvED_Cons	1.01	1	
	TotalCOST	174286.7	4747.84	
unit2	pctMin	0	3.27	unit17 (0.15), unit26 (0.35), unit79 (0.03), unit112 (0.48)
	pctMod	0.4	5.46	
81.13%	pctSev	0	1.09	
	AvgLOS	10.18	10.18	
	AvTotOp	1.86	1.86	
	AvED_Treat	24.46	24.46	
	AvED_Doc	2.07	1.22	
	AvED_Cons	1.23	1	
	TotalCOST	75461.13	2502.58	
unit3	pctMin	0	4.29	unit17 (0.19), unit26 (0.53), unit112 (0.28)
	pctMod	0	7.15	
85.71%	pctSev	0	1.43	
	AvgLOS	13.48	13.48	
	AvTotOp	1.29	1.5	
	AvED_Treat	20	20	
	AvED_Doc	2.59	1.32	
	AvED_Cons	1.17	1	
	TotalCOST	20050.22	3109.24	
unit4	pctMin	1.82	10.54	unit17 (0.33), unit26 (0.42), unit35 (0.14), unit79 (0.04), unit112 (0.07)
	pctMod	18.18	18.18	
88.89%	pctSev	1.82	2.9	
	AvgLOS	19.2	19.2	
	AvTotOp	1.45	1.45	
	AvED_Treat	16.36	16.36	
	AvED_Doc	2.04	1.32	
	AvED_Cons	1.12	1	
	TotalCOST	16661.35	5587.29	
unit5	pctMin	14.19	14.19	unit17 (0.19), unit26 (0.03), unit35 (0.4), unit79 (0.07),
	pctMod	24.32	29.04	
70.37%	pctSev	9.46	9.46	
	AvgLOS	15.64	15.64	

	AvTotOp	2.03	2.03	unit94 (0.19),
	AvED_Treat	17.74	17.74	unit112 (0.13)
	AvED_Doc	3.16	1.61	
	AvED_Cons	1.42	1	
	TotalCOST	40855.36	7256.57	
unit7	pctMin	4.01	5.43	unit17 (0.2),
	pctMod	5.39	13.59	unit26 (0.29),
82.72%	pctSev	9.96	9.96	unit79 (0.04),
	AvgLOS	14.21	14.21	unit94 (0.24),
	AvTotOp	2.01	2.01	unit112 (0.23)
	AvED_Treat	14.82	18.53	
	AvED_Doc	2.06	1.71	
	AvED_Cons	1.21	1	
	TotalCOST	182856.2	5037.93	
unit8	pctMin	3.74	14.41	unit17 (0.65),
	pctMod	4.28	24.02	unit26 (0.01),
98.65%	pctSev	2.14	4.8	unit112 (0.34)
	AvgLOS	24.1	24.1	
	AvTotOp	1.21	1.83	
	AvED_Treat	15.89	23.08	
	AvED_Doc	1.02	1	
	AvED_Cons	1.01	1	
	TotalCOST	50866.6	7651.91	
unit10	pctMin	9.32	11.4	unit17 (0.34),
	pctMod	20.34	20.34	unit26 (0.13),
79.45%	pctSev	4.24	4.24	unit35 (0.16),
	AvgLOS	16.8	16.8	unit94 (0.03),
	AvTotOp	1.28	1.8	unit112 (0.34)
	AvED_Treat	22.49	22.49	
	AvED_Doc	3.27	1.21	
	AvED_Cons	1.26	1	
	TotalCOST	48079.01	5837.43	
unit11	pctMin	1.76	7.25	unit17 (0.33),
	pctMod	2.94	12.09	unit26 (0.39),
92.31%	pctSev	0.59	2.42	unit79 (0.09),
	AvgLOS	17.56	17.56	unit112 (0.2)
	AvTotOp	1.72	1.72	
	AvED_Treat	16.62	18.58	
	AvED_Doc	1.37	1.27	
	AvED_Cons	1.08	1	
	TotalCOST	95175.52	4592.88	
unit12	pctMin	0	12.05	unit17 (0.5),
	pctMod	0.51	20.98	unit79 (0.09),
93.52%	pctSev	0	4.37	unit86 (0.14),

	AvgLOS	21.82	21.82	unit112 (0.27)
	AvTotOp	2.57	2.57	
	AvED_Treat	21.97	21.97	
	AvED_Doc	2.93	1.33	
	AvED_Cons	1.11	1.04	
	TotalCOST	254132.3	25481.63	
unit16	pctMin	0	9.3	unit17 (0.42), unit26 (0.12), unit112 (0.46)
	pctMod	0	15.5	
86.05%	pctSev	2.34	3.1	
	AvgLOS	17.12	17.12	
	AvTotOp	1.6	1.89	
	AvED_Treat	25.04	25.04	
	AvED_Doc	2.07	1.07	
	AvED_Cons	1.16	1	
	TotalCOST	71359.02	5229.76	
unit24	pctMin	1.03	1.67	unit26 (0.22), unit35 (0.07), unit112 (0.71)
	pctMod	3.09	3.09	
85.71%	pctSev	0	0.24	
	AvgLOS	4.19	4.19	
	AvTotOp	1.25	2.07	
	AvED_Treat	28.26	29.65	
	AvED_Doc	2.39	1.16	
	AvED_Cons	1.17	1	
	TotalCOST	29485.37	1265.52	
unit27	pctMin	1.53	3.88	unit17 (0.13), unit26 (0.35), unit79 (0.27), unit94 (0.24), unit112 (0.01)
	pctMod	5.47	11	
89.71%	pctSev	9.41	9.41	
	AvgLOS	14.7	14.7	
	AvTotOp	2.34	2.34	
	AvED_Treat	13.01	13.01	
	AvED_Doc	3.45	1.84	
	AvED_Cons	1.11	1	
	TotalCOST	140968.8	4703.66	
unit29	pctMin	8.3	11.63	unit17 (0.28), unit26 (0.03), unit35 (0.23), unit94 (0.04), unit112 (0.43)
	pctMod	21.13	21.13	
87.5%	pctSev	4.15	4.15	
	AvgLOS	14.37	14.37	
	AvTotOp	1.42	1.94	
	AvED_Treat	24.56	24.56	
	AvED_Doc	2.1	1.19	
	AvED_Cons	1.14	1	
	TotalCOST	75971.6	5607.81	
unit30	pctMin	10	10	unit17 (0.22), unit26 (0.18), unit35 (0.2),
	pctMod	14	19.53	
83.33%	pctSev	6	6	

	AvgLOS	14.44	14.44	unit94 (0.1), unit112 (0.29)
	AvTotOp	1.27	1.83	
	AvED_Treat	19.02	21.1	
	AvED_Doc	1.69	1.41	
	AvED_Cons	1.2	1	
	TotalCOST	14392.24	5474.94	
unit36	pctMin	0	7.99	unit17 (0.36), unit26 (0.33), unit112 (0.31)
	pctMod	0.67	13.32	
73.33%	pctSev	0.67	2.66	
	AvgLOS	17.25	17.25	
	AvTotOp	1.32	1.63	
	AvED_Treat	21.36	21.36	
	AvED_Doc	2.27	1.2	
	AvED_Cons	1.36	1	
	TotalCOST	38675.95	4761	
unit38	pctMin	9.88	21.66	unit6 (0.08), unit21 (0.11), unit40 (0.66), unit50 (0.08), unit110 (0.07)
	pctMod	49.38	49.38	
99.01%	pctSev	17.28	17.28	
	AvgLOS	12.37	16.47	
	AvTotOp	1.38	1.49	
	AvED_Treat	15.88	17.91	
	AvED_Doc	1.91	1.89	
	AvED_Cons	1.29	1.28	
	TotalCOST	24155.8	23916.96	
unit41	pctMin	0	2.97	unit17 (0.12), unit26 (0.41), unit79 (0.11), unit94 (0.08), unit112 (0.29)
	pctMod	5.66	6.5	
76.19%	pctSev	3.77	3.77	
	AvgLOS	11.47	11.47	
	AvTotOp	1.96	1.96	
	AvED_Treat	19.77	19.77	
	AvED_Doc	2.66	1.46	
	AvED_Cons	1.31	1	
	TotalCOST	27117.25	3044.19	
unit42	pctMin	3.51	7.06	unit17 (0.29), unit26 (0.14), unit94 (0.14), unit112 (0.43)
	pctMod	8.77	14.37	
86.67%	pctSev	7.02	7.02	
	AvgLOS	14.39	14.39	
	AvTotOp	1.25	2.04	
	AvED_Treat	20.35	23.62	
	AvED_Doc	1.59	1.38	
	AvED_Cons	1.15	1	
	TotalCOST	28258.04	5007.83	
unit43	pctMin	4.55	4.55	unit17 (0.12), unit26 (0.51), unit35 (0.07),
	pctMod	6.82	8.51	
86.96%	pctSev	2.27	2.27	

	AvgLOS	12	12	unit94 (0.03), unit112 (0.26)
	AvTotOp	1.37	1.53	
	AvED_Treat	19.61	19.61	
	AvED_Doc	2.74	1.41	
	AvED_Cons	1.15	1	
	TotalCOST	15567.44	3118.48	
unit44	pctMin	0	5.88	unit17 (0.26), unit26 (0.15), unit112 (0.59)
	pctMod	0.98	9.8	
88.37%	pctSev	1.96	1.96	
	AvgLOS	11.95	11.95	
	AvTotOp	1.57	1.99	
	AvED_Treat	27.42	27.42	
	AvED_Doc	2.49	1.09	
	AvED_Cons	1.13	1	
	TotalCOST	35686.5	3571.57	
unit45	pctMin	0	6.42	unit17 (0.29), unit26 (0.16), unit79 (0.13), unit112 (0.43)
	pctMod	0	10.7	
84.29%	pctSev	0.58	2.14	
	AvgLOS	14.15	14.15	
	AvTotOp	2.15	2.15	
	AvED_Treat	23.78	23.78	
	AvED_Doc	2.78	1.14	
	AvED_Cons	1.19	1	
	TotalCOST	72712.65	4050.94	
unit51	pctMin	0	9.38	unit17 (0.41), unit79 (0.24), unit86 (0.03), unit112 (0.32)
	pctMod	0	15.83	
83.35%	pctSev	0.83	3.2	
	AvgLOS	18.45	18.45	
	AvTotOp	2.52	2.52	
	AvED_Treat	21.9	21.9	
	AvED_Doc	2.35	1.16	
	AvED_Cons	1.21	1.01	
	TotalCOST	41117.95	9519.72	
unit52	pctMin	2.27	10.33	unit17 (0.44), unit79 (0.23), unit86 (0.08), unit94 (0), unit112 (0.24)
	pctMod	8.33	17.83	
83.86%	pctSev	3.79	3.79	
	AvgLOS	20.25	20.25	
	AvTotOp	2.67	2.67	
	AvED_Treat	20.48	20.48	
	AvED_Doc	2.62	1.28	
	AvED_Cons	1.22	1.02	
	TotalCOST	39815.92	17346.53	
unit53	pctMin	5.92	7.79	unit17 (0.32), unit26 (0.34), unit94 (0.18),
	pctMod	8.33	16.31	
90.65%	pctSev	8.55	8.55	

	AvgLOS	17.82	17.82	unit112 (0.17)
	AvTotOp	1.68	1.74	
	AvED_Treat	17.62	17.62	
	AvED_Doc	1.96	1.58	
	AvED_Cons	1.1	1	
	TotalCOST	140616.3	5771.81	
unit54	pctMin	6.35	11.32	unit17 (0.43), unit79 (0.04), unit86 (0.1), unit94 (0.26), unit112 (0.16)
	pctMod	10.39	24.46	
83.68%	pctSev	12.84	12.84	
	AvgLOS	21.27	21.27	
	AvTotOp	2.57	2.57	
	AvED_Treat	18.37	18.37	
	AvED_Doc	2.34	1.8	
	AvED_Cons	1.23	1.03	
	TotalCOST	283383.5	22121.54	
unit55	pctMin	7	11.83	unit17 (0.37), unit64 (0.12), unit79 (0.08), unit94 (0.05), unit110 (0.29), unit112 (0.09)
	pctMod	10	26.25	
88.1%	pctSev	13.67	13.67	
	AvgLOS	20.34	20.34	
	AvTotOp	1.75	1.75	
	AvED_Treat	19.68	19.68	
	AvED_Doc	1.57	1.38	
	AvED_Cons	1.14	1	
	TotalCOST	149302	14053.74	
unit56	pctMin	0.55	7.42	unit17 (0.33), unit26 (0.11), unit79 (0.5), unit112 (0.05)
	pctMod	0.37	12.36	
85.63%	pctSev	0.74	2.47	
	AvgLOS	18.96	18.96	
	AvTotOp	2.76	2.76	
	AvED_Treat	15.09	15.09	
	AvED_Doc	2.63	1.27	
	AvED_Cons	1.17	1	
	TotalCOST	179197.8	5118.41	
unit57	pctMin	10.1	10.1	unit17 (0.2), unit64 (0.24), unit94 (0.08), unit110 (0.45), unit112 (0.03)
	pctMod	11.4	26.92	
94.87%	pctSev	18.89	18.89	
	AvgLOS	16.16	17.36	
	AvTotOp	1.41	1.49	
	AvED_Treat	19.08	19.08	
	AvED_Doc	1.63	1.54	
	AvED_Cons	1.05	1	
	TotalCOST	84711.92	17531.44	
unit59	pctMin	3.01	4.66	unit17 (0.08), unit26 (0.36),
	pctMod	9.04	9.04	

74.32%	pctSev	2.41	2.41	unit35 (0.11), unit94 (0.04), unit112 (0.4)
	AvgLOS	9.64	9.64	
	AvTotOp	1.69	1.75	
	AvED_Treat	22.84	22.84	
	AvED_Doc	2.81	1.35	
	AvED_Cons	1.35	1	
	TotalCOST	47263.72	2938.84	
unit60	pctMin	2.7	4.18	unit17 (0.17), unit26 (0.53), unit79 (0.08), unit94 (0.11), unit112 (0.11)
	pctMod	4.32	9.05	
86.6%	pctSev	5.14	5.14	
	AvgLOS	14.62	14.62	
	AvTotOp	1.69	1.69	
	AvED_Treat	15.79	15.79	
	AvED_Doc	2.37	1.59	
	AvED_Cons	1.15	1	
	TotalCOST	151921.4	3879.33	
unit61	pctMin	1.12	6.53	unit17 (0.29), unit26 (0.19), unit112 (0.52)
	pctMod	2.61	10.89	
85.26%	pctSev	0.75	2.18	
	AvgLOS	13.43	13.43	
	AvTotOp	1.32	1.9	
	AvED_Treat	25.91	25.91	
	AvED_Doc	1.86	1.11	
	AvED_Cons	1.17	1	
	TotalCOST	74564.64	3926.52	
unit63	pctMin	4.37	4.37	unit17 (0.15), unit26 (0.49), unit35 (0.04), unit94 (0.03), unit112 (0.3)
	pctMod	4.37	7.93	
85.71%	pctSev	2.18	2.18	
	AvgLOS	12.35	12.35	
	AvTotOp	1.29	1.58	
	AvED_Treat	20.46	20.46	
	AvED_Doc	1.96	1.36	
	AvED_Cons	1.17	1	
	TotalCOST	65169.49	3127.1	
unit65	pctMin	0	8.45	unit6 (0.21), unit17 (0.25), unit26 (0.35), unit112 (0.19)
	pctMod	0	13.59	
88.23%	pctSev	7.69	10.78	
	AvgLOS	16.08	16.08	
	AvTotOp	1.5	1.61	
	AvED_Treat	1.92	17.31	
	AvED_Doc	1.37	1.21	
	AvED_Cons	1.14	1	
	TotalCOST	4801.23	4236.11	
unit66	pctMin	7.95	7.95	unit17 (0.26),

86.32%	pctMod	14.94	18.93	unit26 (0.01), unit35 (0.04), unit94 (0.29), unit112 (0.39)
	pctSev	12.29	12.29	
	AvgLOS	14.13	14.13	
	AvTotOp	1.71	2.28	
	AvED_Treat	22.51	22.51	
	AvED_Doc	2.91	1.65	
	AvED_Cons	1.16	1	
	TotalCOST	175056.2	6124.51	
unit67	pctMin	1.43	7.66	unit6 (0.01), unit17 (0.34), unit79 (0.14), unit112 (0.51)
	pctMod	1.43	12.74	
85.97%	pctSev	2.86	2.86	
	AvgLOS	14.56	14.56	
	AvTotOp	2.35	2.35	
	AvED_Treat	1.8	25.74	
	AvED_Doc	1.23	1.06	
	AvED_Cons	1.21	1	
	TotalCOST	8798	4527.5	
unit68	pctMin	3.84	5.35	unit17 (0.2), unit26 (0.14), unit79 (0.34), unit94 (0.21), unit112 (0.11)
	pctMod	5.37	12.84	
73.95%	pctSev	8.83	8.83	
	AvgLOS	15.29	15.29	
	AvTotOp	2.67	2.67	
	AvED_Treat	15.71	15.71	
	AvED_Doc	2.91	1.67	
	AvED_Cons	1.35	1	
	TotalCOST	194089.5	5156.89	
unit69	pctMin	2.06	4.57	unit26 (0.7), unit35 (0.18), unit94 (0.08), unit112 (0.04)
	pctMod	9.88	9.88	
81.32%	pctSev	3.29	3.29	
	AvgLOS	11.56	11.56	
	AvTotOp	1.09	1.28	
	AvED_Treat	9.94	14.46	
	AvED_Doc	2.39	1.66	
	AvED_Cons	1.23	1	
	TotalCOST	132765	3124.12	
unit70	pctMin	0	4.31	unit17 (0.19), unit26 (0.57), unit79 (0.13), unit112 (0.1)
	pctMod	0	7.18	
93.62%	pctSev	0.32	1.44	
	AvgLOS	15.25	15.25	
	AvTotOp	1.65	1.65	
	AvED_Treat	15.91	15.91	
	AvED_Doc	2.45	1.4	
	AvED_Cons	1.07	1	
	TotalCOST	98216.33	3369.66	
unit71	pctMin	9.8	10.7	unit35 (0.26),

53.85%	pctMod	30.07	30.07	unit94 (0.29), unit110 (0.3), unit112 (0.15)
	pctSev	18.95	18.95	
	AvgLOS	9.13	10.67	
	AvTotOp	1.58	1.96	
	AvED_Treat	21.86	21.86	
	AvED_Doc	4.15	1.98	
	AvED_Cons	1.86	1	
	TotalCOST	43638.2	12882.49	
unit74 86.21%	pctMin	3.01	12.16	unit17 (0.53), unit26 (0.03), unit79 (0.07), unit94 (0.08), unit112 (0.29)
	pctMod	6.02	21.71	
	pctSev	6.63	6.63	
	AvgLOS	21.79	21.79	
	AvTotOp	2.04	2.04	
	AvED_Treat	21.28	21.28	
	AvED_Doc	2.92	1.21	
	AvED_Cons	1.16	1	
	TotalCOST	47478.52	7153.41	
unit76 94.44%	pctMin	0.63	1.39	unit17 (0.06), unit26 (0.74), unit79 (0.08), unit112 (0.12)
	pctMod	0.63	2.32	
	pctSev	0	0.46	
	AvgLOS	11.79	11.79	
	AvTotOp	1.45	1.45	
	AvED_Treat	16.01	16.01	
	AvED_Doc	1.7	1.47	
	AvED_Cons	1.06	1	
	TotalCOST	48447.84	1981.94	
unit77 89.28%	pctMin	7.59	10.52	unit6 (0.25), unit17 (0.25), unit64 (0.35), unit103 (0.02), unit109 (0.13)
	pctMod	15.19	17.51	
	pctSev	18.99	18.99	
	AvgLOS	9.22	20.62	
	AvTotOp	1.42	1.55	
	AvED_Treat	7.71	7.71	
	AvED_Doc	1.12	1	
	AvED_Cons	1.12	1	
	TotalCOST	17381.6	15517.86	
unit78 73.24%	pctMin	12.26	17.04	unit17 (0.05), unit26 (0.03), unit35 (0.67), unit94 (0.09), unit112 (0.17)
	pctMod	33.02	33.02	
	pctSev	5.66	5.66	
	AvgLOS	12.27	12.27	
	AvTotOp	1.57	1.74	
	AvED_Treat	19.55	19.55	
	AvED_Doc	2.85	1.47	
	AvED_Cons	1.37	1	
	TotalCOST	30249.42	6782.69	
unit81	pctMin	4.2	12.53	unit6 (0.15),

	pctMod	6.99	20.52	unit17 (0.47), unit112 (0.38)
71.84%	pctSev	0.7	9.92	
	AvgLOS	19.45	19.45	
	AvTotOp	1.6	1.94	
	AvED_Treat	22.68	22.68	
	AvED_Doc	1.39	1	
	AvED_Cons	1.6	1	
	TotalCOST	41482.13	6160.55	
unit82	pctMin	0.98	8.56	unit17 (0.39), unit26 (0.61)
	pctMod	0	14.27	
92.31%	pctSev	0	2.85	
	AvgLOS	21.19	21.19	
	AvTotOp	1.09	1.19	
	AvED_Treat	8.95	14.3	
	AvED_Doc	1.66	1.37	
	AvED_Cons	1.08	1	
	TotalCOST	35013.16	5279.3	
unit83	pctMin	3.88	4.79	unit17 (0.21), unit26 (0.53), unit79 (0.12), unit94 (0.01), unit112 (0.13)
	pctMod	5.83	8.17	
76.79%	pctSev	1.94	1.94	
	AvgLOS	15.48	15.48	
	AvTotOp	1.66	1.66	
	AvED_Treat	16.58	16.58	
	AvED_Doc	2.34	1.39	
	AvED_Cons	1.3	1	
	TotalCOST	51057.36	3608.89	
unit84	pctMin	1.07	6.34	unit17 (0.29), unit26 (0.15), unit112 (0.57)
	pctMod	1.88	10.57	
82.93%	pctSev	0.8	2.11	
	AvgLOS	12.67	12.67	
	AvTotOp	1.47	1.97	
	AvED_Treat	12.55	27.05	
	AvED_Doc	1.31	1.09	
	AvED_Cons	1.21	1	
	TotalCOST	125796.8	3795.19	
unit85	pctMin	0.54	6.97	unit17 (0.31), unit26 (0.53), unit112 (0.16)
	pctMod	2.7	11.62	
93.94%	pctSev	0	2.32	
	AvgLOS	17.7	17.7	
	AvTotOp	1.15	1.39	
	AvED_Treat	6.56	17.76	
	AvED_Doc	1.4	1.32	
	AvED_Cons	1.06	1	
	TotalCOST	48413.07	4422.15	
unit87	pctMin	3	5.15	unit17 (0.22),

87.5%	pctMod	6.74	9.92	unit26 (0.67), unit94 (0.07), unit112 (0.04)
	pctSev	4.12	4.12	
	AvgLOS	16.69	16.69	
	AvTotOp	1.25	1.3	
	AvED_Treat	14.45	14.45	
	AvED_Doc	2.07	1.56	
	AvED_Cons	1.14	1	
	TotalCOST	79667.95	4095.22	
unit90	pctMin	15.17	15.17	unit17 (0.06), unit35 (0.42), unit110 (0.34), unit112 (0.17)
	pctMod	22.07	33.46	
81.82%	pctSev	10.34	10.74	
	AvgLOS	12.17	12.17	
	AvTotOp	1.54	1.57	
	AvED_Treat	24.59	24.59	
	AvED_Doc	2.92	1.45	
	AvED_Cons	1.22	1	
	TotalCOST	42751.69	13409.25	
unit91	pctMin	0	5.33	unit17 (0.24), unit26 (0.36), unit112 (0.4)
	pctMod	0	8.88	
88.89%	pctSev	0	1.78	
	AvgLOS	13.3	13.3	
	AvTotOp	1.67	1.71	
	AvED_Treat	23.08	23.08	
	AvED_Doc	1.95	1.21	
	AvED_Cons	1.12	1	
	TotalCOST	58445.45	3475.28	
unit92	pctMin	0	8.15	unit17 (0.37), unit26 (0.06), unit79 (0.1), unit112 (0.47)
	pctMod	0	13.58	
70.59%	pctSev	0	2.72	
	AvgLOS	15.67	15.67	
	AvTotOp	2.18	2.18	
	AvED_Treat	24.98	24.98	
	AvED_Doc	2.86	1.08	
	AvED_Cons	1.42	1	
	TotalCOST	27983.19	4784.34	
unit93	pctMin	6.56	14.14	unit17 (0.49), unit79 (0.08), unit86 (0.02), unit110 (0.28), unit112 (0.13)
	pctMod	28.96	28.96	
78.15%	pctSev	3.83	11.11	
	AvgLOS	22.36	22.36	
	AvTotOp	1.84	1.84	
	AvED_Treat	22.52	22.52	
	AvED_Doc	3.39	1.3	
	AvED_Cons	1.29	1	
	TotalCOST	50758.72	16017.96	
unit95	pctMin	4.82	7.18	unit17 (0.13),

81.82%	pctMod	14.46	14.46	unit26 (0.49), unit35 (0.16), unit94 (0.09), unit112 (0.12)
	pctSev	4.82	4.82	
	AvgLOS	13.96	13.96	
	AvTotOp	1.3	1.5	
	AvED_Treat	16.72	16.72	
	AvED_Doc	1.97	1.56	
	AvED_Cons	1.22	1	
	TotalCOST	31455.36	4406.9	
unit96	pctMin	0.6	5.87	unit17 (0.26), unit26 (0.46), unit112 (0.27)
	pctMod	1.19	9.78	
77.5%	pctSev	0	1.96	
	AvgLOS	15.26	15.26	
	AvTotOp	1.19	1.53	
	AvED_Treat	20.2	20.2	
	AvED_Doc	2.35	1.28	
	AvED_Cons	1.29	1	
	TotalCOST	47938	3827.09	
unit97	pctMin	0	6.02	unit17 (0.27), unit26 (0.61), unit79 (0.12)
	pctMod	0	10.03	
88.46%	pctSev	0	2.01	
	AvgLOS	18.24	18.24	
	AvTotOp	1.5	1.5	
	AvED_Treat	11.28	13.86	
	AvED_Doc	1.77	1.41	
	AvED_Cons	1.13	1	
	TotalCOST	52848.63	4220.58	
unit98	pctMin	0.66	3.82	unit17 (0.17), unit26 (0.57), unit79 (0.11), unit112 (0.15)
	pctMod	0	6.37	
89.29%	pctSev	0	1.27	
	AvgLOS	14.23	14.23	
	AvTotOp	1.63	1.63	
	AvED_Treat	16.93	16.93	
	AvED_Doc	2.1	1.39	
	AvED_Cons	1.12	1	
	TotalCOST	43552.33	3090.99	
unit100	pctMin	0.43	5.83	unit17 (0.26), unit26 (0.46), unit112 (0.28)
	pctMod	1.28	9.72	
85.42%	pctSev	0.43	1.94	
	AvgLOS	15.2	15.2	
	AvTotOp	1.41	1.54	
	AvED_Treat	19.43	20.24	
	AvED_Doc	1.49	1.28	
	AvED_Cons	1.17	1	
	TotalCOST	64084.89	3809.45	
unit101	pctMin	1.42	5.37	unit17 (0.24),

84.78%	pctMod	0.94	8.95	unit26 (0.44), unit112 (0.32)
	pctSev	0	1.79	
	AvgLOS	14.19	14.19	
	AvTotOp	1.51	1.59	
	AvED_Treat	21.24	21.24	
	AvED_Doc	2.46	1.26	
	AvED_Cons	1.18	1	
	TotalCOST	96004	3560.72	
unit102	pctMin	6.83	8.79	unit17 (0.36), unit64 (0.04), unit94 (0.19), unit112 (0.41)
	pctMod	12.68	18.26	
54.74%	pctSev	9.76	9.76	
	AvgLOS	16.43	16.43	
	AvTotOp	1.33	2.15	
	AvED_Treat	12.9	22.92	
	AvED_Doc	2.57	1.41	
	AvED_Cons	1.83	1	
	TotalCOST	43157.86	6401.6	
unit104	pctMin	12.17	17.79	unit17 (0.04), unit35 (0.64), unit94 (0.01), unit110 (0.16), unit112 (0.15)
	pctMod	35.65	35.65	
89.19%	pctSev	6.96	6.96	
	AvgLOS	12.33	12.33	
	AvTotOp	1.51	1.58	
	AvED_Treat	21.85	21.85	
	AvED_Doc	1.75	1.4	
	AvED_Cons	1.12	1	
	TotalCOST	63952.02	10202.18	
unit105	pctMin	11.11	11.11	unit17 (0.18), unit35 (0.28), unit94 (0.08), unit110 (0.02), unit112 (0.44)
	pctMod	7.41	21.61	
90.48%	pctSev	5.56	5.56	
	AvgLOS	12.04	12.04	
	AvTotOp	1.32	2.01	
	AvED_Treat	25.09	25.09	
	AvED_Doc	1.91	1.29	
	AvED_Cons	1.11	1	
	TotalCOST	16375.89	5851.53	
unit106	pctMin	17	17	unit17 (0.03), unit35 (0.48), unit72 (0.07), unit79 (0.1), unit86 (0.02), unit110 (0.29), unit112 (0.01)
	pctMod	35.5	35.5	
87.74%	pctSev	10.5	10.5	
	AvgLOS	13.19	13.19	
	AvTotOp	1.74	1.74	
	AvED_Treat	20.37	20.37	
	AvED_Doc	1.82	1.53	
	AvED_Cons	1.15	1.01	
	TotalCOST	58258.06	17558.19	
unit107	pctMin	2.68	3.55	unit17 (0.1),

	pctMod	8.04	8.04	unit26 (0.52), unit35 (0.04), unit94 (0.1), unit112 (0.24)
83.93%	pctSev	4.46	4.46	
	AvgLOS	11.57	11.57	
	AvTotOp	1.57	1.61	
	AvED_Treat	12.91	18.82	
	AvED_Doc	1.85	1.55	
	AvED_Cons	1.19	1	
	TotalCOST	36540.75	3201.4	
unit108	pctMin	3.42	7.76	unit17 (0.34), unit26 (0.41), unit79 (0.18), unit94 (0.07)
	pctMod	5.62	14.35	
85.23%	pctSev	5.13	5.13	
	AvgLOS	19.84	19.84	
	AvTotOp	1.86	1.86	
	AvED_Treat	12.86	13.9	
	AvED_Doc	2.68	1.48	
	AvED_Cons	1.17	1	
	TotalCOST	111566.4	5480.9	
unit111	pctMin	1.13	4.38	unit17 (0.2), unit26 (0.36), unit112 (0.45)
	pctMod	1.69	7.3	
96.77%	pctSev	1.13	1.46	
	AvgLOS	11.78	11.78	
	AvTotOp	1.74	1.75	
	AvED_Treat	23.92	23.92	
	AvED_Doc	1.87	1.21	
	AvED_Cons	1.03	1	
	TotalCOST	48420.68	3008.73	
unit113	pctMin	1.07	5.07	unit17 (0.22), unit33 (0.4), unit99 (0.07), unit110 (0.02), unit112 (0.29)
	pctMod	4.28	8.98	
66.59%	pctSev	2.14	2.14	
	AvgLOS	20.92	20.92	
	AvTotOp	1.4	1.78	
	AvED_Treat	25.32	25.32	
	AvED_Doc	2.03	1.35	
	AvED_Cons	1.51	1.01	
	TotalCOST	48232.92	13555.18	
unit114	pctMin	0	6.66	unit17 (0.3), unit26 (0.07), unit112 (0.63)
	pctMod	0	11.1	
85.42%	pctSev	1.14	2.22	
	AvgLOS	12.37	12.37	
	AvTotOp	1.24	2.07	
	AvED_Treat	28.52	28.52	
	AvED_Doc	1.98	1.04	
	AvED_Cons	1.17	1	
	TotalCOST	64419.87	3889.47	

Year 2011

HOSPITAL	I/O	Actual	Target	Peers(lamda)
unit2	pctMin	0.37	8.38	unit20 (0.32), unit24 (0.33), unit32 (0.06), unit44 (0.23), unit79 (0.05)
	pctMod	0.74	22.76	
82.56%	pctSev	0.37	8.01	
	AvgLOS	8.67	31.22	
	AvTotOp	1.74	1.74	
	AvED_Treat	21.14	21.14	
	AvED_Doc	2.07	1.71	
	AvED_Cons	1.26	1.04	
	TotalCOST	757.26	625.23	
unit3	pctMin	2.7	6.54	unit15 (0.12), unit17 (0.22), unit22 (0.48), unit44 (0.18)
	pctMod	10.81	21.31	
70.38%	pctSev	5.41	5.41	
	AvgLOS	13.73	16.34	
	AvTotOp	1.21	1.21	
	AvED_Treat	19.58	19.58	
	AvED_Doc	2.89	1.34	
	AvED_Cons	1.44	1.02	
	TotalCOST	543.43	382.45	
unit7	pctMin	2.36	11.79	unit20 (0.55), unit79 (0.22), unit86 (0.01), unit109 (0.22)
	pctMod	4.84	32.12	
95.25%	pctSev	22.46	22.46	
	AvgLOS	11.78	13.44	
	AvTotOp	1.88	1.88	
	AvED_Treat	14.02	15.87	
	AvED_Doc	1.31	1.15	
	AvED_Cons	1.05	1	
	TotalCOST	2188.07	2084.14	
unit8	pctMin	0.5	1	unit22 (0.8), unit32 (0.02), unit79 (0.1), unit99 (0.08)
	pctMod	0.5	19.17	
92.91%	pctSev	0.5	1.82	
	AvgLOS	26.91	26.91	
	AvTotOp	1.35	1.35	
	AvED_Treat	16.77	18.53	
	AvED_Doc	1.16	1.08	
	AvED_Cons	1.08	1	
	TotalCOST	851.54	658.95	
unit9	pctMin	1.82	5.5	unit20 (0.28), unit24 (0.12), unit25 (0.29), unit44 (0.29), unit79 (0.01)
	pctMod	0	16.16	
84.19%	pctSev	5.45	6.53	
	AvgLOS	12.65	12.65	
	AvTotOp	1.45	1.45	

	AvED_Treat	21.51	21.51	
	AvED_Doc	2.65	1.61	
	AvED_Cons	1.2	1.01	
	TotalCOST	664.33	559.27	
unit10	pctMin	6.33	6.49	unit20 (0.52), unit22 (0), unit25 (0.44), unit44 (0.04)
	pctMod	17.72	21.23	
63.64%	pctSev	3.16	7.28	
	AvgLOS	14.04	14.04	
	AvTotOp	1.43	1.43	
	AvED_Treat	18.78	18.78	
	AvED_Doc	3.08	1.25	
	AvED_Cons	1.57	1	
	TotalCOST	2546.63	612.03	
unit11	pctMin	1.59	5.93	unit20 (0.36), unit24 (0.09), unit25 (0.47), unit32 (0.01), unit79 (0.07)
	pctMod	9.84	18.01	
88.64%	pctSev	5.71	6.19	
	AvgLOS	17.32	17.32	
	AvTotOp	1.63	1.63	
	AvED_Treat	15.74	18.28	
	AvED_Doc	1.56	1.39	
	AvED_Cons	1.14	1.01	
	TotalCOST	887.14	786.36	
unit12	pctMin	0	7.11	unit32 (0.11), unit34 (0.18), unit79 (0.71)
	pctMod	0.5	22.75	
87.95%	pctSev	0.74	15.47	
	AvgLOS	20.77	56.18	
	AvTotOp	2.87	2.87	
	AvED_Treat	21.11	21.11	
	AvED_Doc	3.02	1.63	
	AvED_Cons	1.18	1.04	
	TotalCOST	4663.92	2962.43	
unit13	pctMin	3.95	7.64	unit20 (0.62), unit22 (0.35), unit32 (0.02)
	pctMod	16.23	31.76	
98.47%	pctSev	8.33	8.33	
	AvgLOS	17.84	21.92	
	AvTotOp	1.28	1.37	
	AvED_Treat	12.7	18.22	
	AvED_Doc	1.02	1	
	AvED_Cons	1.02	1	
	TotalCOST	1607.86	513.69	
unit14	pctMin	10.14	10.14	unit17 (0.2), unit20 (0.52), unit22 (0.18), unit25 (0.1)
	pctMod	16.22	29.5	
95.65%	pctSev	3.38	9.01	
	AvgLOS	13.66	13.66	

	AvTotOp	1.37	1.37	
	AvED_Treat	13.17	17.44	
	AvED_Doc	1.21	1.06	
	AvED_Cons	1.05	1	
	TotalCOST	1019.18	553.9	
unit16 86.28%	pctMin	0.34	4.21	unit20 (0.21), unit24 (0.07), unit25 (0.37), unit32 (0.01), unit44 (0.32), unit79 (0.01)
	pctMod	0.34	12.66	
	pctSev	0.67	5.71	
	AvgLOS	18.43	18.43	
	AvTotOp	1.41	1.41	
	AvED_Treat	22.07	22.07	
	AvED_Doc	1.85	1.6	
	AvED_Cons	1.17	1.01	
	TotalCOST	658.94	568.56	
unit18 71.16%	pctMin	6.67	9.69	unit20 (0.21), unit24 (0.07), unit25 (0.37), unit32 (0.01), unit44 (0.32), unit79 (0.01)
	pctMod	13.66	29.13	
	pctSev	15.93	15.93	
	AvgLOS	18.9	18.9	
	AvTotOp	2.6	2.6	
	AvED_Treat	18.51	18.51	
	AvED_Doc	4.23	1.48	
	AvED_Cons	1.43	1.02	
	TotalCOST	3550.93	2526.95	
unit23 99.64%	pctMin	0	6.55	unit20 (0.4), unit32 (0.27), unit67 (0.11), unit79 (0.22)
	pctMod	3.39	20.99	
	pctSev	1.69	8.66	
	AvgLOS	13.53	110.29	
	AvTotOp	2.07	2.07	
	AvED_Treat	17.93	19.41	
	AvED_Doc	1.12	1.12	
	AvED_Cons	1.07	1.06	
	TotalCOST	2014.81	2007.65	
unit26 92.93%	pctMin	0	4.7	unit20 (0.19), unit24 (0), unit25 (0.33), unit32 (0), unit44 (0.26), unit79 (0.22)
	pctMod	0	14.7	
	pctSev	1.11	7.88	
	AvgLOS	16.48	16.48	
	AvTotOp	1.77	1.77	
	AvED_Treat	21.17	21.17	
	AvED_Doc	1.66	1.54	
	AvED_Cons	1.08	1	
	TotalCOST	1366.82	1270.2	
unit27	pctMin	11.21	11.48	unit20 (0.19),

	pctMod	17.18	28.37	unit79 (0.45), unit109 (0.19), unit110 (0.16)
90.77%	pctSev	23	23	
	AvgLOS	14.94	16.24	
	AvTotOp	2.25	2.25	
	AvED_Treat	17.8	17.8	
	AvED_Doc	2.89	1.37	
	AvED_Cons	1.1	1	
	TotalCOST	3630.78	2814.58	
unit28	pctMin	13.46	13.46	unit20 (0.23), unit32 (0.01), unit79 (0.23), unit99 (0.01), unit110 (0.5)
	pctMod	28.85	33.65	
82.28%	pctSev	13.46	17.17	
	AvgLOS	10.77	19.49	
	AvTotOp	1.8	1.8	
	AvED_Treat	23.83	23.83	
	AvED_Doc	1.81	1.49	
	AvED_Cons	1.22	1	
	TotalCOST	3036.15	1715.82	
unit31	pctMin	0.6	0.6	unit20 (0.05), unit22 (0.55), unit32 (0.4)
	pctMod	0.6	12.52	
96.3%	pctSev	0	0.65	
	AvgLOS	9.78	161.4	
	AvTotOp	1.13	1.49	
	AvED_Treat	18.71	22.58	
	AvED_Doc	1.04	1	
	AvED_Cons	1.12	1.08	
	TotalCOST	901.22	285.32	
unit33	pctMin	0	6.09	unit24 (0.37), unit32 (0.42), unit44 (0.05), unit79 (0.04), unit86 (0.12)
	pctMod	1.08	11.71	
91.55%	pctSev	0	3.56	
	AvgLOS	16.18	162.83	
	AvTotOp	2.31	2.31	
	AvED_Treat	23.46	23.46	
	AvED_Doc	2.01	1.84	
	AvED_Cons	1.26	1.16	
	TotalCOST	692.11	633.65	
unit38	pctMin	14.4	14.4	unit20 (0.62), unit50 (0.17), unit77 (0.14), unit103 (0.06), unit104 (0.01)
	pctMod	42.4	42.4	
98.51%	pctSev	12	16.17	
	AvgLOS	11.73	12.43	
	AvTotOp	1.09	1.37	
	AvED_Treat	16.42	16.42	
	AvED_Doc	1.71	1.06	
	AvED_Cons	1.04	1.03	
	TotalCOST	754.91	743.69	

unit41 91.18%	pctMin	0	7.61	unit20 (0.49), unit44 (0.44), unit79 (0.07)
	pctMod	0	24.44	
	pctSev	0	10.93	
	AvgLOS	6.53	11.32	
	AvTotOp	1.46	1.46	
	AvED_Treat	23.23	23.23	
	AvED_Doc	2.49	1.49	
	AvED_Cons	1.1	1	
	TotalCOST	1038.92	799.14	
unit43 94.12%	pctMin	6.56	7.23	unit20 (0.44), unit44 (0.48), unit79 (0.08)
	pctMod	16.39	23.18	
	pctSev	4.92	10.74	
	AvgLOS	10.2	11.44	
	AvTotOp	1.46	1.46	
	AvED_Treat	23.64	23.64	
	AvED_Doc	2.59	1.53	
	AvED_Cons	1.06	1	
	TotalCOST	1736.62	813.01	
unit45 73.7%	pctMin	0	5.31	unit20 (0.1), unit24 (0.18), unit25 (0.26), unit44 (0.26), unit79 (0.21)
	pctMod	0.62	14.42	
	pctSev	1.85	7.1	
	AvgLOS	13.99	13.99	
	AvTotOp	1.87	1.87	
	AvED_Treat	20.88	20.88	
	AvED_Doc	2.8	1.74	
	AvED_Cons	1.38	1.01	
	TotalCOST	1599.64	1178.96	
unit46 85.71%	pctMin	3.7	5.23	unit20 (0.41), unit22 (0.49), unit44 (0.11)
	pctMod	2.47	26.44	
	pctSev	2.47	6.22	
	AvgLOS	13.62	14.99	
	AvTotOp	1.27	1.27	
	AvED_Treat	19.07	19.07	
	AvED_Doc	2.5	1.11	
	AvED_Cons	1.17	1	
	TotalCOST	1182.4	445.99	
unit47 87.15%	pctMin	16.22	18.05	unit20 (0.3), unit22 (0.06), unit32 (0.01), unit104 (0.64)
	pctMod	41.89	41.89	
	pctSev	4.95	10.15	
	AvgLOS	13.81	13.81	
	AvTotOp	1.16	1.46	
	AvED_Treat	17.19	19.91	
	AvED_Doc	2.19	1.63	
	AvED_Cons	1.2	1.05	

	TotalCOST	604.68	526.97	
unit51 89.08%	pctMin	0	5.96	unit24 (0.29), unit25 (0.13), unit32 (0.01), unit44 (0.28), unit79 (0.29)
	pctMod	0.61	14.86	
	pctSev	1.21	7.6	
	AvgLOS	15.75	15.75	
	AvTotOp	2.1	2.1	
	AvED_Treat	21.03	21.03	
	AvED_Doc	2.34	1.89	
	AvED_Cons	1.15	1.03	
	TotalCOST	1566.82	1395.74	
unit52 87.94%	pctMin	11.19	11.54	unit20 (0.7), unit24 (0.03), unit32 (0.01), unit44 (0.06), unit79 (0.09), unit110 (0.1)
	pctMod	35.07	35.07	
	pctSev	0	13.49	
	AvgLOS	16.06	16.06	
	AvTotOp	1.63	1.63	
	AvED_Treat	20.1	20.1	
	AvED_Doc	2.38	1.22	
	AvED_Cons	1.14	1	
	TotalCOST	1130.3	993.93	
unit53 75%	pctMin	16.24	16.52	unit20 (0.45), unit25 (0.01), unit50 (0.35), unit79 (0.19)
	pctMod	24.83	36.05	
	pctSev	14.39	14.39	
	AvgLOS	15.25	15.25	
	AvTotOp	1.74	1.74	
	AvED_Treat	16.54	17.38	
	AvED_Doc	2.05	1.11	
	AvED_Cons	1.33	1	
	TotalCOST	2371.09	1330.25	
unit55 89.49%	pctMin	18.6	18.6	unit32 (0), unit50 (0.45), unit79 (0.17), unit99 (0.06), unit109 (0.22), unit110 (0.1)
	pctMod	23.95	31	
	pctSev	23.26	23.26	
	AvgLOS	18.49	18.49	
	AvTotOp	1.6	1.6	
	AvED_Treat	16.71	16.71	
	AvED_Doc	1.82	1.2	
	AvED_Cons	1.12	1	
	TotalCOST	3171.6	2055.63	
unit56 85.85%	pctMin	15.54	15.54	unit19 (0.23), unit72 (0.02), unit79 (0.52), unit109 (0.19), unit110 (0.03)
	pctMod	15.73	25.82	
	pctSev	21.72	21.72	
	AvgLOS	17.16	17.24	
	AvTotOp	2.42	2.42	
	AvED_Treat	15.17	15.17	

	AvED_Doc	2.62	1.44	
	AvED_Cons	1.16	1	
	TotalCOST	4978.11	3066.9	
unit57	pctMin	7.35	15.76	unit20 (0.56), unit25 (0.11), unit50 (0.32), unit79 (0.01)
	pctMod	10.29	35.21	
98%	pctSev	12.65	12.65	
	AvgLOS	14.11	14.11	
	AvTotOp	1.4	1.4	
	AvED_Treat	17.46	17.56	
	AvED_Doc	1.57	1.06	
	AvED_Cons	1.02	1	
	TotalCOST	2853.18	742.07	
unit59	pctMin	23.16	23.16	unit20 (0.07), unit32 (0), unit50 (0.41), unit103 (0.06), unit104 (0.39), unit110 (0.07)
	pctMod	42.11	42.11	
84.94%	pctSev	10	13.4	
	AvgLOS	15.35	15.35	
	AvTotOp	1.34	1.34	
	AvED_Treat	19.19	19.19	
	AvED_Doc	2.64	1.45	
	AvED_Cons	1.22	1.04	
	TotalCOST	1829.49	730.83	
unit60	pctMin	0	8.73	unit20 (0.42), unit25 (0.11), unit79 (0.47)
	pctMod	0.17	27.6	
88.37%	pctSev	0.69	12.79	
	AvgLOS	15.64	15.64	
	AvTotOp	2.34	2.34	
	AvED_Treat	16.57	17.95	
	AvED_Doc	1.86	1.31	
	AvED_Cons	1.13	1	
	TotalCOST	2473.8	2133.9	
unit61	pctMin	8.95	8.95	unit20 (0.53), unit44 (0.32), unit50 (0.01), unit79 (0.06), unit99 (0.02), unit110 (0.05)
	pctMod	27.78	27.78	
79.81%	pctSev	7.41	11.76	
	AvgLOS	11.58	11.58	
	AvTotOp	1.47	1.47	
	AvED_Treat	22.56	22.56	
	AvED_Doc	2.35	1.4	
	AvED_Cons	1.25	1	
	TotalCOST	2712.32	840.96	
unit63	pctMin	16.22	16.22	unit17 (0.55), unit44 (0.26), unit50 (0.2)
	pctMod	15.77	23.79	
89.39%	pctSev	4.95	10.69	
	AvgLOS	11.61	14.85	
	AvTotOp	1.18	1.23	

	AvED_Treat	19.03	19.03	
	AvED_Doc	2.12	1.31	
	AvED_Cons	1.12	1	
	TotalCOST	1450.78	578.45	
unit64	pctMin	1.03	15.21	unit20 (0.36), unit50 (0.19), unit79 (0.14), unit109 (0.31)
	pctMod	3.09	31.9	
86.21%	pctSev	26.12	26.12	
	AvgLOS	14.89	14.89	
	AvTotOp	1.63	1.63	
	AvED_Treat	1.83	14.68	
	AvED_Doc	1.81	1.1	
	AvED_Cons	1.16	1	
	TotalCOST	8223.56	2121.92	
unit66	pctMin	12.91	16.82	unit20 (0.49), unit50 (0.26), unit79 (0.05), unit109 (0.05), unit110 (0.15)
	pctMod	27.93	37.48	
96.49%	pctSev	17.12	17.12	
	AvgLOS	13.86	13.86	
	AvTotOp	1.47	1.47	
	AvED_Treat	18.75	18.75	
	AvED_Doc	2.51	1.14	
	AvED_Cons	1.04	1	
	TotalCOST	2422.58	1133.87	
unit68	pctMin	8.5	11.98	unit20 (0.28), unit79 (0.31), unit86 (0.19), unit109 (0.22)
	pctMod	25.98	27.76	
69.46%	pctSev	22.05	22.05	
	AvgLOS	14.61	15.14	
	AvTotOp	2.54	2.54	
	AvED_Treat	12.81	16.11	
	AvED_Doc	3.52	1.62	
	AvED_Cons	1.53	1.06	
	TotalCOST	3769.28	2618.28	
unit69	pctMin	14.96	14.96	unit17 (0.4), unit20 (0.51), unit44 (0.05), unit50 (0.04)
	pctMod	23.93	32.79	
75.8%	pctSev	11.97	11.97	
	AvgLOS	11.41	12.32	
	AvTotOp	1.15	1.38	
	AvED_Treat	17.35	17.35	
	AvED_Doc	2.81	1.08	
	AvED_Cons	1.32	1	
	TotalCOST	2310.03	610.14	
unit70	pctMin	0	7.95	unit20 (0.46), unit25 (0.17), unit44 (0.1), unit79 (0.27)
	pctMod	0.78	25.37	
81.74%	pctSev	0.26	11.07	
	AvgLOS	14.39	14.39	

	AvTotOp	1.94	1.94	
	AvED_Treat	19.22	19.22	
	AvED_Doc	2.7	1.33	
	AvED_Cons	1.22	1	
	TotalCOST	1862	1496.09	
unit74 99.84%	pctMin	11.44	16.18	unit32 (0), unit79 (0.23), unit86 (0.07), unit103 (0.4), unit104 (0.17), unit110 (0.13)
	pctMod	40.25	40.25	
	pctSev	13.98	14.37	
	AvgLOS	16.49	16.49	
	AvTotOp	1.99	1.99	
	AvED_Treat	20.32	20.32	
	AvED_Doc	2.49	1.65	
	AvED_Cons	1.09	1.09	
	TotalCOST	1658.8	1656.1	
unit75 99.26%	pctMin	0.9	7.87	unit20 (0.46), unit22 (0.15), unit24 (0.22), unit32 (0.17)
	pctMod	1.81	25.69	
	pctSev	0.45	6.86	
	AvgLOS	14.07	73.82	
	AvTotOp	1.66	1.66	
	AvED_Treat	16.05	19.89	
	AvED_Doc	1.3	1.29	
	AvED_Cons	1.06	1.05	
	TotalCOST	451.98	448.62	
unit76 84.73%	pctMin	0	8.57	unit20 (0.63), unit24 (0.07), unit25 (0.29), unit72 (0.01)
	pctMod	1.12	26.85	
	pctSev	1.69	8.71	
	AvgLOS	12.29	12.29	
	AvTotOp	1.51	1.51	
	AvED_Treat	17.24	18.17	
	AvED_Doc	1.52	1.24	
	AvED_Cons	1.19	1.01	
	TotalCOST	719.64	609.76	
unit81 94.7%	pctMin	19.47	19.47	unit6 (0.55), unit32 (0.18), unit35 (0.08), unit104 (0.19)
	pctMod	35.79	36.93	
	pctSev	5.79	11.76	
	AvgLOS	15.22	77.24	
	AvTotOp	1.47	1.51	
	AvED_Treat	21.86	21.86	
	AvED_Doc	1.44	1.37	
	AvED_Cons	1.19	1.11	
	TotalCOST	616.09	583.45	
unit82	pctMin	3.68	3.68	unit22 (0.61), unit50 (0.1),
	pctMod	1.47	21.03	

78.57%	pctSev	0.74	2.68	unit99 (0.29)
	AvgLOS	19.99	19.99	
	AvTotOp	1.09	1.12	
	AvED_Treat	16.62	20.15	
	AvED_Doc	1.5	1.09	
	AvED_Cons	1.27	1	
	TotalCOST	1261.96	482.83	
unit83 85.08%	pctMin	17.78	17.78	unit20 (0.43), unit32 (0), unit44 (0.02), unit50 (0.04), unit104 (0.47), unit110 (0.04)
	pctMod	41.78	41.78	
	pctSev	8.89	11.91	
	AvgLOS	11.8	11.8	
	AvTotOp	1.39	1.45	
	AvED_Treat	19.96	19.96	
	AvED_Doc	2.42	1.51	
	AvED_Cons	1.21	1.03	
	TotalCOST	719.29	611.97	
unit84 88.72%	pctMin	2.97	10.89	unit20 (0.76), unit24 (0.13), unit25 (0.08), unit72 (0), unit79 (0.02)
	pctMod	8.07	33.67	
	pctSev	2.97	10.94	
	AvgLOS	10.31	10.31	
	AvTotOp	1.6	1.6	
	AvED_Treat	17.91	18.02	
	AvED_Doc	1.39	1.23	
	AvED_Cons	1.14	1.01	
	TotalCOST	763.32	677.19	
unit85 97.3%	pctMin	18.07	18.07	unit17 (0.02), unit20 (0.33), unit22 (0.15), unit50 (0.5)
	pctMod	36.14	36.14	
	pctSev	10.04	12.44	
	AvgLOS	16.25	16.25	
	AvTotOp	1.12	1.29	
	AvED_Treat	16.72	17.03	
	AvED_Doc	1.35	1.01	
	AvED_Cons	1.03	1	
	TotalCOST	860.44	695.27	
unit87 90%	pctMin	9.26	10.44	unit20 (0.7), unit22 (0.23), unit50 (0.07)
	pctMod	35.19	35.19	
	pctSev	9.26	10.44	
	AvgLOS	12.86	12.86	
	AvTotOp	1.29	1.38	
	AvED_Treat	17.79	17.89	
	AvED_Doc	1.66	1	
	AvED_Cons	1.11	1	

	TotalCOST	820.65	585.6	
unit91 93.89%	pctMin	8.11	8.11	unit20 (0.56), unit22 (0.13), unit25 (0.13), unit50 (0.02), unit79 (0.06), unit99 (0.1)
	pctMod	13.51	28.92	
	pctSev	5.41	9.1	
	AvgLOS	14.22	14.22	
	AvTotOp	1.5	1.5	
	AvED_Treat	18.95	18.95	
	AvED_Doc	1.2	1.13	
	AvED_Cons	1.07	1	
	TotalCOST	1092.05	816.99	
unit92 70.57%	pctMin	0	4.56	unit24 (0.06), unit32 (0.02), unit44 (0.64), unit79 (0.26), unit86 (0.02)
	pctMod	0.86	12.54	
	pctSev	0	9.28	
	AvgLOS	20.34	20.34	
	AvTotOp	1.85	1.85	
	AvED_Treat	25.62	25.62	
	AvED_Doc	3.04	1.92	
	AvED_Cons	1.44	1.02	
	TotalCOST	1915.1	1351.45	
unit93 86.8%	pctMin	6.7	9.22	unit20 (0.11), unit24 (0.35), unit32 (0.01), unit44 (0.21), unit79 (0.18), unit110 (0.14)
	pctMod	22.35	22.35	
	pctSev	5.59	9.86	
	AvgLOS	16	16	
	AvTotOp	1.93	1.93	
	AvED_Treat	21.8	21.8	
	AvED_Doc	3.07	1.87	
	AvED_Cons	1.19	1.03	
	TotalCOST	1302.97	1130.93	
unit94 85.79%	pctMin	5.26	7.3	unit20 (0.13), unit22 (0.02), unit25 (0.59), unit32 (0), unit44 (0.04), unit50 (0.2)
	pctMod	10.53	14.07	
	pctSev	5.26	5.26	
	AvgLOS	19.21	19.21	
	AvTotOp	1.35	1.35	
	AvED_Treat	18.47	18.47	
	AvED_Doc	2.75	1.33	
	AvED_Cons	1.17	1	
	TotalCOST	723.37	620.57	
unit96 86.36%	pctMin	1.42	1.42	unit17 (0.01), unit20 (0.06), unit22 (0.73), unit44 (0.2)
	pctMod	1.9	18.28	
	pctSev	0	2.46	
	AvgLOS	12.99	17.57	
	AvTotOp	1.14	1.14	
	AvED_Treat	20	20	

	AvED_Doc	2.21	1.2	
	AvED_Cons	1.16	1	
	TotalCOST	1093.79	328.04	
unit97	pctMin	0	6.21	unit20 (0.47), unit22 (0.21), unit25 (0.13), unit44 (0.19)
	pctMod	0.95	24.27	
81.25%	pctSev	0	7.68	
	AvgLOS	13.57	13.57	
	AvTotOp	1.33	1.33	
	AvED_Treat	20.23	20.23	
	AvED_Doc	2.08	1.25	
	AvED_Cons	1.23	1	
	TotalCOST	1121.33	528.91	
unit100	pctMin	1.52	6.19	unit20 (0.41), unit25 (0.26), unit44 (0.27), unit79 (0.06)
	pctMod	7.22	19.93	
87.65%	pctSev	1.52	8.46	
	AvgLOS	13.36	13.36	
	AvTotOp	1.48	1.48	
	AvED_Treat	21.3	21.3	
	AvED_Doc	2.11	1.43	
	AvED_Cons	1.14	1	
	TotalCOST	1074.28	778.18	
unit101	pctMin	0	1.64	unit20 (0.11), unit22 (0.75), unit44 (0.14)
	pctMod	0.5	19.78	
87.5%	pctSev	0.5	2.46	
	AvgLOS	15.01	17.72	
	AvTotOp	1.15	1.15	
	AvED_Treat	19.3	19.3	
	AvED_Doc	2.17	1.14	
	AvED_Cons	1.14	1	
	TotalCOST	1485.75	329.72	
unit102	pctMin	0.33	5.31	unit20 (0.43), unit25 (0.56), unit79 (0.01)
	pctMod	0.66	17.35	
80%	pctSev	2.97	5.85	
	AvgLOS	15.23	15.23	
	AvTotOp	1.45	1.45	
	AvED_Treat	11.8	18.36	
	AvED_Doc	2.3	1.27	
	AvED_Cons	1.25	1	
	TotalCOST	1928.42	632.24	
unit105	pctMin	4.76	5.04	unit20 (0.2), unit44 (0.49), unit79 (0.09), unit99 (0.22)
	pctMod	2.38	17.87	
77.78%	pctSev	0	8.61	
	AvgLOS	10.1	13.9	
	AvTotOp	1.41	1.41	

	AvED_Treat	25.67	25.67	
	AvED_Doc	2.07	1.61	
	AvED_Cons	1.29	1	
	TotalCOST	2017.05	904.79	
unit107	pctMin	12.07	12.07	unit20 (0.6), unit24 (0.14), unit32 (0.06), unit72 (0.02), unit79 (0.02), unit110 (0.15)
	pctMod	10.34	33.75	
85.37%	pctSev	6.9	12.22	
	AvgLOS	7.57	32.11	
	AvTotOp	1.62	1.62	
	AvED_Treat	20.26	20.26	
	AvED_Doc	1.54	1.32	
	AvED_Cons	1.2	1.02	
	TotalCOST	902.52	770.5	
unit108	pctMin	3.43	6.32	unit20 (0.39), unit25 (0.41), unit79 (0.21)
	pctMod	6.6	20.26	
83.46%	pctSev	4.22	8.35	
	AvgLOS	15.77	15.77	
	AvTotOp	1.83	1.83	
	AvED_Treat	14.36	18.2	
	AvED_Doc	2.72	1.31	
	AvED_Cons	1.2	1	
	TotalCOST	3053.96	1282.2	
unit111	pctMin	0.76	7.87	unit20 (0.51), unit25 (0.09), unit44 (0.28), unit79 (0.13)
	pctMod	3.82	25.29	
84.78%	pctSev	1.53	10.81	
	AvgLOS	12.47	12.47	
	AvTotOp	1.62	1.62	
	AvED_Treat	21.31	21.31	
	AvED_Doc	1.99	1.39	
	AvED_Cons	1.18	1	
	TotalCOST	1237.15	1006.92	
unit113	pctMin	0	6.72	unit20 (0.29), unit22 (0.33), unit24 (0.29), unit32 (0.03), unit44 (0.06)
	pctMod	0.3	24.5	
81.6%	pctSev	0.6	5.38	
	AvgLOS	22.09	22.58	
	AvTotOp	1.54	1.54	
	AvED_Treat	18.68	18.68	
	AvED_Doc	1.77	1.44	
	AvED_Cons	1.26	1.03	
	TotalCOST	480	391.67	
unit114	pctMin	0	3.61	unit20 (0.24), unit22 (0.51), unit44 (0.25)
	pctMod	0.65	21.42	
89.74%	pctSev	1.3	5.14	

	AvgLOS	12.69	15.41	
	AvTotOp	1.21	1.21	
	AvED_Treat	20.7	20.7	
	AvED_Doc	1.92	1.25	
	AvED_Cons	1.11	1	
	TotalCOST	896.82	410	

Year2012

HOSPITAL	I/O	Actual	Target	Peers(lamda)
unit2	pctMin	0.85	15.36	unit6 (0.01),
	pctMod	0.42	0.42	unit25 (0.06),
68.06%	pctSev	0.42	1.63	unit73 (0.22),
	AvgLOS	7.87	7.87	unit94 (0.1),
	AvTotOp	1.74	1.74	unit95 (0.01)
	AvED_Treat	20.95	20.95	unit24 (0.6),
	AvED_Doc	2.2	1.49	
	AvED_Cons	1.47	1	
	TotalCOST	643.76	381.23	
unit3	pctMin	14.63	14.63	unit6 (0.22),
	pctMod	19.51	19.99	unit43 (0.06),
76.4%	pctSev	19.51	19.51	unit50 (0.06),
	AvgLOS	15.93	15.93	unit58 (0.12),
	AvTotOp	1.26	1.26	unit94 (0.01)
	AvED_Treat	17.88	17.88	unit24 (0.03),
	AvED_Doc	2.61	1.59	
	AvED_Cons	1.33	1.02	
	TotalCOST	775.9	592.76	
unit9	pctMin	5.26	15.7	unit6 (0.54),

	pctMod	2.63	26.64	unit43 (0.15),
87.5%	pctSev	13.16	13.16	unit79 (0.27)
	AvgLOS	10.63	11.83	unit24 (0.04),
	AvTotOp	1.48	1.48	
	AvED_Treat	20.95	20.95	
	AvED_Doc	2.68	2.03	
	AvED_Cons	1.14	1	
	TotalCOST	1116.74	506.13	
unit10	pctMin	4.17	15.04	unit6 (0.49),
	pctMod	16.67	21.38	
85.71%	pctSev	4.17	8.52	
	AvgLOS	13.88	13.88	unit94 (0.33)
	AvTotOp	1.1	1.41	unit24 (0.17),
	AvED_Treat	18.75	18.75	
	AvED_Doc	2.8	1.54	
	AvED_Cons	1.17	1	
	TotalCOST	1445.5	265.32	
unit14	pctMin	22.55	37.04	unit6 (0.07),
	pctMod	36.27	36.27	unit50 (0.76)
95.83%	pctSev	9.8	10.31	unit24 (0.05),
	AvgLOS	11.25	11.9	unit22 (0.13),
	AvTotOp	1.35	1.35	
	AvED_Treat	15.57	16.11	
	AvED_Doc	1.18	1.13	
	AvED_Cons	1.04	1	
	TotalCOST	767.29	369.84	

unit16	pctMin	0	3.86	unit6 (0.17),
	pctMod	0.46	7.78	unit58 (0.01)
90.99%	pctSev	1.38	1.38	unit31 (0.3),
	AvgLOS	16.61	16.61	unit36 (0.25),
	AvTotOp	1.38	1.38	unit43 (0.01),
	AvED_Treat	21.43	21.43	unit25 (0.25),
	AvED_Doc	1.88	1.49	
	AvED_Cons	1.1	1	
	TotalCOST	1133.49	1031.38	
unit19	pctMin	24.38	24.38	unit1 (0.07), unit50 (0.22),
	pctMod	32.84	34.11	unit95 (0.01)
85.2%	pctSev	13.43	13.43	unit79 (0.14),
	AvgLOS	12.68	12.68	unit24 (0.07),
	AvTotOp	1.41	1.41	unit6 (0.5),
	AvED_Treat	19.79	19.79	
	AvED_Doc	2.93	1.71	
	AvED_Cons	1.17	1	
	TotalCOST	986.21	752.25	
unit21	pctMin	4.6	13.93	unit6 (0.18),
	pctMod	26.44	26.44	unit79 (0.2),
90.08%	pctSev	25.29	25.29	unit86 (0.29),
	AvgLOS	12.97	13.34	unit109 (0.26)
	AvTotOp	2.39	2.39	unit43 (0.07),
	AvED_Treat	16.49	17.73	
	AvED_Doc	2.9	2.54	
	AvED_Cons	1.27	1.14	

	TotalCOST	2590.05	2333.18	
unit23	pctMin	0	26.53	unit24 (0.12),
	pctMod	2.13	31.84	unit50 (0.5),
95.50%	pctSev	2.13	8.01	unit58 (0.07),
	AvgLOS	12.13	12.13	unit60 (0.15)
	AvTotOp	1.5	1.5	unit30 (0.17),
	AvED_Treat	18.83	18.83	
	AvED_Doc	1.17	1.12	
	AvED_Cons	1.25	1.07	
	TotalCOST	645.32	616.31	
unit27	pctMin	12.62	14	unit7 (0.28),
	pctMod	28.57	28.57	unit78 (0.29),
95.53%	pctSev	29.87	29.87	unit109 (0.05)
	AvgLOS	14.33	14.33	unit74 (0.03),
	AvTotOp	2.17	2.17	unit54 (0.3),
	AvED_Treat	18.47	18.47	unit58 (0.03),
	AvED_Doc	3.27	2.16	unit44 (0.02),
	AvED_Cons	1.27	1.21	
	TotalCOST	2385.4	2278.73	
unit32	pctMin	0	10.81	
	pctMod	0.96	10.38	
75.12%	pctSev	0.96	3.96	
	AvgLOS	8.47	8.47	
	AvTotOp	1.61	1.61	unit24 (0.23),
	AvED_Treat	25.97	25.97	unit31 (0.06), unit34 (0.28),
	AvED_Doc	2.75	2.07	unit36 (0.25), unit43 (0.17)

	AvED_Cons	1.35	1.01	
	TotalCOST	1841.69	609.08	
unit35	pctMin	21.82	21.82	unit6 (0.31), unit24 (0.1), unit50 (0.29), unit94 (0.3)
	pctMod	24.55	25.06	
86.36%	pctSev	4.55	10.17	
	AvgLOS	14.39	14.39	
	AvTotOp	1.14	1.34	
	AvED_Treat	16.71	16.71	
	AvED_Doc	1.93	1.34	
	AvED_Cons	1.16	1	
	TotalCOST	441.96	293.87	
unit37	pctMin	16.54	16.54	unit1 (0.09), unit50 (0.05), unit60 (0.07), unit86 (0.2), unit103 (0.05), unit109 (0.53)
	pctMod	30.31	30.31	
84.81%	pctSev	33.27	33.27	
	AvgLOS	12.18	14.75	
	AvTotOp	2.07	2.07	
	AvED_Treat	15.54	16.19	
	AvED_Doc	2.36	2	
	AvED_Cons	1.3	1.11	
	TotalCOST	4205.06	3067.64	
unit38	pctMin	9.52	21.74	unit6 (0.1), unit24 (0.12), unit34 (0.16), unit79 (0.04), unit95 (0.54), unit103 (0.02), unit109 (0.02)
	pctMod	23.81	23.81	
78.89%	pctSev	14.29	14.29	
	AvgLOS	8.21	12.09	
	AvTotOp	1.23	1.23	
	AvED_Treat	21.32	21.32	

	AvED_Doc	1.73	1.37	
	AvED_Cons	1.28	1.01	
	TotalCOST	674.79	532.32	
unit41	pctMin	0	9.55	
	pctMod	2.27	3.06	
78.09%	pctSev	0	1.17	
	AvgLOS	8.7	8.7	
	AvTotOp	1.43	1.6	
	AvED_Treat	24.59	24.59	
	AvED_Doc	2.5	1.95	
	AvED_Cons	1.29	1	
	TotalCOST	797.5	366.82	unit24 (0.32), unit34 (0.08), unit36 (0.5), unit43 (0.1)
unit45	pctMin	0.71	18.63	
	pctMod	0	18.03	
68.42%	pctSev	2.14	5.07	
	AvgLOS	9.14	9.14	
	AvTotOp	1.71	1.71	
	AvED_Treat	21.92	21.92	
	AvED_Doc	2.87	1.83	
	AvED_Cons	1.46	1	
	TotalCOST	1063.99	314.4	unit6 (0.41), unit24 (0.38), unit43 (0.07), unit94 (0.13)
unit47	pctMin	15.17	18.11	
	pctMod	46.21	46.21	
82.77%	pctSev	9.66	9.66	
	AvgLOS	14.41	14.41	
	AvTotOp	1.32	1.32	unit6 (0.58), unit58 (0.09), unit89 (0.02), unit103 (0.27), unit109 (0.04)

	AvED_Treat	17.29	20.45	
	AvED_Doc	1.94	1.51	
	AvED_Cons	1.22	1.01	
	TotalCOST	965.1	520	
unit53	pctMin	16.99	16.99	unit1 (0.05), unit6 (0.24), unit24 (0.09), unit34 (0.16), unit54 (0.08), unit60 (0.13), unit86 (0.05), unit109 (0.2)
	pctMod	28.85	28.85	
84.38%	pctSev	20.51	20.51	
	AvgLOS	12.67	12.67	
	AvTotOp	1.81	1.81	
	AvED_Treat	21.03	21.03	
	AvED_Doc	2.19	1.85	
	AvED_Cons	1.25	1.06	
	TotalCOST	2241.81	1881.49	
unit55	pctMin	20.7	20.7	unit6 (0.05), unit34 (0.2), unit50 (0.13), unit54 (0.22), unit103 (0.06), ' unit109 (0.34)
	pctMod	34.04	34.04	
94.24%	pctSev	30.18	30.18	
	AvgLOS	13.4	14.27	
	AvTotOp	1.56	1.56	
	AvED_Treat	18.84	18.84	
	AvED_Doc	2.27	1.61	
	AvED_Cons	1.13	1.07	
	TotalCOST	2326.41	2146.26	
unit56	pctMin	17.58	17.58	unit50 (0.18), unit58 (0.03), unit60 (0.33), unit86 (0.18), unit109 (0.28)
	pctMod	25.42	25.87	
96.65%	pctSev	22.25	22.25	
	AvgLOS	14.61	14.61	

	AvTotOp	2.25	2.25	
	AvED_Treat	13.04	16.33	
	AvED_Doc	2.19	1.69	
	AvED_Cons	1.14	1.1	
	TotalCOST	3319.03	2369.31	
unit57	pctMin	17.49	21.45	unit1 (0.13), unit25 (0.19), unit43 (0.1), unit50 (0.42), unit79 (0.12), unit109 (0.04)
	pctMod	22.87	22.87	
94.61%	pctSev	15.25	15.25	
	AvgLOS	13.83	13.83	
	AvTotOp	1.48	1.48	
	AvED_Treat	16.66	17.28	
	AvED_Doc	1.9	1.8	
	AvED_Cons	1.06	1	
	TotalCOST	2910.95	1355.27	
unit59	pctMin	20.28	20.28	unit6 (0.17), unit50 (0.2), unit58 (0.07), unit86 (0.06), unit103 (0.5)
	pctMod	50.35	50.35	
87.24%	pctSev	7.69	10.2	
	AvgLOS	12.92	12.92	
	AvTotOp	1.48	1.48	
	AvED_Treat	17.19	17.59	
	AvED_Doc	2.27	1.42	
	AvED_Cons	1.19	1.04	
	TotalCOST	1877.68	681.13	
unit61	pctMin	17.92	17.92	unit1 (0.02), unit6 (0.44), unit24 (0.04), unit34 (0.16), unit43 (0.1), unit54 (0.07),
	pctMod	32.26	32.26	
84.07%	pctSev	17.2	17.2	

	AvgLOS	11.49	12.18	unit109 (0.18)
	AvTotOp	1.56	1.56	
	AvED_Treat	22.54	22.54	
	AvED_Doc	2.61	1.97	
	AvED_Cons	1.22	1.03	
	TotalCOST	1471.05	1236.75	
unit63	pctMin	19.41	19.41	unit6 (0.41), unit24 (0.32), unit50 (0.06), unit94 (0.22)
	pctMod	20.15	20.15	
85.21%	pctSev	6.59	6.92	
	AvgLOS	11	11.23	
	AvTotOp	1.21	1.56	
	AvED_Treat	19.99	19.99	
	AvED_Doc	2.44	1.58	
	AvED_Cons	1.17	1	
	TotalCOST	1419.69	282.1	
unit64	pctMin	0.46	5.8	unit1 (0.45), unit25 (0.24), unit43 (0.08), unit79 (0.23)
	pctMod	5.48	14.87	
83.19%	pctSev	22.37	22.37	
	AvgLOS	15.05	15.05	
	AvTotOp	1.53	1.53	
	AvED_Treat	1.57	19.41	
	AvED_Doc	4.02	2.62	
	AvED_Cons	1.21	1	
	TotalCOST	8501.63	2860.53	
unit67	pctMin	1.64	3.06	unit1 (0), unit25 (0.36), unit43 (0.2), unit60 (0.43)
	pctMod	1.64	6.07	

94.74%	pctSev	4.92	4.92	
	AvgLOS	13.67	13.67	
	AvTotOp	2.06	2.06	
	AvED_Treat	2.46	19.31	
	AvED_Doc	2.41	1.81	
	AvED_Cons	1.07	1.01	
	TotalCOST	7380.2	1426.74	
unit68	pctMin	14	14	unit7 (0.13), unit24 (0), unit50 (0.03), unit51 (0.27), unit78 (0.06), unit86 (0.29), unit109 (0.22)
	pctMod	25.97	26.45	
85.21%	pctSev	22.65	22.65	
	AvgLOS	14.29	14.29	
	AvTotOp	2.87	2.87	
	AvED_Treat	18.51	18.51	
	AvED_Doc	3.82	2.73	
	AvED_Cons	1.46	1.25	
	TotalCOST	3063.97	2610.7	
unit69	pctMin	27.73	27.73	unit6 (0.07), unit50 (0.45), unit79 (0.27), unit94 (0.07), unit95 (0.14)
	pctMod	26.82	27.09	
80.41%	pctSev	18.18	18.18	
	AvgLOS	11	14.18	
	AvTotOp	1.19	1.19	
	AvED_Treat	15.2	15.2	
	AvED_Doc	2.28	1.2	
	AvED_Cons	1.24	1	
	TotalCOST	992.73	482.41	
unit70	pctMin	0.93	2.51	unit25 (0.22), unit43 (0.44),

	pctMod	2.48	5.5	unit58 (0.09), unit60 (0.25), unit86 (0.01)
71.97%	pctSev	2.17	3.38	
	AvgLOS	12.35	12.35	
	AvTotOp	2.09	2.09	
	AvED_Treat	22.03	22.03	
	AvED_Doc	3.4	2.45	
	AvED_Cons	1.42	1.02	
	TotalCOST	2540.19	1132.35	
unit75	pctMin	0	12.15	
	pctMod	0	0	
93.75%	pctSev	0	7.34	
	AvgLOS	9.92	11.67	
	AvTotOp	1.29	1.55	
	AvED_Treat	16.85	16.85	
	AvED_Doc	1.47	1.36	
	AvED_Cons	1.07	1	
	TotalCOST	584.74	216.78	unit24 (0.49), unit94 (0.51)
unit76	pctMin	0	19.68	
	pctMod	2.56	27.39	
80.76%	pctSev	0.85	10.39	
	AvgLOS	12.21	13.4	
	AvTotOp	1.55	1.55	
	AvED_Treat	16.63	16.63	
	AvED_Doc	1.27	1.03	
	AvED_Cons	1.33	1.05	unit30 (0.14), unit50 (0.39),
	TotalCOST	1122.19	906.3	unit60 (0.34), unit94 (0.13)

unit80	pctMin	14.71	17.63	
	pctMod	44.12	44.12	
92.86%	pctSev	8.82	8.82	
	AvgLOS	10.43	13.2	
	AvTotOp	1	1.33	
	AvED_Treat	17.75	20	
	AvED_Doc	1.74	1.58	
	AvED_Cons	1.08	1	
	TotalCOST	849.79	345.96	unit6 (0.66), unit94 (0.1), unit103 (0.24)
unit82	pctMin	0	7.63	
	pctMod	5.62	13.56	
75%	pctSev	1.12	8.28	
	AvgLOS	15.69	15.69	
	AvTotOp	1.1	1.14	
	AvED_Treat	15.79	15.79	
	AvED_Doc	1.35	1.01	
	AvED_Cons	1.33	1	
	TotalCOST	1823.37	700.76	unit17 (0.36), unit31 (0.15), unit73 (0.26), unit94 (0.22)
unit83	pctMin	19.34	19.34	
	pctMod	45.86	45.86	
90.52%	pctSev	9.39	10.98	
	AvgLOS	11.72	11.72	
	AvTotOp	1.56	1.56	
	AvED_Treat	22.82	22.82	
	AvED_Doc	2.08	1.88	
	AvED_Cons	1.19	1.07	unit6 (0.34), unit40 (0.07), unit50 (0.06), unit74 (0.01), unit86 (0.08), unit103 (0.12), unit110 (0.33)

	TotalCOST	1195.03	801.87	
unit84	pctMin	4.55	16.16	unit24 (0.23), unit25 (0.23), unit31 (0.07), unit50 (0.24), unit73 (0.23)
	pctMod	6.2	9.48	
88.68%	pctSev	1.24	2.84	
	AvgLOS	12.72	12.72	
	AvTotOp	1.53	1.53	
	AvED_Treat	18.83	18.83	
	AvED_Doc	1.47	1.3	
	AvED_Cons	1.13	1	
	TotalCOST	1020.53	682.03	
unit85	pctMin	18.27	18.27	unit31 (0.06), unit34 (0.07), unit50 (0.2), unit58 (0.12), unit91 (0.04), unit103 (0.51)
	pctMod	46.19	46.19	
93.1%	pctSev	9.14	9.72	
	AvgLOS	14.1	14.1	
	AvTotOp	1.18	1.22	
	AvED_Treat	18.14	18.14	
	AvED_Doc	1.19	1.11	
	AvED_Cons	1.1	1.02	
	TotalCOST	731.76	630.25	
unit87	pctMin	10.49	18.71	unit6 (0.19), unit79 (0.05), unit94 (0.02), unit95 (0.41), unit103 (0.33), unit109 (0)
	pctMod	38.46	38.46	
90%	pctSev	13.29	13.29	
	AvgLOS	12.83	12.83	
	AvTotOp	1.09	1.15	
	AvED_Treat	18.31	18.31	
	AvED_Doc	1.4	1.26	

	AvED_Cons	1.11	1	
	TotalCOST	788.77	439.77	
unit90	pctMin	11.26	18.99	unit6 (0.35), unit34 (0.53), unit44 (0.08), unit79 (0.02), unit109 (0.02)
	pctMod	38.29	38.29	
77.67%	pctSev	13.06	13.06	
	AvgLOS	10.81	11.97	
	AvTotOp	1.16	1.26	
	AvED_Treat	26.26	26.26	
	AvED_Doc	2.69	1.73	
	AvED_Cons	1.32	1.03	
	TotalCOST	858.25	666.57	
unit92	pctMin	12.68	19.14	unit6 (0.63), unit34 (0.16), unit86 (0.11), unit110 (0.1)
	pctMod	40.85	40.85	
90.01%	pctSev	8.45	10.47	
	AvgLOS	12.24	12.33	
	AvTotOp	1.75	1.75	
	AvED_Treat	24.1	24.1	
	AvED_Doc	2.87	2.12	
	AvED_Cons	1.19	1.07	
	TotalCOST	1326.06	908.98	
unit93	pctMin	9.15	9.15	unit6 (0.33), unit24 (0), unit25 (0.25), unit43 (0.16), unit58 (0.04), unit60 (0.23)
	pctMod	12.42	18.4	
80.5%	pctSev	3.27	5.29	
	AvgLOS	14.18	14.18	
	AvTotOp	1.81	1.81	
	AvED_Treat	20.9	20.9	

	AvED_Doc	3.13	1.87	
	AvED_Cons	1.26	1.01	
	TotalCOST	1205.8	970.64	
unit96	pctMin	0	17.94	
	pctMod	3.23	32.36	
81.25%	pctSev	0	6.96	
	AvgLOS	12.13	12.13	
	AvTotOp	1.26	1.41	
	AvED_Treat	21.05	21.05	
	AvED_Doc	2	1.62	
	AvED_Cons	1.23	1	unit6 (0.65), unit22 (0.19),
	TotalCOST	540.23	298.73	unit24 (0.1), unit94 (0.07)
unit97	pctMin	0	18.92	
	pctMod	0	35.24	
81.41%	pctSev	0	6.38	
	AvgLOS	13.64	13.64	
	AvTotOp	1.43	1.43	
	AvED_Treat	23.07	23.07	
	AvED_Doc	2.15	1.75	unit6 (0.77), unit24 (0.06),
	AvED_Cons	1.24	1.01	unit31 (0.04), unit34 (0.02),
	TotalCOST	508.36	413.88	unit36 (0.07), unit58 (0.04)
unit98	pctMin	9.09	14.96	
	pctMod	23.64	23.64	
88.24%	pctSev	8.18	8.86	
	AvgLOS	12.55	14.41	unit6 (0.54),
	AvTotOp	1.3	1.38	unit24 (0.13), unit94 (0.33)

	AvED_Treat	18.73	18.73	
	AvED_Doc	2.11	1.55	
	AvED_Cons	1.13	1	
	TotalCOST	919.25	268.6	
unit99	pctMin	7.65	10.01	unit6 (0.23), unit31 (0.17), unit34 (0.08), unit36 (0.2), unit58 (0.25), unit95 (0.07)
	pctMod	19.67	19.67	
97.08%	pctSev	1.64	5.3	
	AvgLOS	19.55	19.55	
	AvTotOp	1.16	1.24	
	AvED_Treat	23.09	23.09	
	AvED_Doc	1.46	1.41	
	AvED_Cons	1.07	1.04	
	TotalCOST	728.16	706.91	
unit100	pctMin	9.04	12.72	unit6 (0.44), unit24 (0.13), unit43 (0.11), unit94 (0.32)
	pctMod	16.49	18.95	
88.06%	pctSev	5.32	7.95	
	AvgLOS	13.22	13.22	
	AvTotOp	1.48	1.48	
	AvED_Treat	19.28	19.28	
	AvED_Doc	2.12	1.79	
	AvED_Cons	1.14	1	
	TotalCOST	637.93	312.29	
unit101	pctMin	0	2.12	unit6 (0.1), unit36 (0.5), unit94 (0.4)
	pctMod	0.95	4.24	
76.32%	pctSev	0	6.48	
	AvgLOS	16.94	16.94	

	AvTotOp	1.07	1.12	
	AvED_Treat	17.93	17.93	
	AvED_Doc	1.96	1.45	
	AvED_Cons	1.31	1	
	TotalCOST	664.23	237.53	
unit102	pctMin	0	1.23	
	pctMod	0	0.1	
82.37%	pctSev	0	0.08	
	AvgLOS	16.12	16.12	
	AvTotOp	1.8	1.8	
	AvED_Treat	11.36	19.3	
	AvED_Doc	2.3	1.89	
	AvED_Cons	1.21	1	unit24 (0.05), unit25 (0.79),
	TotalCOST	1200	982.76	unit43 (0.16), unit60 (0.01)
unit104	pctMin	26.09	26.09	
	pctMod	44.2	44.2	
90.48%	pctSev	9.42	9.42	
	AvgLOS	11.17	12.81	
	AvTotOp	1.24	1.35	
	AvED_Treat	17.05	19.15	
	AvED_Doc	1.84	1.47	
	AvED_Cons	1.11	1	unit6 (0.53), unit50 (0.28),
	TotalCOST	412.72	365.31	unit94 (0.03), unit103 (0.15)
unit105	pctMin	3.03	21.3	
	pctMod	6.06	41.52	unit6 (0.96),
87.5%	pctSev	0	7.6	unit24 (0.02), unit94 (0.02)

	AvgLOS	13.15	13.15	
	AvTotOp	1.11	1.44	
	AvED_Treat	22.58	22.58	
	AvED_Doc	2.25	1.81	
	AvED_Cons	1.14	1	
	TotalCOST	1887.7	327.94	
unit106	pctMin	21.97	21.97	unit6 (0.66), unit25 (0.02), unit50 (0.11), unit58 (0.05), unit89 (0.01), unit103 (0.13), unit109 (0.01)
	pctMod	43.35	43.35	
94.35%	pctSev	8.67	8.67	
	AvgLOS	13.97	13.97	
	AvTotOp	1.38	1.38	
	AvED_Treat	19.32	20.7	
	AvED_Doc	1.68	1.58	
	AvED_Cons	1.07	1.01	
	TotalCOST	690.91	431.21	
unit108	pctMin	1.76	4.96	unit25 (0.3), unit60 (0.69), unit86 (0.01)
	pctMod	4.71	9.87	
83.08%	pctSev	1.18	7.93	
	AvgLOS	15.39	15.39	
	AvTotOp	2.09	2.09	
	AvED_Treat	16.5	17.28	
	AvED_Doc	3.03	1.19	
	AvED_Cons	1.24	1.03	
	TotalCOST	6404.08	1767.62	
unit111	pctMin	2.08	17.88	unit6 (0.5), unit22 (0.09), unit24 (0.25), unit94 (0.16)
	pctMod	3.12	23.63	

83.33%	pctSev	0	6.54	
	AvgLOS	11.25	11.25	
	AvTotOp	1.35	1.52	
	AvED_Treat	20.66	20.66	
	AvED_Doc	1.93	1.61	
	AvED_Cons	1.2	1	
	TotalCOST	595.52	283.36	
unit113	pctMin	0.89	9.37	unit22 (0.37), unit24 (0.18), unit58 (0.07), unit73 (0.07), unit94 (0.25), unit95 (0.06)
	pctMod	0	11.15	
63.19%	pctSev	0	6.89	
	AvgLOS	13.9	13.9	
	AvTotOp	1.27	1.27	
	AvED_Treat	17.29	17.29	
	AvED_Doc	1.86	1.18	
	AvED_Cons	1.6	1.01	
	TotalCOST	447.86	283.01	
unit114	pctMin	0	12.33	unit22 (0.18), unit24 (0.09), unit36 (0.31), unit94 (0.05), unit95 (0.37)
	pctMod	0	11.87	
85%	pctSev	0	7.63	
	AvgLOS	12.75	12.75	
	AvTotOp	1.18	1.18	
	AvED_Treat	20.1	20.1	
	AvED_Doc	1.59	1.35	
	AvED_Cons	1.18	1	
	TotalCOST	862.42	325.86	

Hospital Code

Unit	Hospital Code
unit1	HOSPITAL_10
unit2	HOSPITAL_102
unit3	HOSPITAL_104
unit4	HOSPITAL_105
unit5	HOSPITAL_107
unit6	HOSPITAL_108
unit7	HOSPITAL_11
unit8	HOSPITAL_110
unit9	HOSPITAL_111
unit10	HOSPITAL_115
unit11	HOSPITAL_119
unit12	HOSPITAL_12
unit13	HOSPITAL_120
unit14	HOSPITAL_121
unit15	HOSPITAL_122
unit16	HOSPITAL_123
unit17	HOSPITAL_124
unit18	HOSPITAL_125
unit19	HOSPITAL_128
unit20	HOSPITAL_129
unit21	HOSPITAL_13
unit22	HOSPITAL_130
unit23	HOSPITAL_132
unit24	HOSPITAL_133
unit25	HOSPITAL_136
unit26	HOSPITAL_138
unit27	HOSPITAL_14
unit28	HOSPITAL_145
unit29	HOSPITAL_146
unit30	HOSPITAL_147
unit31	HOSPITAL_148
unit32	HOSPITAL_150
unit33	HOSPITAL_152
unit34	HOSPITAL_153
unit35	HOSPITAL_157
unit36	HOSPITAL_158
unit37	HOSPITAL_16
unit38	HOSPITAL_160
unit39	HOSPITAL_161
unit40	HOSPITAL_162
unit41	HOSPITAL_163
unit42	HOSPITAL_164
unit43	HOSPITAL_165
unit44	HOSPITAL_166

unit45	HOSPITAL_167
unit46	HOSPITAL_169
unit47	HOSPITAL_17
unit48	HOSPITAL_171
unit49	HOSPITAL_172
unit50	HOSPITAL_175
unit51	HOSPITAL_178
unit52	HOSPITAL_179
unit53	HOSPITAL_19
unit54	HOSPITAL_2
unit55	HOSPITAL_20
unit56	HOSPITAL_21
unit57	HOSPITAL_22
unit58	HOSPITAL_24
unit59	HOSPITAL_26
unit60	HOSPITAL_27
unit61	HOSPITAL_29
unit62	HOSPITAL_3
unit63	HOSPITAL_30
unit64	HOSPITAL_31
unit65	HOSPITAL_32
unit66	HOSPITAL_34
unit67	HOSPITAL_36
unit68	HOSPITAL_38
unit69	HOSPITAL_40
unit70	HOSPITAL_41
unit71	HOSPITAL_42
unit72	HOSPITAL_44
unit73	HOSPITAL_45
unit74	HOSPITAL_46
unit75	HOSPITAL_47
unit76	HOSPITAL_49
unit77	HOSPITAL_5
unit78	HOSPITAL_50
unit79	HOSPITAL_51
unit80	HOSPITAL_52
unit81	HOSPITAL_53
unit82	HOSPITAL_54
unit83	HOSPITAL_55
unit84	HOSPITAL_58
unit85	HOSPITAL_59
unit86	HOSPITAL_6
unit87	HOSPITAL_61
unit88	HOSPITAL_62
unit89	HOSPITAL_63
unit90	HOSPITAL_64

unit91	HOSPITAL_67
unit92	HOSPITAL_68
unit93	HOSPITAL_69
unit94	HOSPITAL_7
unit95	HOSPITAL_71
unit96	HOSPITAL_72
unit97	HOSPITAL_73
unit98	HOSPITAL_74
unit99	HOSPITAL_75
unit100	HOSPITAL_76
unit101	HOSPITAL_79
unit102	HOSPITAL_8
unit103	HOSPITAL_80
unit104	HOSPITAL_81
unit105	HOSPITAL_82
unit106	HOSPITAL_86
unit107	HOSPITAL_87
unit108	HOSPITAL_89
unit109	HOSPITAL_9
unit110	HOSPITAL_91
unit111	HOSPITAL_94
unit112	HOSPITAL_95
unit113	HOSPITAL_97
unit114	HOSPITAL_99

Appendix D Summary of hospital bootstrap DEA efficiency scores Year2009

Hospital Code	Original DEA scores	Bootstrapping DEA Scores		Confidence Interval 5%	
		Mean	Median	LB	UB
HOSPITAL_10	97.64	97.36	97.39	96.94	97.68

HOSPITAL_102	65.14	62.66	64.3	54.81	65.18
HOSPITAL_104	100	100	100	100	100
HOSPITAL_105	87.19	85.16	85.85	80.06	87.24
HOSPITAL_107	90.54	86.44	87.58	81.08	90.59
HOSPITAL_108	100	100	100	100	100
HOSPITAL_11	86.42	85.93	85.96	85.23	86.47
HOSPITAL_110	100	100	100	100	100
HOSPITAL_111	100	100	100	100	100
HOSPITAL_115	100	100	100	100	100
HOSPITAL_119	96.46	95.43	95.66	92.93	96.53
HOSPITAL_12	90.78	90.08	90.15	88.92	90.83
HOSPITAL_120	100	100	100	100	100
HOSPITAL_121	100	100	100	100	100
HOSPITAL_122	77.56	73.61	74.56	64.99	77.6
HOSPITAL_123	91.45	90.22	90.61	86.86	91.49
HOSPITAL_124	100	100	100	100	100
HOSPITAL_125	100	100	100	100	100
HOSPITAL_128	100	100	100	100	100
HOSPITAL_129	96.43	95.06	95.63	92.86	96.47
HOSPITAL_13	77.56	75.16	75.52	70.32	77.61
HOSPITAL_130	100	100	100	100	100
HOSPITAL_132	100	100	100	100	100
HOSPITAL_133	87.8	87.5	87.62	86.32	87.82
HOSPITAL_136	100	100	100	100	100
HOSPITAL_138	90.91	90.79	90.81	90.55	90.92
HOSPITAL_14	86.54	85.47	85.83	83.98	86.58
HOSPITAL_145	46.65	44.06	45.05	36.52	46.68
HOSPITAL_146	97.3	96.82	96.99	94.91	97.32
HOSPITAL_147	74.96	72.2	73.06	65.14	75
HOSPITAL_148	100	100	100	100	100
HOSPITAL_150	100	100	100	100	100
HOSPITAL_152	92.35	91.44	91.69	89.28	92.4
HOSPITAL_153	100	100	100	100	100
HOSPITAL_157	88.13	86.5	86.94	82.47	88.18
HOSPITAL_158	85	82.63	84.34	74.4	85.02
HOSPITAL_16	90.33	86.61	88.26	80.66	90.38
HOSPITAL_160	100	100	100	100	100
HOSPITAL_161	82.27	80.92	81.47	77.03	82.31
HOSPITAL_162	100	100	100	100	100
HOSPITAL_163	100	100	100	100	100
HOSPITAL_164	100	100	100	100	100

Year2009

Hospital Code	Original DEA scores	Bootstrapping DEA Scores		Confidence Interval 5%	
		Mean	Median	LB	UB
HOSPITAL_166	75.39	74.42	74.77	70.94	75.42
HOSPITAL_167	77.55	76.87	76.96	75.48	77.6

HOSPITAL_169	100	100	100	100	100
HOSPITAL_17	92.31	90.37	91.62	84.62	92.34
HOSPITAL_171	77.56	74.8	75.92	66.88	77.6
HOSPITAL_172	100	100	100	100	100
HOSPITAL_175	100	100	100	100	100
HOSPITAL_178	85.64	84.88	85.06	83.11	85.7
HOSPITAL_179	89.13	87.14	87.89	81.76	89.19
HOSPITAL_19	88.74	86.86	87.47	82.22	88.8
HOSPITAL_2	96.92	96.12	96.19	94.95	96.99
HOSPITAL_20	92.41	89.25	91.13	84.81	92.46
HOSPITAL_21	87.84	86.89	87.04	84.96	87.89
HOSPITAL_22	90.39	87.48	89.07	80.79	90.44
HOSPITAL_24	87.93	87.37	87.43	86.6	87.97
HOSPITAL_26	80	79.89	79.91	79.7	80.01
HOSPITAL_27	83.33	83.26	83.27	83.11	83.34
HOSPITAL_29	97.78	97.25	97.42	95.66	97.8
HOSPITAL_3	73.67	72.51	72.64	70.19	73.71
HOSPITAL_30	92.86	92.72	92.75	92.46	92.87
HOSPITAL_31	100	100	100	100	100
HOSPITAL_32	83.75	79.58	80.95	67.51	83.81
HOSPITAL_34	93	91.73	92.1	88.86	93.05
HOSPITAL_36	97.41	97.22	97.24	96.89	97.44
HOSPITAL_38	65.14	63.13	63.5	58.74	65.17
HOSPITAL_40	85.71	85.65	85.66	85.52	85.72
HOSPITAL_41	90.76	89.99	90.04	89.13	90.8
HOSPITAL_42	77.75	74.01	76.06	61.79	77.8
HOSPITAL_44	100	100	100	100	100
HOSPITAL_45	100	100	100	100	100
HOSPITAL_46	85.41	84.56	84.62	83.22	85.46
HOSPITAL_47	81.1	79.46	80.19	74.89	81.14
HOSPITAL_49	77.99	77.37	77.4	76.26	78.04
HOSPITAL_5	92.01	90.38	90.99	85.82	92.06
HOSPITAL_50	73.21	71.21	71.93	65.71	73.26
HOSPITAL_51	95.45	93.46	94.53	90.89	95.49
HOSPITAL_52	96	95.67	95.77	94.79	96.02
HOSPITAL_53	100	100	100	100	100
HOSPITAL_54	100	100	100	100	100
HOSPITAL_55	90.24	89.99	90.04	89.54	90.27
HOSPITAL_58	97.11	96.33	96.38	95.2	97.16
HOSPITAL_59	100	100	100	100	100
HOSPITAL_6	100	100	100	100	100

Year2009

Hospital Code	Original DEA scores	Bootstrapping DEA Scores		Confidence Interval 5%	
		Mean	Median	LB	UB
HOSPITAL_61	75.01	74.8	74.83	74.43	75.04
HOSPITAL_63	90.63	88.35	88.9	83.49	90.67

HOSPITAL_64	100	100	100	100	100
HOSPITAL_67	88.35	87.92	87.93	87.47	88.39
HOSPITAL_68	65.81	64.22	65.1	58.94	65.84
HOSPITAL_69	87.33	84.41	84.93	78.83	87.4
HOSPITAL_7	100	100	100	100	100
HOSPITAL_71	100	100	100	100	100
HOSPITAL_72	69.81	69.55	69.61	68.96	69.83
HOSPITAL_73	94.36	91.9	93.19	88.72	94.41
HOSPITAL_74	100	100	100	100	100
HOSPITAL_75	100	100	100	100	100
HOSPITAL_76	83.73	82.9	83.06	81.22	83.79
HOSPITAL_79	88.37	88.22	88.24	87.99	88.4
HOSPITAL_8	97.51	96.12	96.39	95.02	97.58
HOSPITAL_80	100	100	100	100	100
HOSPITAL_81	93.17	90.68	92.24	86.34	93.22
HOSPITAL_82	87.81	85.41	86.27	78.32	87.86
HOSPITAL_86	88.18	86.59	87.13	82.37	88.22
HOSPITAL_87	81.82	81.6	81.63	81.16	81.84
HOSPITAL_89	92.88	92.58	92.62	92.13	92.93
HOSPITAL_9	100	100	100	100	100
HOSPITAL_91	100	100	100	100	100
HOSPITAL_94	87.81	86.59	86.96	83.54	87.85
HOSPITAL_95	100	100	100	100	100
HOSPITAL_97	65.34	62.86	63.85	56.34	65.37
HOSPITAL_99	92.86	91.62	92.35	87.63	92.89

Year2010

Hospital Code	Original DEA scores	Bootstrapping DEA Scores		Confidence Interval 5%	
		Mean	Median	LB	UB
HOSPITAL_10	99.15	99.06	99.07	98.91	99.15
HOSPITAL_102	81.13	80.69	80.92	79.14	81.15
HOSPITAL_104	85.71	85.58	85.61	85.31	85.73
HOSPITAL_105	88.89	87.98	88.6	84.19	88.91
HOSPITAL_107	70.37	69.32	69.74	66.58	70.4
HOSPITAL_108	100	100	100	100	100
HOSPITAL_11	82.72	82.52	82.56	82.09	82.75
HOSPITAL_110	98.65	97.92	98.05	97.3	98.67
HOSPITAL_111	100	100	100	100	100
HOSPITAL_115	79.45	79.17	79.26	78.26	79.48
HOSPITAL_119	92.31	91.93	92.07	90.51	92.33
HOSPITAL_12	93.52	91.15	92.2	87.03	93.56
HOSPITAL_120	100	100	100	100	100
HOSPITAL_121	100	100	100	100	100
HOSPITAL_122	100	100	100	100	100
HOSPITAL_123	86.05	85.46	85.7	83.43	86.08

HOSPITAL_124	100	100	100	100	100
HOSPITAL_125	100	100	100	100	100
HOSPITAL_128	100	100	100	100	100
HOSPITAL_129	100	100	100	100	100
HOSPITAL_13	100	100	100	100	100
HOSPITAL_130	100	100	100	100	100
HOSPITAL_132	100	100	100	100	100
HOSPITAL_133	85.71	84.78	85.47	79.27	85.73
HOSPITAL_136	100	100	100	100	100
HOSPITAL_138	100	100	100	100	100
HOSPITAL_14	89.71	89.44	89.52	88.39	89.73
HOSPITAL_145	100	100	100	100	100
HOSPITAL_146	87.5	86.78	87.21	84.06	87.54
HOSPITAL_147	83.33	82.34	82.83	78.92	83.36
HOSPITAL_148	100	100	100	100	100
HOSPITAL_150	100	100	100	100	100
HOSPITAL_152	100	100	100	100	100
HOSPITAL_153	100	100	100	100	100
HOSPITAL_157	100	100	100	100	100
HOSPITAL_158	73.33	73.14	73.2	72.33	73.35
HOSPITAL_16	100	100	100	100	100
HOSPITAL_160	99.01	98.25	98.02	98.02	99.06
HOSPITAL_161	100	100	100	100	100
HOSPITAL_162	100	100	100	100	100
HOSPITAL_163	76.19	75.99	76.06	75.2	76.21
HOSPITAL_164	86.67	86.27	86.41	84.84	86.7
HOSPITAL_165	86.96	86.72	86.79	85.95	86.98
HOSPITAL_166	88.37	87.49	88.08	83.09	88.4
HOSPITAL_167	84.29	83.78	84	81.75	84.31
HOSPITAL_169	100	100	100	100	100
HOSPITAL_17	100	100	100	100	100
HOSPITAL_171	100	100	100	100	100
HOSPITAL_172	100	100	100	100	100
HOSPITAL_175	100	100	100	100	100
HOSPITAL_178	83.35	81.51	82.3	76.35	83.38
HOSPITAL_179	83.86	81.06	81.87	74.27	83.89
HOSPITAL_19	90.65	90.48	90.51	90.11	90.67
HOSPITAL_2	83.68	80.61	81.66	73.43	83.71
HOSPITAL_20	88.1	85.97	87.23	79.78	88.14
HOSPITAL_21	85.63	84.19	85.01	80.66	85.67
HOSPITAL_22	94.87	93.52	94.27	89.74	94.92
HOSPITAL_24	100	100	100	100	100
HOSPITAL_26	74.32	74.21	74.23	74	74.34
HOSPITAL_27	86.6	86.54	86.55	86.45	86.61
HOSPITAL_29	85.26	84.79	85.01	82.6	85.3
HOSPITAL_3	100	100	100	100	100
HOSPITAL_30	85.71	85.64	85.65	85.53	85.72

HOSPITAL_31	100	100	100	100	100
HOSPITAL_32	88.23	84.75	86.73	76.46	88.28
HOSPITAL_34	86.32	85.84	86.07	83.85	86.36
HOSPITAL_36	85.97	82.63	84.17	73.26	86.01
HOSPITAL_38	73.95	73.17	73.56	70.62	73.98
HOSPITAL_40	81.32	81.28	81.29	81.22	81.32
HOSPITAL_41	93.62	93.56	93.57	93.47	93.62
HOSPITAL_42	53.85	52.56	53.55	47.95	53.87
HOSPITAL_44	100	100	100	100	100
HOSPITAL_45	100	100	100	100	100
HOSPITAL_46	86.21	84.7	85.39	80.18	86.25
HOSPITAL_47	100	100	100	100	100
HOSPITAL_49	94.44	94.39	94.4	94.3	94.45
HOSPITAL_5	89.28	86.84	88.52	78.55	89.32
HOSPITAL_50	73.24	72.72	72.99	69.51	73.26
HOSPITAL_51	100	100	100	100	100
HOSPITAL_52	100	100	100	100	100
HOSPITAL_53	71.84	68.44	70.9	58.24	71.87
HOSPITAL_54	92.31	91.99	92.16	90.18	92.32
HOSPITAL_55	76.79	76.71	76.72	76.59	76.8
HOSPITAL_58	82.93	82.67	82.76	81.9	82.95
HOSPITAL_59	93.94	93.81	93.84	93.51	93.95
HOSPITAL_6	100	100	100	100	100
HOSPITAL_61	87.5	87.44	87.45	87.33	87.51
HOSPITAL_62	100	100	100	100	100
HOSPITAL_63	100	100	100	100	100
HOSPITAL_64	81.82	79.04	80.45	72.05	81.86
HOSPITAL_67	88.89	88.74	88.77	88.42	88.91
HOSPITAL_68	70.59	68.79	69.95	63.37	70.62
HOSPITAL_69	78.15	74.83	76.83	65.69	78.18
HOSPITAL_7	100	100	100	100	100
HOSPITAL_71	81.82	81.72	81.74	81.57	81.83
HOSPITAL_72	77.5	77.43	77.44	77.32	77.51
HOSPITAL_73	88.46	88.35	88.37	88.11	88.47
HOSPITAL_74	89.29	89.22	89.23	89.12	89.29
HOSPITAL_75	100	100	100	100	100
HOSPITAL_76	85.42	85.11	85.22	84.1	85.44
HOSPITAL_79	84.78	84.72	84.73	84.62	84.79
HOSPITAL_8	54.74	54.57	54.62	54.08	54.76
HOSPITAL_80	100	100	100	100	100
HOSPITAL_81	89.19	87.58	88.64	82.21	89.23
HOSPITAL_82	90.48	88.27	89.65	80.95	90.52
HOSPITAL_86	87.73	85.29	86.26	79.59	87.79
HOSPITAL_87	83.93	83.84	83.86	83.71	83.94
HOSPITAL_89	85.23	85.04	85.1	84.6	85.24
HOSPITAL_9	100	100	100	100	100
HOSPITAL_91	100	100	100	100	100

HOSPITAL_94	96.77	96.57	96.62	95.99	96.8
HOSPITAL_95	100	100	100	100	100
HOSPITAL_97	66.59	63.84	65.14	56.71	66.62
HOSPITAL_99	85.42	84.13	84.99	78.39	85.45

Year2011

Hospital Code	Original DEA scores	Bootstrapping DEA Scores		Confidence Interval 5%	
		Mean	Median	LB	UB
HOSPITAL_10	100	100	100	100	100
HOSPITAL_102	82.56	81.77	81.99	79.99	82.59
HOSPITAL_104	70.37	69.31	69.86	66.07	70.4
HOSPITAL_105	100	100	100	100	100
HOSPITAL_107	100	100	100	100	100
HOSPITAL_108	100	100	100	100	100
HOSPITAL_11	95.25	93.37	94.53	90.5	95.28
HOSPITAL_110	92.91	92.36	92.47	91.2	92.95
HOSPITAL_111	84.19	83.37	83.7	81.45	84.21
HOSPITAL_115	63.64	63.59	63.59	63.52	63.64
HOSPITAL_119	88.64	88.11	88.21	87.05	88.67
HOSPITAL_12	87.95	85.83	87.45	76.7	87.97
HOSPITAL_120	98.47	97.85	98.02	96.95	98.49
HOSPITAL_121	95.65	95.48	95.51	95.07	95.67
HOSPITAL_122	100	100	100	100	100
HOSPITAL_123	86.28	85.51	85.81	83.39	86.31
HOSPITAL_124	100	100	100	100	100
HOSPITAL_125	71.16	69.63	70.64	64.54	71.18
HOSPITAL_128	100	100	100	100	100
HOSPITAL_129	100	100	100	100	100
HOSPITAL_13	100	100	100	100	100
HOSPITAL_130	100	100	100	100	100
HOSPITAL_132	99.64	99.34	99.29	99.29	99.67
HOSPITAL_133	100	100	100	100	100
HOSPITAL_136	100	100	100	100	100
HOSPITAL_138	92.93	92.18	92.37	90.61	92.95
HOSPITAL_14	90.77	89.35	90.19	84.55	90.8
HOSPITAL_145	82.28	79.9	81.66	72.37	82.3
HOSPITAL_146	100	100	100	100	100
HOSPITAL_147	100	100	100	100	100
HOSPITAL_148	96.3	95.61	96.01	92.59	96.32
HOSPITAL_150	100	100	100	100	100
HOSPITAL_152	91.55	89.19	90.69	83.11	91.59
HOSPITAL_153	100	100	100	100	100
HOSPITAL_157	100	100	100	100	100
HOSPITAL_158	100	100	100	100	100

HOSPITAL_16	100	100	100	100	100
HOSPITAL_160	98.51	97.81	97.96	97.03	98.54
HOSPITAL_161	100	100	100	100	100
HOSPITAL_162	100	100	100	100	100
HOSPITAL_163	91.18	90.85	90.93	90.07	91.2
HOSPITAL_164	100	100	100	100	100
HOSPITAL_165	94.12	93.89	93.96	92.93	94.14
HOSPITAL_166	100	100	100	100	100
HOSPITAL_167	73.7	73.39	73.44	72.78	73.73
HOSPITAL_169	85.71	85.66	85.66	85.57	85.72
HOSPITAL_17	87.15	85.81	86.54	79.51	87.18
HOSPITAL_171	100	100	100	100	100
HOSPITAL_172	100	100	100	100	100
HOSPITAL_175	100	100	100	100	100
HOSPITAL_178	89.08	88.26	88.47	86.48	89.11
HOSPITAL_179	87.94	86.75	87.21	84.07	87.96
HOSPITAL_19	75	74.67	74.78	73.62	75.02
HOSPITAL_2	100	100	100	100	100
HOSPITAL_20	89.49	88.13	88.88	83.4	89.51
HOSPITAL_21	85.85	83.16	85.15	75.44	85.88
HOSPITAL_22	98	97.9	97.91	97.73	98.02
HOSPITAL_24	100	100	100	100	100
HOSPITAL_26	84.94	83.85	84.39	80.02	84.97
HOSPITAL_27	88.37	87.08	88.08	82.05	88.4
HOSPITAL_29	79.81	79.5	79.62	78.27	79.83
HOSPITAL_3	100	100	100	100	100
HOSPITAL_30	89.39	89.24	89.28	88.74	89.4
HOSPITAL_31	86.21	85.44	85.97	82.24	86.23
HOSPITAL_32	100	100	100	100	100
HOSPITAL_34	96.49	96.22	96.3	95.51	96.51
HOSPITAL_36	100	100	100	100	100
HOSPITAL_38	69.46	67.83	68.89	62.86	69.48
HOSPITAL_40	75.8	75.72	75.73	75.57	75.8
HOSPITAL_41	81.74	81.38	81.45	80.53	81.76
HOSPITAL_42	100	100	100	100	100
HOSPITAL_44	100	100	100	100	100
HOSPITAL_45	100	100	100	100	100
HOSPITAL_46	99.84	99.68	99.67	99.67	99.87
HOSPITAL_47	99.26	98.72	98.51	98.51	99.29
HOSPITAL_49	84.73	84.24	84.36	83.17	84.76
HOSPITAL_5	100	100	100	100	100
HOSPITAL_50	100	100	100	100	100
HOSPITAL_51	100	100	100	100	100
HOSPITAL_52	100	100	100	100	100
HOSPITAL_53	94.7	92.63	93.83	89.39	94.72
HOSPITAL_54	78.57	78.36	78.38	77.99	78.59

HOSPITAL_55	85.08	83.75	84.48	79.15	85.1
HOSPITAL_58	88.72	87.78	88.18	85.44	88.74
HOSPITAL_59	97.3	96.57	96.95	94.59	97.32
HOSPITAL_6	100	100	100	100	100
HOSPITAL_61	90	89.36	89.66	87.4	90.02
HOSPITAL_62	100	100	100	100	100
HOSPITAL_63	100	100	100	100	100
HOSPITAL_64	100	100	100	100	100
HOSPITAL_67	93.89	93.14	93.49	90.57	93.92
HOSPITAL_68	70.57	69.33	70.1	66.15	70.6
HOSPITAL_69	86.8	85.68	85.95	83.46	86.82
HOSPITAL_7	85.79	85.38	85.41	84.77	85.81
HOSPITAL_71	100	100	100	100	100
HOSPITAL_72	86.36	86.3	86.31	86.19	86.37
HOSPITAL_73	81.25	81.17	81.18	81.04	81.26
HOSPITAL_74	100	100	100	100	100
HOSPITAL_75	100	100	100	100	100
HOSPITAL_76	87.65	87.46	87.49	87.16	87.68
HOSPITAL_79	87.5	87.44	87.45	87.34	87.51
HOSPITAL_8	80	79.95	79.95	79.87	80.01
HOSPITAL_80	100	100	100	100	100
HOSPITAL_81	100	100	100	100	100
HOSPITAL_82	77.78	77.2	77.54	73.57	77.8
HOSPITAL_86	100	100	100	100	100
HOSPITAL_87	85.37	84.28	84.73	81.54	85.4
HOSPITAL_89	83.46	83.35	83.38	83.03	83.47
HOSPITAL_9	100	100	100	100	100
HOSPITAL_91	100	100	100	100	100
HOSPITAL_94	84.78	84.44	84.49	83.95	84.81
HOSPITAL_95	100	100	100	100	100
HOSPITAL_97	81.6	80.22	80.91	76.79	81.62
HOSPITAL_99	89.74	89.63	89.65	89.38	89.75

Year2012

Hospital Code	Original DEA scores	Bootstrapping DEA Scores		Confidence Interval 5%	
		Mean	Median	LB	UB
HOSPITAL_10	100	100	100	100	100
HOSPITAL_102	68.06	66.76	67.76	59.74	68.08
HOSPITAL_104	76.4	74.56	75.9	67.76	76.42
HOSPITAL_105	100	100	100	100	100
HOSPITAL_107	100	100	100	100	100
HOSPITAL_108	100	100	100	100	100

HOSPITAL_11	100	100	100	100	100
HOSPITAL_110	100	100	100	100	100
HOSPITAL_111	87.5	87.07	87.16	86.16	87.53
HOSPITAL_115	85.71	85.63	85.64	85.51	85.73
HOSPITAL_119	100	100	100	100	100
HOSPITAL_12	100	100	100	100	100
HOSPITAL_120	100	100	100	100	100
HOSPITAL_121	95.83	94.87	95.5	91.67	95.85
HOSPITAL_122	100	100	100	100	100
HOSPITAL_123	90.99	90.22	90.44	88.56	91.02
HOSPITAL_124	100	100	100	100	100
HOSPITAL_125	100	100	100	100	100
HOSPITAL_128	85.2	84.07	84.7	80.13	85.22
HOSPITAL_129	100	100	100	100	100
HOSPITAL_13	90.08	88.76	89.48	84.93	90.11
HOSPITAL_130	100	100	100	100	100
HOSPITAL_132	95.5	93.76	94.74	91.01	95.53
HOSPITAL_133	100	100	100	100	100
HOSPITAL_136	100	100	100	100	100
HOSPITAL_138	100	100	100	100	100
HOSPITAL_14	95.53	93.99	94.89	91.06	95.55
HOSPITAL_145	100	100	100	100	100
HOSPITAL_146	100	100	100	100	100
HOSPITAL_147	100	100	100	100	100
HOSPITAL_148	100	100	100	100	100
HOSPITAL_150	75.12	73.96	74.66	69.46	75.14
HOSPITAL_152	100	100	100	100	100
HOSPITAL_153	100	100	100	100	100
HOSPITAL_157	86.36	85.64	85.97	82.59	86.39
HOSPITAL_158	100	100	100	100	100
HOSPITAL_16	84.81	83.22	84.29	78.04	84.83
HOSPITAL_160	78.89	77.56	78.3	73.32	78.91
HOSPITAL_161	100	100	100	100	100
HOSPITAL_162	100	100	100	100	100
HOSPITAL_163	78.09	77.48	77.64	75.84	78.11

HOSPITAL_164	100	100	100	100	100
HOSPITAL_165	100	100	100	100	100
HOSPITAL_166	100	100	100	100	100
HOSPITAL_167	68.42	68.08	68.24	66.44	68.44
HOSPITAL_169	100	100	100	100	100
HOSPITAL_17	82.77	81.78	82.28	78.88	82.79
HOSPITAL_171	100	100	100	100	100
HOSPITAL_172	100	100	100	100	100
HOSPITAL_175	100	100	100	100	100
HOSPITAL_178	100	100	100	100	100
HOSPITAL_179	100	100	100	100	100
HOSPITAL_19	84.38	83	83.72	79.4	84.41
HOSPITAL_2	100	100	100	100	100
HOSPITAL_20	94.24	92.29	93.54	88.47	94.26
HOSPITAL_21	96.65	95.32	95.98	93.31	96.68
HOSPITAL_22	94.61	94.05	94.18	92.74	94.63
HOSPITAL_24	100	100	100	100	100
HOSPITAL_26	87.24	85.75	86.59	80	87.27
HOSPITAL_27	100	100	100	100	100
HOSPITAL_29	84.07	82.92	83.44	80.33	84.1
HOSPITAL_3	100	100	100	100	100
HOSPITAL_30	85.21	85.03	85.07	84.67	85.22
HOSPITAL_31	83.19	82.64	82.86	80	83.22
HOSPITAL_32	100	100	100	100	100
HOSPITAL_34	100	100	100	100	100
HOSPITAL_36	94.74	93.93	94.27	91.89	94.77
HOSPITAL_38	85.21	83.27	84.61	74.13	85.23
HOSPITAL_40	80.41	79.09	80.07	72.88	80.44
HOSPITAL_41	71.97	70.82	71.5	67.8	71.99
HOSPITAL_42	100	100	100	100	100
HOSPITAL_44	100	100	100	100	100
HOSPITAL_45	100	100	100	100	100
HOSPITAL_46	100	100	100	100	100
HOSPITAL_47	93.75	93.67	93.68	93.54	93.76
HOSPITAL_49	80.76	79	80.23	72.4	80.79

HOSPITAL_5	100	100	100	100	100
HOSPITAL_50	100	100	100	100	100
HOSPITAL_51	100	100	100	100	100
HOSPITAL_52	92.86	92.55	92.65	91.61	92.88
HOSPITAL_53	100	100	100	100	100
HOSPITAL_54	75	74.63	74.79	73.45	75.02
HOSPITAL_55	90.52	88.15	89.64	81.04	90.55
HOSPITAL_58	88.68	88.17	88.34	86.56	88.7
HOSPITAL_59	93.1	91.07	92.49	86.2	93.12
HOSPITAL_6	100	100	100	100	100
HOSPITAL_61	90	89.32	89.51	87.73	90.03
HOSPITAL_62	100	100	100	100	100
HOSPITAL_63	100	100	100	100	100
HOSPITAL_64	77.67	76.43	77.27	69.67	77.69
HOSPITAL_67	100	100	100	100	100
HOSPITAL_68	90.01	88.07	89.38	81.64	90.04
HOSPITAL_69	80.5	79.47	79.92	76.91	80.52
HOSPITAL_7	100	100	100	100	100
HOSPITAL_71	100	100	100	100	100
HOSPITAL_72	81.25	81.02	81.11	79.96	81.26
HOSPITAL_73	81.41	80.42	80.95	75.55	81.43
HOSPITAL_74	88.24	88.11	88.12	87.94	88.25
HOSPITAL_75	97.08	95.95	96.36	94.16	97.11
HOSPITAL_76	88.06	87.68	87.8	86.61	88.08
HOSPITAL_79	76.32	75.84	76.03	74.39	76.34
HOSPITAL_8	82.37	81.15	81.91	77.24	82.4
HOSPITAL_80	100	100	100	100	100
HOSPITAL_81	90.48	88.71	89.98	80.95	90.5
HOSPITAL_82	87.5	87.26	87.32	86.73	87.51
HOSPITAL_86	94.35	92.84	93.76	88.69	94.37
HOSPITAL_87	100	100	100	100	100
HOSPITAL_89	83.08	82.14	82.67	79.16	83.1
HOSPITAL_9	100	100	100	100	100
HOSPITAL_91	100	100	100	100	100
HOSPITAL_94	83.33	83.18	83.21	82.86	83.35

HOSPITAL_95	100	100	100	100	100
HOSPITAL_97	63.19	61.89	62.78	57.46	63.21
HOSPITAL_99	85	84.83	84.86	84.43	85.02

Appendix E Summary of Malmquist productivity indices and its components Year 2009-2010

Hospital Code	Technological change (TECHCH)	Change in scale efficiency (SECH)	Change in pure technical Efficiency (PECH)	Technical efficiency change (EFFCH)	Total factor Productivity change (TFPCH)

HOSPITAL_10	1	1.03	1.02	1.05	1.04
HOSPITAL_102	0.81	0.89	1.25	1.11	0.9
HOSPITAL_104	1	0.83	0.86	0.71	0.72
HOSPITAL_105	0.96	0.71	0.96	0.68	0.66
HOSPITAL_107	0.96	0.94	0.78	0.73	0.7
HOSPITAL_108	1	1	1	1.00	1
HOSPITAL_11	1	1.12	0.96	1.08	1.08
HOSPITAL_110	1.01	1.03	0.99	1.02	1.02
HOSPITAL_111	0.91	0.9	1	0.90	0.82
HOSPITAL_115	1	1.03	0.79	0.81	0.82
HOSPITAL_119	0.98	0.88	0.96	0.84	0.83
HOSPITAL_12	0.95	1.02	1.03	1.05	1
HOSPITAL_120	0.93	0.97	1	0.97	0.9
HOSPITAL_121	1	0.84	1	0.84	0.84
HOSPITAL_122	0.88	1.12	1.29	1.44	1.27
HOSPITAL_123	0.96	0.97	0.94	0.91	0.88
HOSPITAL_124	1	1	1	1.00	1
HOSPITAL_125	1	0.84	1	0.84	0.84
HOSPITAL_128	1	0.7	1	0.70	0.7
HOSPITAL_129	0.98	1.28	1.04	1.33	1.3
HOSPITAL_13	0.88	1.08	1.29	1.39	1.23
HOSPITAL_130	1	0.62	1	0.62	0.62
HOSPITAL_132	1	1.1	1	1.10	1.1
HOSPITAL_133	1	1.05	0.98	1.03	1.02
HOSPITAL_136	0.94	0.92	1	0.92	0.86
HOSPITAL_138	1	1.65	1.1	1.82	1.81
HOSPITAL_14	1	1.13	1.04	1.18	1.17
HOSPITAL_145	0.68	1.36	2.14	2.91	1.98
HOSPITAL_146	1	0.98	0.9	0.88	0.89
HOSPITAL_147	0.83	0.97	1.22	1.18	0.98
HOSPITAL_148	0.96	0.71	1.09	0.77	0.74
HOSPITAL_150	0.99	0.76	1	0.76	0.75
HOSPITAL_152	0.96	0.99	1.08	1.07	1.03
HOSPITAL_153	1	0.94	1	0.94	0.94
HOSPITAL_157	0.93	1.37	1.16	1.59	1.48
HOSPITAL_158	0.92	0.91	0.86	0.78	0.72
HOSPITAL_16	0.95	1.04	1.11	1.15	1.09
HOSPITAL_160	0.98	0.94	0.99	0.93	0.91
HOSPITAL_161	0.91	0.92	1.22	1.12	1.02
HOSPITAL_162	1	0.98	1	0.98	0.98
HOSPITAL_163	1	0.74	0.76	0.56	0.56
HOSPITAL_164	1	0.8	0.87	0.70	0.69
HOSPITAL_165	0.9	0.74	1.06	0.78	0.71
HOSPITAL_166	0.87	1.82	1.17	2.13	1.85
HOSPITAL_167	0.89	0.94	1.09	1.02	0.91
HOSPITAL_169	1	1	1	1.00	1
HOSPITAL_17	0.96	1.02	1.08	1.10	1.07
HOSPITAL_171	0.84	0.68	1.41	0.96	0.8
HOSPITAL_172	1	1	1	1.00	1
HOSPITAL_175	1	1	1	1.00	1
HOSPITAL_178	1.01	0.92	0.97	0.89	0.91
HOSPITAL_179	0.95	0.93	0.94	0.87	0.84

HOSPITAL_19	0.94	0.78	1.02	0.80	0.75
HOSPITAL_2	1.01	1.08	0.86	0.93	0.94
HOSPITAL_20	0.97	0.94	0.95	0.89	0.87
HOSPITAL_21	0.95	0.95	0.97	0.92	0.88
HOSPITAL_22	0.95	0.95	1.05	1.00	0.95
HOSPITAL_24	1	1.23	1.14	1.40	1.4
HOSPITAL_26	1	1.18	0.93	1.10	1.09
HOSPITAL_27	1	1.39	1.04	1.45	1.44
HOSPITAL_29	1	1.24	0.87	1.08	1.08
HOSPITAL_3	0.73	1.05	1.36	1.43	1.03
HOSPITAL_30	1	1	0.92	0.92	0.92
HOSPITAL_31	1	1.79	1	1.79	1.79
HOSPITAL_32	1	0.74	0.88	0.65	0.66
HOSPITAL_34	0.96	0.93	0.93	0.86	0.83
HOSPITAL_36	1	1.47	0.88	1.29	1.3
HOSPITAL_38	0.83	0.96	1.14	1.09	0.91
HOSPITAL_40	1	1.19	0.95	1.13	1.13
HOSPITAL_41	0.95	0.77	1.03	0.79	0.76
HOSPITAL_42	0.88	0.89	0.69	0.61	0.54
HOSPITAL_44	1	1	1	1.00	1
HOSPITAL_45	1	1.28	1	1.28	1.28
HOSPITAL_46	0.93	0.98	1.01	0.99	0.92
HOSPITAL_47	0.9	0.99	1.23	1.22	1.1
HOSPITAL_49	1	0.79	1.21	0.96	0.96
HOSPITAL_5	1.02	0.99	0.97	0.96	0.98
HOSPITAL_50	0.86	0.94	1	0.94	0.81
HOSPITAL_51	0.98	0.98	1.05	1.03	1
HOSPITAL_52	1	0.93	1.04	0.97	0.97
HOSPITAL_53	1.04	1.39	0.72	1.00	1.04
HOSPITAL_54	1	1.07	0.92	0.98	0.98
HOSPITAL_55	1	0.8	0.85	0.68	0.68
HOSPITAL_58	0.99	0.73	0.85	0.62	0.61
HOSPITAL_59	1	0.52	0.94	0.49	0.48
HOSPITAL_6	1	1	1	1.00	1
HOSPITAL_61	0.87	0.81	1.17	0.95	0.82
HOSPITAL_62	1	0.54	1	0.54	0.54
HOSPITAL_63	0.96	0.86	1.1	0.95	0.9
HOSPITAL_64	1	1.16	0.82	0.95	0.95
HOSPITAL_67	1.01	1	1.01	1.01	1.02
HOSPITAL_68	0.82	0.95	1.07	1.02	0.84
HOSPITAL_69	0.94	0.95	0.89	0.85	0.8
HOSPITAL_7	1	1	1	1.00	1
HOSPITAL_71	1	1.27	0.82	1.04	1.04
HOSPITAL_72	0.84	0.93	1.11	1.03	0.87
HOSPITAL_73	0.97	1.07	0.94	1.01	0.97
HOSPITAL_74	1	0.7	0.89	0.62	0.63
HOSPITAL_75	1	1	1	1.00	1
HOSPITAL_76	0.92	0.84	1.02	0.86	0.79
HOSPITAL_79	1	1.21	0.96	1.16	1.16
HOSPITAL_8	1	0.67	0.55	0.37	0.37
HOSPITAL_80	1	1	1	1.00	1
HOSPITAL_81	0.97	0.95	0.96	0.91	0.88

HOSPITAL_82	0.94	0.97	1.03	1.00	0.94
HOSPITAL_86	0.95	1.04	0.99	1.03	0.99
HOSPITAL_87	1	1.01	1.03	1.04	1.04
HOSPITAL_89	1	0.91	0.92	0.84	0.84
HOSPITAL_9	1	1.07	1	1.07	1.07
HOSPITAL_91	1	1	1	1.00	1
HOSPITAL_94	0.94	0.91	1.1	1.00	0.95
HOSPITAL_95	1	1	1	1.00	1
HOSPITAL_97	0.82	1.01	1.02	1.03	0.84
HOSPITAL_99	1	1.01	0.92	0.93	0.93
Average	0.96	0.99	1.01	1.01	0.96

Year 2010-2011

Hospital Code	Technological change (TECHCH)	Change in scale efficiency (SECH)	Change in pure technical Efficiency (PECH)	Technical efficiency change (EFFCH)	Total factor Productivity change (TFPCH)
HOSPITAL_10	1	1.39	1.01	1.40	1.4
HOSPITAL_102	1.1	1.04	1.02	1.06	1.16
HOSPITAL_104	1.19	1.2	0.82	0.98	1.17
HOSPITAL_105	1	1.16	1.12	1.30	1.31
HOSPITAL_107	1	1.09	1.42	1.55	1.55
HOSPITAL_108	1	1	1	1.00	1
HOSPITAL_11	1.02	1.33	1.15	1.53	1.57
HOSPITAL_110	1.04	1.14	0.94	1.07	1.11
HOSPITAL_111	1.2	1.02	0.84	0.86	1.03
HOSPITAL_115	1.25	1.02	0.8	0.82	1.03
HOSPITAL_119	1.06	1.18	0.96	1.13	1.2
HOSPITAL_12	1.08	1	0.94	0.94	1.02
HOSPITAL_120	1.11	1.09	0.98	1.07	1.19
HOSPITAL_121	1.02	1.39	0.96	1.33	1.36
HOSPITAL_122	1.05	1.02	1	1.02	1.07
HOSPITAL_123	1.08	0.98	1	0.98	1.06
HOSPITAL_124	1	1	1	1.00	1
HOSPITAL_125	1.19	1.28	0.71	0.91	1.08
HOSPITAL_128	1	1.44	1	1.44	1.44
HOSPITAL_129	1	1.54	1	1.54	1.54
HOSPITAL_13	1	1	1	1.00	1
HOSPITAL_130	1	1.86	1	1.86	1.86
HOSPITAL_132	1	0.98	1	0.98	0.98
HOSPITAL_133	1	1.11	1.17	1.30	1.29
HOSPITAL_136	1.07	1.23	1	1.23	1.31
HOSPITAL_138	1.04	1.3	0.93	1.21	1.25
HOSPITAL_14	1.05	1.31	1.01	1.32	1.39
HOSPITAL_145	1.1	0.99	0.82	0.81	0.9
HOSPITAL_146	1	1.09	1.14	1.24	1.25
HOSPITAL_147	1	1.15	1.2	1.38	1.38
HOSPITAL_148	1.02	1.4	0.96	1.34	1.37
HOSPITAL_150	1.04	1.29	1	1.29	1.34
HOSPITAL_152	1.05	1.06	0.92	0.98	1.02

HOSPITAL_153	1	1.05	1	1.05	1.05
HOSPITAL_157	1	1	1	1.00	1
HOSPITAL_158	1	1.13	1.36	1.54	1.54
HOSPITAL_16	1	1.08	1	1.08	1.08
HOSPITAL_160	1.08	1.01	0.99	1.00	1.08
HOSPITAL_161	1	1.25	1	1.25	1.25
HOSPITAL_162	1	1.01	1	1.01	1.01
HOSPITAL_163	1.02	1.15	1.2	1.38	1.4
HOSPITAL_164	1	1.29	1.15	1.48	1.49
HOSPITAL_165	1.03	1.28	1.08	1.38	1.42
HOSPITAL_166	1	1.04	1.13	1.18	1.17
HOSPITAL_167	1.16	0.99	0.87	0.86	1.01
HOSPITAL_169	1.08	1.12	0.86	0.96	1.04
HOSPITAL_17	1.09	0.99	0.87	0.86	0.95
HOSPITAL_171	1	1.39	1	1.39	1.39
HOSPITAL_172	1	0.87	1	0.87	0.87
HOSPITAL_175	1	1	1	1.00	1
HOSPITAL_178	1.06	0.98	1.07	1.05	1.11
HOSPITAL_179	1.08	1	1.05	1.05	1.13
HOSPITAL_19	1.15	1.21	0.83	1.00	1.15
HOSPITAL_2	1.01	1.04	1.2	1.25	1.26
HOSPITAL_20	1.06	1.08	1.02	1.10	1.16
HOSPITAL_21	1.08	1.17	1	1.17	1.26
HOSPITAL_22	1.01	1.01	1.03	1.04	1.06
HOSPITAL_24	1	0.96	1	0.96	0.96
HOSPITAL_26	1.09	1.19	1.14	1.36	1.48
HOSPITAL_27	1.06	1.31	1.02	1.34	1.42
HOSPITAL_29	1.12	1	0.94	0.94	1.05
HOSPITAL_3	1	1.1	1	1.10	1.1
HOSPITAL_30	1.06	1.17	1.04	1.22	1.3
HOSPITAL_31	1	1.15	0.86	0.99	0.99
HOSPITAL_32	1	0.76	1.13	0.86	0.86
HOSPITAL_34	1.02	1.03	1.12	1.15	1.18
HOSPITAL_36	0.96	0.91	1.16	1.06	1.01
HOSPITAL_38	1.2	1.16	0.94	1.09	1.31
HOSPITAL_40	1.15	1.85	0.93	1.72	1.98
HOSPITAL_41	1.11	1.32	0.87	1.15	1.27
HOSPITAL_42	1	1.09	1.86	2.03	2.02
HOSPITAL_44	1	1.04	1	1.04	1.04
HOSPITAL_45	1	1.41	1	1.41	1.41
HOSPITAL_46	1	1.07	1.16	1.24	1.23
HOSPITAL_47	1	1.32	0.99	1.31	1.31
HOSPITAL_49	1.09	1.32	0.9	1.19	1.29
HOSPITAL_5	1	1.36	1.12	1.52	1.52
HOSPITAL_50	1	1.11	1.37	1.52	1.52
HOSPITAL_51	1	1	1	1.00	1
HOSPITAL_52	1	1.25	1	1.25	1.25
HOSPITAL_53	1.03	1.13	1.32	1.49	1.52
HOSPITAL_54	1.13	1.59	0.85	1.35	1.53
HOSPITAL_55	1.08	1.36	1.11	1.51	1.64
HOSPITAL_58	1.06	1.42	1.07	1.52	1.61
HOSPITAL_59	1.01	1.96	1.04	2.04	2.06

HOSPITAL_6	1	1	1	1.00	1
HOSPITAL_61	1.05	1.5	1.03	1.55	1.63
HOSPITAL_62	1	1.5	1	1.50	1.5
HOSPITAL_63	1	1.53	1	1.53	1.53
HOSPITAL_64	1	0.94	1.22	1.15	1.15
HOSPITAL_67	1.03	1.06	1.06	1.12	1.16
HOSPITAL_68	1.17	1.02	1	1.02	1.19
HOSPITAL_69	1.07	1.01	1.11	1.12	1.21
HOSPITAL_7	1.08	0.88	0.86	0.76	0.82
HOSPITAL_71	1	1.44	1.22	1.76	1.76
HOSPITAL_72	1.08	1.13	1.11	1.25	1.35
HOSPITAL_73	1.11	1.49	0.92	1.37	1.52
HOSPITAL_74	1	1.24	1.12	1.39	1.39
HOSPITAL_75	1.02	1	1	1.00	1.02
HOSPITAL_76	1.07	1.19	1.03	1.23	1.31
HOSPITAL_79	1.07	1.05	1.03	1.08	1.16
HOSPITAL_8	1.12	1.19	1.46	1.74	1.94
HOSPITAL_80	1	1	1	1.00	1
HOSPITAL_81	1	1.06	1.12	1.19	1.19
HOSPITAL_82	1.13	1.06	0.86	0.91	1.04
HOSPITAL_86	1	1.03	1.14	1.17	1.17
HOSPITAL_87	1.08	1.59	1.02	1.62	1.75
HOSPITAL_89	1.09	1.19	0.98	1.17	1.27
HOSPITAL_9	1	1.22	1	1.22	1.22
HOSPITAL_91	1	1	1	1.00	1
HOSPITAL_94	1.09	1.06	0.88	0.93	1
HOSPITAL_95	1	0.95	1	0.95	0.95
HOSPITAL_97	1.11	0.92	1.23	1.13	1.25
HOSPITAL_99	1.06	0.9	1.05	0.95	1
Average	1.05	1.16	1.03	1.20	1.25

Year2011-2012

Hospital Code	Technologil change (TECHCH)	Change in scale efficiency (SECH)	Change in pure technical Efficiency (PECH)	Technicl efficiency change (EFFCH)	Total factor Productivity change (TFPCH)
HOSPITAL_10	1	1	1	1.00	1
HOSPITAL_102	1.05	1	0.82	0.82	0.86
HOSPITAL_104	1.06	1.19	1.09	1.30	1.38
HOSPITAL_105	1	1.35	1	1.35	1.35
HOSPITAL_107	1	0.85	1	0.85	0.85
HOSPITAL_108	1	1	1	1.00	1
HOSPITAL_11	0.99	1.02	1.05	1.07	1.06
HOSPITAL_110	0.95	0.88	1.08	0.95	0.9
HOSPITAL_111	1.01	1	1.04	1.04	1.05
HOSPITAL_115	1	0.93	1.35	1.26	1.25
HOSPITAL_119	0.99	0.99	1.13	1.12	1.11
HOSPITAL_12	0.91	0.97	1.14	1.11	1.01

HOSPITAL_120	1	1.03	1.02	1.05	1.05
HOSPITAL_121	1	1.21	1	1.21	1.22
HOSPITAL_122	1	1	1	1.00	1
HOSPITAL_123	0.99	0.97	1.05	1.02	1.01
HOSPITAL_124	1	1.04	1	1.04	1.04
HOSPITAL_125	0.92	0.89	1.41	1.25	1.15
HOSPITAL_128	1.03	0.99	0.85	0.84	0.87
HOSPITAL_129	1	1	1	1.00	1
HOSPITAL_13	0.98	0.98	0.9	0.88	0.87
HOSPITAL_130	1	0.99	1	0.99	0.99
HOSPITAL_132	0.96	0.95	0.96	0.91	0.88
HOSPITAL_133	1	1	1	1.00	1
HOSPITAL_136	1	1.03	1	1.03	1.03
HOSPITAL_138	0.98	0.82	1.08	0.89	0.87
HOSPITAL_14	0.94	1.02	1.05	1.07	1.01
HOSPITAL_145	0.96	1.02	1.22	1.24	1.18
HOSPITAL_146	0.99	1.05	1	1.05	1.03
HOSPITAL_147	1	1.17	1	1.17	1.17
HOSPITAL_148	1	1.21	1.04	1.26	1.25
HOSPITAL_150	0.99	0.97	0.75	0.73	0.73
HOSPITAL_152	0.96	0.73	1.09	0.80	0.76
HOSPITAL_153	1	1	1	1.00	1
HOSPITAL_157	1.09	0.93	0.86	0.80	0.87
HOSPITAL_158	1	1.05	1	1.05	1.05
HOSPITAL_16	1.16	0.99	0.85	0.84	0.98
HOSPITAL_160	1.06	1.1	0.8	0.88	0.94
HOSPITAL_161	1	1.06	1	1.06	1.06
HOSPITAL_162	1	1.12	1	1.12	1.12
HOSPITAL_163	1	1.05	0.86	0.90	0.9
HOSPITAL_164	1	0.97	1	0.97	0.97
HOSPITAL_165	1	1.1	1.06	1.17	1.17
HOSPITAL_166	1	1	1	1.00	1
HOSPITAL_167	1.02	0.98	0.93	0.91	0.92
HOSPITAL_169	1	1.07	1.17	1.25	1.25
HOSPITAL_17	1.05	1.05	0.95	1.00	1.05
HOSPITAL_171	1	0.94	1	0.94	0.94
HOSPITAL_172	1	1.14	1	1.14	1.14
HOSPITAL_175	1	1	1	1.00	1
HOSPITAL_178	0.95	1.04	1.12	1.16	1.12
HOSPITAL_179	0.98	1.04	1.14	1.19	1.17
HOSPITAL_19	0.97	1.08	1.13	1.22	1.18
HOSPITAL_2	1	1.03	1	1.03	1.03
HOSPITAL_20	1	1.02	1.05	1.07	1.07
HOSPITAL_21	0.88	0.99	1.13	1.12	0.99
HOSPITAL_22	1	1.1	0.97	1.07	1.07
HOSPITAL_24	0.98	1.22	1	1.22	1.2
HOSPITAL_26	1.08	0.99	1.03	1.02	1.1
HOSPITAL_27	0.94	1.08	1.13	1.22	1.15
HOSPITAL_29	0.99	1.1	1.05	1.16	1.15
HOSPITAL_3	1	1.07	1	1.07	1.07
HOSPITAL_30	1	1.07	0.95	1.02	1.02
HOSPITAL_31	0.99	0.91	0.96	0.87	0.87

HOSPITAL_32	1	0.91	1	0.91	0.91
HOSPITAL_34	1	1.15	1.04	1.20	1.19
HOSPITAL_36	0.99	0.8	0.95	0.76	0.75
HOSPITAL_38	0.93	1.04	1.23	1.28	1.18
HOSPITAL_40	1.12	1.19	1.06	1.26	1.41
HOSPITAL_41	0.99	1.07	0.88	0.94	0.93
HOSPITAL_42	0.92	0.97	1	0.97	0.9
HOSPITAL_44	1	0.73	1	0.73	0.73
HOSPITAL_45	1	0.99	1	0.99	0.99
HOSPITAL_46	1	0.94	1	0.94	0.94
HOSPITAL_47	1	0.8	0.94	0.75	0.76
HOSPITAL_49	0.99	1.06	0.95	1.01	1
HOSPITAL_5	1	1	1	1.00	1
HOSPITAL_50	1	1.02	1	1.02	1.02
HOSPITAL_51	1	1	1	1.00	1
HOSPITAL_52	1.12	0.93	0.93	0.86	0.96
HOSPITAL_53	0.99	1.02	1.06	1.08	1.07
HOSPITAL_54	1	0.98	0.95	0.93	0.93
HOSPITAL_55	1.07	1.01	1.06	1.07	1.14
HOSPITAL_58	1	0.96	1	0.96	0.96
HOSPITAL_59	1.03	1.12	0.96	1.08	1.11
HOSPITAL_6	1	1	1	1.00	1
HOSPITAL_61	1	1.04	1	1.04	1.04
HOSPITAL_62	1	0.91	1	0.91	0.91
HOSPITAL_63	1	1.04	1	1.04	1.04
HOSPITAL_64	1.13	1.17	0.78	0.91	1.02
HOSPITAL_67	0.99	1.12	1.07	1.20	1.18
HOSPITAL_68	0.88	1.09	1.28	1.40	1.22
HOSPITAL_69	0.99	0.97	0.93	0.90	0.89
HOSPITAL_7	0.99	1.2	1.17	1.40	1.39
HOSPITAL_71	1	1.05	1	1.05	1.05
HOSPITAL_72	1	1.09	0.94	1.02	1.03
HOSPITAL_73	1.01	1.12	1	1.12	1.13
HOSPITAL_74	1	1.02	0.88	0.90	0.9
HOSPITAL_75	0.98	0.92	0.97	0.89	0.88
HOSPITAL_76	1	1.01	1	1.01	1.02
HOSPITAL_79	1	0.97	0.87	0.84	0.85
HOSPITAL_8	1.01	1.23	1.03	1.27	1.28
HOSPITAL_80	1	1	1	1.00	1
HOSPITAL_81	1.06	0.99	0.9	0.89	0.95
HOSPITAL_82	0.99	0.88	1.12	0.99	0.98
HOSPITAL_86	1.02	0.98	0.94	0.92	0.94
HOSPITAL_87	1.01	0.91	1.17	1.06	1.08
HOSPITAL_89	0.98	1.11	1	1.11	1.08
HOSPITAL_9	1	1	1	1.00	1
HOSPITAL_91	1	1	1	1.00	1
HOSPITAL_94	1	0.93	0.98	0.91	0.92
HOSPITAL_95	1	1	1	1.00	1
HOSPITAL_97	0.97	0.93	0.77	0.72	0.7
HOSPITAL_99	1	0.99	0.95	0.94	0.94
Average	1.00	1.02	1.01	1.03	1.02

<u>Appendix F</u> Summary of the cumulative Malmquist productivity indices and its components
Year 2009-2011

Hospital Code	Technological change (TECHCH)	Change in scale efficiency (SECH)	Change in pure technical Efficiency (PECH)	Technical efficiency change (EFFCH)	Total factor Productivity change (TFPCH)
HOSPITAL_10	1	1.56	1.02	1.59	1.6
HOSPITAL_102	0.95	0.9	1.27	1.14	1.08
HOSPITAL_104	0.99	1.02	0.7	0.71	0.71
HOSPITAL_105	0.96	0.7	1.08	0.76	0.72
HOSPITAL_107	0.99	1	1.1	1.10	1.09
HOSPITAL_108	1	1	1	1.00	1
HOSPITAL_11	1.02	1.54	1.1	1.69	1.74
HOSPITAL_110	1.01	1.09	0.93	1.01	1.02
HOSPITAL_111	0.99	0.81	0.84	0.68	0.68
HOSPITAL_115	1	1.04	0.64	0.67	0.66
HOSPITAL_119	1	1.04	0.92	0.96	0.95
HOSPITAL_12	1.02	0.99	0.97	0.96	0.98
HOSPITAL_120	1.01	0.79	0.98	0.77	0.78
HOSPITAL_121	1	1.14	0.96	1.09	1.09
HOSPITAL_122	1.04	1	1.29	1.29	1.35
HOSPITAL_123	0.99	0.9	0.94	0.85	0.84
HOSPITAL_124	1	1	1	1.00	1
HOSPITAL_125	1.01	1.01	0.71	0.72	0.73
HOSPITAL_128	1	1	1	1.00	1
HOSPITAL_129	1	3.01	1.04	3.13	3.12
HOSPITAL_13	1.02	1.19	1.29	1.54	1.55
HOSPITAL_130	1	1.47	1	1.47	1.47
HOSPITAL_132	0.99	1.04	1	1.04	1.02
HOSPITAL_133	1	1.15	1.14	1.31	1.31
HOSPITAL_136	1	1.11	1	1.11	1.11
HOSPITAL_138	1	2.06	1.02	2.10	2.12
HOSPITAL_14	1.02	1.55	1.05	1.63	1.66
HOSPITAL_145	0.81	1.12	1.76	1.97	1.6
HOSPITAL_146	1	1.17	1.03	1.21	1.2
HOSPITAL_147	0.85	1.27	1.46	1.85	1.57
HOSPITAL_148	0.97	0.86	1.05	0.90	0.87
HOSPITAL_150	1	1.08	1	1.08	1.08
HOSPITAL_152	0.95	1.08	0.99	1.07	1.01
HOSPITAL_153	1	1	1	1.00	1
HOSPITAL_157	0.93	1.37	1.16	1.59	1.48
HOSPITAL_158	0.99	1.03	1.18	1.22	1.21
HOSPITAL_16	1.13	0.95	1.11	1.05	1.19
HOSPITAL_160	1	1	0.99	0.99	0.98
HOSPITAL_161	1	1.41	1.22	1.72	1.71
HOSPITAL_162	1	1.05	1	1.05	1.05
HOSPITAL_163	1	0.84	0.91	0.76	0.77
HOSPITAL_164	0.97	0.99	1	0.99	0.95
HOSPITAL_165	0.99	0.89	1.15	1.02	1.02
HOSPITAL_166	0.99	2.2	1.33	2.93	2.88

HOSPITAL_167	0.99	0.88	0.95	0.84	0.83
HOSPITAL_169	1	1.05	0.86	0.90	0.9
HOSPITAL_17	1.07	1.08	0.94	1.02	1.09
HOSPITAL_171	0.88	0.94	1.41	1.33	1.16
HOSPITAL_172	1	0.84	1	0.84	0.84
HOSPITAL_175	1	1	1	1.00	1
HOSPITAL_178	0.98	0.89	1.04	0.93	0.9
HOSPITAL_179	0.99	1	0.99	0.99	0.97
HOSPITAL_19	1.01	0.99	0.85	0.84	0.85
HOSPITAL_2	1.01	1.26	1.03	1.30	1.31
HOSPITAL_20	1.13	1.05	0.97	1.02	1.16
HOSPITAL_21	1.11	1.16	0.98	1.14	1.26
HOSPITAL_22	1	0.81	1.08	0.87	0.88
HOSPITAL_24	1	1.26	1.14	1.44	1.44
HOSPITAL_26	1.09	1.47	1.06	1.56	1.69
HOSPITAL_27	1.01	2.06	1.06	2.18	2.21
HOSPITAL_29	1	1.15	0.82	0.94	0.94
HOSPITAL_3	0.99	0.96	1.36	1.31	1.29
HOSPITAL_30	1	1.12	0.96	1.08	1.08
HOSPITAL_31	1.08	1.8	0.86	1.55	1.67
HOSPITAL_32	1	0.74	1	0.74	0.74
HOSPITAL_34	1	0.95	1.04	0.99	0.99
HOSPITAL_36	1	1.33	1.03	1.37	1.37
HOSPITAL_38	1.01	1.05	1.07	1.12	1.13
HOSPITAL_40	1	2.45	0.88	2.16	2.17
HOSPITAL_41	1	1.02	0.9	0.92	0.92
HOSPITAL_42	0.96	0.98	1.29	1.26	1.21
HOSPITAL_44	1	1.03	1	1.03	1.03
HOSPITAL_45	1	2.27	1	2.27	2.27
HOSPITAL_46	0.95	1.12	1.17	1.31	1.24
HOSPITAL_47	0.98	1.68	1.22	2.05	2
HOSPITAL_49	1	0.99	1.09	1.08	1.07
HOSPITAL_5	1	1.32	1.09	1.44	1.44
HOSPITAL_50	0.97	1.04	1.37	1.42	1.39
HOSPITAL_51	0.98	1	1.05	1.05	1.02
HOSPITAL_52	1	1.14	1.04	1.19	1.19
HOSPITAL_53	1.03	1.54	0.95	1.46	1.5
HOSPITAL_54	1	2.13	0.79	1.68	1.68
HOSPITAL_55	1.08	1.15	0.94	1.08	1.17
HOSPITAL_58	0.99	1.01	0.91	0.92	0.92
HOSPITAL_59	1.01	1.07	0.97	1.04	1.06
HOSPITAL_6	1	1	1	1.00	1
HOSPITAL_61	1	1.42	1.2	1.70	1.71
HOSPITAL_62	1	0.9	1	0.90	0.9
HOSPITAL_63	1	1.41	1.1	1.55	1.56
HOSPITAL_64	1	1.03	1	1.03	1.03
HOSPITAL_67	1.01	1.06	1.06	1.12	1.13
HOSPITAL_68	0.96	0.99	1.07	1.06	1.03
HOSPITAL_69	1	0.89	0.99	0.88	0.88
HOSPITAL_7	1	0.75	0.86	0.65	0.64
HOSPITAL_71	1	2.05	1	2.05	2.05
HOSPITAL_72	1	0.96	1.24	1.19	1.19

HOSPITAL_73	0.97	1.83	0.86	1.57	1.54
HOSPITAL_74	1	0.8	1	0.80	0.8
HOSPITAL_75	1.02	1.02	1	1.02	1.05
HOSPITAL_76	1	0.9	1.05	0.95	0.94
HOSPITAL_79	1	1.1	0.99	1.09	1.09
HOSPITAL_8	1	0.53	0.8	0.42	0.42
HOSPITAL_80	1.05	1.02	1	1.02	1.08
HOSPITAL_81	1.01	1.03	1.07	1.10	1.11
HOSPITAL_82	1.04	0.94	0.89	0.84	0.87
HOSPITAL_86	1.02	1.05	1.13	1.19	1.21
HOSPITAL_87	0.99	1.94	1.04	2.02	2.01
HOSPITAL_89	1	1.05	0.9	0.95	0.94
HOSPITAL_9	1	1.24	1	1.24	1.24
HOSPITAL_91	1	1	1	1.00	1
HOSPITAL_94	0.97	0.92	0.97	0.89	0.86
HOSPITAL_95	1	0.9	1	0.90	0.9
HOSPITAL_97	0.98	0.82	1.25	1.03	1
HOSPITAL_99	1	0.8	0.97	0.78	0.77
Average	1.00	1.16	1.03	1.20	1.20

Year2009-2012

Hospital Code	Technological change (TECHCH)	Change in scale efficiency (SECH)	Change in pure technical Efficiency (PECH)	Technical efficiency change (EFFCH)	Total factor Productivity change (TFPCH)
HOSPITAL_10	1	1.39	1.02	1.42	1.42
HOSPITAL_102	0.94	0.89	1.04	0.93	0.88
HOSPITAL_104	1.14	1.22	0.76	0.93	1.06
HOSPITAL_105	0.96	0.99	1.08	1.07	1.02
HOSPITAL_107	0.96	0.85	1.1	0.94	0.91
HOSPITAL_108	1	1	1	1.00	1
HOSPITAL_11	1	1.41	1.16	1.64	1.63
HOSPITAL_110	1	1.08	1	1.08	1.08
HOSPITAL_111	1	0.84	0.87	0.73	0.73
HOSPITAL_115	1	1.08	0.86	0.93	0.92
HOSPITAL_119	0.98	1.02	1.04	1.06	1.04
HOSPITAL_12	0.87	1.03	1.1	1.13	0.99
HOSPITAL_120	1	0.85	1	0.85	0.85
HOSPITAL_121	1.02	1.35	0.96	1.30	1.32
HOSPITAL_122	0.98	1	1.29	1.29	1.27
HOSPITAL_123	0.96	0.91	1	0.91	0.86
HOSPITAL_124	1	1	1	1.00	1
HOSPITAL_125	1	0.92	1	0.92	0.92
HOSPITAL_128	1.08	0.99	0.85	0.84	0.91
HOSPITAL_129	1	2.69	1.04	2.80	2.78
HOSPITAL_13	0.96	1.1	1.16	1.28	1.22
HOSPITAL_130	1	1.27	1	1.27	1.27
HOSPITAL_132	0.98	1.15	0.96	1.10	1.07
HOSPITAL_133	1	1.12	1.14	1.28	1.27

HOSPITAL_136	1	1.12	1	1.12	1.12
HOSPITAL_138	1	1.44	1.1	1.58	1.59
HOSPITAL_14	0.99	1.35	1.1	1.49	1.48
HOSPITAL_145	0.74	1.18	2.14	2.53	1.87
HOSPITAL_146	0.95	1.13	1.03	1.16	1.1
HOSPITAL_147	0.98	1.29	1.46	1.88	1.85
HOSPITAL_148	0.96	1.12	1.09	1.22	1.17
HOSPITAL_150	1	1.01	0.75	0.76	0.76
HOSPITAL_152	0.99	0.78	1.08	0.84	0.84
HOSPITAL_153	1	1	1	1.00	1
HOSPITAL_157	1	1.27	1	1.27	1.27
HOSPITAL_158	0.99	1.02	1.18	1.20	1.19
HOSPITAL_16	1.19	1.01	0.94	0.95	1.12
HOSPITAL_160	1.13	1.03	0.79	0.81	0.92
HOSPITAL_161	0.94	1.47	1.22	1.79	1.67
HOSPITAL_162	1	1.07	1	1.07	1.07
HOSPITAL_163	1	0.89	0.78	0.69	0.69
HOSPITAL_164	0.97	0.95	1	0.95	0.92
HOSPITAL_165	0.96	1.01	1.22	1.23	1.19
HOSPITAL_166	1	2.08	1.33	2.77	2.75
HOSPITAL_167	0.97	0.91	0.88	0.80	0.78
HOSPITAL_169	1	1.08	1	1.08	1.08
HOSPITAL_17	1.02	1.05	0.9	0.95	0.97
HOSPITAL_171	0.84	0.97	1.41	1.37	1.15
HOSPITAL_172	1.01	0.97	1	0.97	0.98
HOSPITAL_175	1	1	1	1.00	1
HOSPITAL_178	0.86	1.07	1.17	1.25	1.07
HOSPITAL_179	0.92	0.93	1.12	1.04	0.95
HOSPITAL_19	0.98	1.04	0.95	0.99	0.97
HOSPITAL_2	0.98	1.17	1.03	1.21	1.19
HOSPITAL_20	1.07	1.01	1.02	1.03	1.1
HOSPITAL_21	0.95	1.12	1.1	1.23	1.18
HOSPITAL_22	0.95	0.96	1.05	1.01	0.96
HOSPITAL_24	0.97	1.4	1.14	1.60	1.55
HOSPITAL_26	1.07	1.38	1.09	1.50	1.62
HOSPITAL_27	1	2.24	1.2	2.69	2.69
HOSPITAL_29	1	1.25	0.86	1.08	1.08
HOSPITAL_3	0.92	1	1.36	1.36	1.25
HOSPITAL_30	1.01	1.17	0.92	1.08	1.09
HOSPITAL_31	1	1.72	0.83	1.43	1.43
HOSPITAL_32	1	0.61	1	0.61	0.61
HOSPITAL_34	0.98	1.09	1.08	1.18	1.15
HOSPITAL_36	0.99	1.25	0.97	1.21	1.2
HOSPITAL_38	1.02	0.95	1.31	1.24	1.27
HOSPITAL_40	1.12	2.39	0.94	2.25	2.5
HOSPITAL_41	0.97	1.08	0.79	0.85	0.83
HOSPITAL_42	0.91	0.93	1.29	1.20	1.09
HOSPITAL_44	1	0.74	1	0.74	0.74
HOSPITAL_45	1	2.17	1	2.17	2.17
HOSPITAL_46	0.96	1.12	1.17	1.31	1.26
HOSPITAL_47	1	1.39	1.16	1.61	1.61
HOSPITAL_49	1	1.09	1.04	1.13	1.12

HOSPITAL_5	1	1.27	1.09	1.38	1.38
HOSPITAL_50	1	1.08	1.37	1.48	1.47
HOSPITAL_51	0.98	1	1.05	1.05	1.02
HOSPITAL_52	1.02	1.04	0.97	1.01	1.02
HOSPITAL_53	1	1.44	1	1.44	1.44
HOSPITAL_54	1.02	1.82	0.75	1.37	1.39
HOSPITAL_55	1.05	1.12	1	1.12	1.17
HOSPITAL_58	1	1.03	0.91	0.94	0.94
HOSPITAL_59	1.04	1.15	0.93	1.07	1.11
HOSPITAL_6	1	0.97	1	0.97	0.97
HOSPITAL_61	1.02	1.42	1.2	1.70	1.74
HOSPITAL_62	1	0.9	1	0.90	0.9
HOSPITAL_63	1	1.41	1.1	1.55	1.56
HOSPITAL_64	1.1	1.17	0.78	0.91	1
HOSPITAL_67	0.99	1.17	1.13	1.32	1.31
HOSPITAL_68	0.79	1.13	1.37	1.55	1.23
HOSPITAL_69	0.93	0.9	0.92	0.83	0.78
HOSPITAL_7	1	1	1	1.00	1
HOSPITAL_71	1	1.91	1	1.91	1.91
HOSPITAL_72	1	1.02	1.16	1.18	1.19
HOSPITAL_73	1	1.78	0.87	1.55	1.54
HOSPITAL_74	1	0.82	0.88	0.72	0.72
HOSPITAL_75	0.99	0.95	0.97	0.92	0.91
HOSPITAL_76	0.99	0.94	1.05	0.99	0.97
HOSPITAL_79	1	1.08	0.86	0.93	0.94
HOSPITAL_8	1	0.67	0.82	0.55	0.56
HOSPITAL_80	1	1	1	1.00	1
HOSPITAL_81	1.03	1	0.97	0.97	1.01
HOSPITAL_82	1.02	0.84	1	0.84	0.85
HOSPITAL_86	1	1.01	1.07	1.08	1.08
HOSPITAL_87	1	1.56	1.22	1.90	1.9
HOSPITAL_89	0.99	1.09	0.89	0.97	0.96
HOSPITAL_9	1	1.12	1	1.12	1.12
HOSPITAL_91	1	1	1	1.00	1
HOSPITAL_94	0.94	0.91	0.95	0.86	0.82
HOSPITAL_95	1	0.94	1	0.94	0.94
HOSPITAL_97	0.98	0.86	0.97	0.83	0.81
HOSPITAL_99	0.99	0.87	0.92	0.80	0.78
Average	0.99	1.15	1.04	1.20	1.18