Modelling the Efficiency of Health Care Foodservice Operations:

A Stochastic Frontier Approach

by

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Abstract

The important role of efficiency in the health care foodservice sector has been widely addressed in the literature. Different methods for assessing performance have been proposed. In general, most measures were calculated as simple ratios such as food and labour cost per meal or limited parametric techniques such as regression analysis. These approaches are meaningful indicators of which operational performance areas require attentions; however, problems arise when managers interpret partial productivity measures of this type as indicators of overall performance without considering the effects of other related variables. This could create further problems in complex applications such as the health care foodservice sector where multiple inputs (number of full time employees, energy cost, capital, overheads) outputs (number of meals and patient satisfaction) and environmental or interfering variables (age of equipment, quality of labour or skill level of employees and the degree of readiness of materials) should be considered in the assessment of efficiency.

This study contributes to overcoming these limitations by introducing the stochastic frontier approach to assess the efficiency of the health care foodservice sector. It is superior to the traditional productivity approaches as it allows for the integrations of multiple inputs and outputs in evaluating relative efficiencies. The overall objective of the study was to determine the level of cost, technical and allocative efficiency in a sample of health care foodservice operations. More specifically, the objective was pursued by estimating stochastic production and cost frontiers models, which provided the basis for measuring technical (TE), allocative (AE) and cost efficiency (CE). The factors that significantly contribute to increasing inefficiency in health care foodservice operations

were also identified. In this way, this study has policy implications because it not only provided empirical measures of different efficiency indices, but also identifies some key variables that are correlated with these indices. It goes beyond much of the published literature concerning efficiency because most research in the area of efficiency analysis focuses exclusively on the measurement of technical and cost efficiency.

The stochastic frontier approach was tested in a cross sectional data set from a sample of 101 health care foodservice operations in Australia and the USA. Results showed that the models and all the parameters coefficients were plausible, significant and satisfy all theoretical requirements. Further, results also showed that the average cost, technical and cost efficiency were around 70 percent, 80 percent and 88 percent respectively. These figures suggest that substantial gains in output and/or decreases in cost can be attained if hospital foodservice operations were to improve their current performance. Finally, the results indicated that an increase in the level of manager's experience and the level of manager's education could have a positive impact on decreasing the level of inefficiency in health care foodservice operations.

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This thesis is dedicated with love to the strong and dedicated man who has shaped my life – my father.

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Chapter 1: Introduction

1.1 Introduction

This study analyzes the technical, allocative and cost efficiency of health care foodservice operations. The need for this study arises from two sets of related issues. The first, discussed in the next section, relates to the limitations of efficiency studies currently available in the health care foodservice literature. The second set of issues, identified as the statement of problem of this study, addresses the current characteristics of the health care foodservice industry, leading to the potential benefits and objectives of the study.

1.2 Background

During the past decade, the increased size of meal production in health care foodservice operations has created additional pressure on foodservice managers to reduce operational costs and to improve profitability (ADA, 2005). To illustrate, in Australia, over 40 million meals per annum are provided by the New South Wales Health Department at a cost of $300 million (NSW Health, 2006), and in the state of Victoria 10 million meals are produced per annum with a provision for meal costs of around $90 million. In the United States, the food contracts in hospitals alone represent around $US 3.778 billion with an annual growth of 8.8%,while in the United Kingdom 300 million meals are served each year at a cost of around £500 million (Krassie, 2005). These new challenges have also necessitated improvements in the efficiency measurement of health care foodservice operations. Efficiency can be described as an assisting tool for identifying areas of cost containment and cost reduction. Today, accounting and finance departments in many hospitals generate and distribute a variety of reports, in order to assist foodservice managers in assessing the efficiency of their foodservice operations. For example, in

Australia quarterly reports are usually issued in each ‘Area Health Service’ which contain key performance indicators of different areas of the foodservice operations such as food and labour costs. These reports can be useful in directing department operations; however, many times they fail to provide the detail necessary to fully evaluate the overall performance.

Despite the fact that hospital foodservice managers have recognized the current need to control multiple resource cost, information addressing efficiency and management practices in the health care foodservice literature have been limited and insufficient in comparison with other sectors of the hospitality industry such as hotels and restaurants. Traditionally, efficiency has been measured by means of ratio analysis (food cost per meal, number of meals per full- time equivalent employee, etc.) (Greathouse et al., 1989) and limited parametric techniques such as linear regression (Clark, 1997). Ratio analysis gives useful information about a firm’s performance but it also has several shortcomings which will be discussed later in this paper. Several partial productivity measures may be sometimes used collectively to obtain a broad picture of efficiency. However, the presentation of a large number of partial measures will be difficult to comprehend and interpret if some indicators move in opposite directions over a given period of time. Similarly, the use of regression analysis is also subject to the limitation that the estimated equation provides a picture of the shape of an average function, as opposed to providing a ‘best practice’ function against which the efficiency of firms can be measured and interpreted (Coelli, 1995).

Given these shortcomings, the efficiency literature has much to say about the use of the so-called efficiency frontier approaches which overcome the limitations of the traditional productivity approaches by explicitly considering multiple inputs and outputs in the measurement of efficiency. These approaches are based on the concept of efficiency originated by Farrell (1957), and which renders itself different from the traditional concept of productivity defined in the literature. Productivity is defined as the ratio of input to output. The ratio can be calculated using a single input and output or by aggregating multiple inputs and outputs. It is, however, more useful for the assessment of partial areas of the foodservice operation, because of the aggregation problem posed when combining multiple factors. Efficiency, on the other hand, is based on the concept of production possibility frontier (Barros, 2005). The production frontier represents the maximum output attainable from each input level. Hence, it reflects the current state of technology in the industry. Knowing the frontier, one can estimate technical and allocative efficiency. The former reflects the ability of a firm to obtain maximum outputs from a given set of inputs, while the latter reflects the ability of a firm to use the inputs in optimal proportions given their input prices. These two measures are then combined to provide a measure of total cost efficiency. Thus, if an organisation uses its resources completely allocatively and technically efficiently, then it can be said to have achieved total cost efficiency. Alternatively, to the extent that either allocative or technical inefficiency is present, then the organisation will be operating at less than total cost efficiency.

Different approaches have been proposed in the literature to measure efficiency. The two most widely used methodologies are data envelopment analysis (DEA) and stochastic frontier analysis (SFA). DEA is a non-parametric method and involves the use of linear programming techniques and is especially suitable for analysis of firms that are characterized by multiple resources and multiple services, while SFA is based on parametric techniques and requires a functional specification of the cost structure or production structure. Each of these techniques has its advantages and disadvantages. While DEA can easily allow for the integration of multiple inputs and outputs, it is sensitive to measurement errors and does not allow for random deviations from the efficiency frontier**.** SFA, on the other hand, takes into account measurement error, but it needs an arbitrary pre-specification for a functional form of the production frontier. The overall agreement in the literature is that there is no approach that is strictly preferable to any other. A careful consideration of them, of the data set utilized, and of the intrinsic characteristics of the industry under analysis, will help the researcher in the correct implementation of these techniques.

In this study, SFA is used as it is deemed to be more relevant in the health care foodservice application where the data are usually influenced by the inherent diversity of hospitals and the effects of other environmental variables on efficiency outcomes. The methodology used in this study differentiates between all three types of efficiency; technical and allocative and cost efficiency. A stochastic frontier production function is estimated to derive measures of technical efficiency while a stochastic cost frontier is estimated to derive measures of cost efficiency. The study even goes beyond the measurement of efficiency to examine and statistically test the factors that exogenously influence cost and technical efficiency. The Battese and Coelli (1995) formulation is adopted. This formulation has the advantages of simultaneously estimating the parameters of the stochastic frontier and the factors affecting efficiency, given appropriate distributional assumptions associated with the error terms.

In summary, the sequence of the model estimation is as follows: first, the different types of efficiency of the health care foodservice operations represented in the sample are measured and analyzed. Second, the determinants of efficiency variation among these operations are analysed. Moreover, alternative methodological assumptions about stochastic frontiers including choice of functional form and the significance of inefficiency effects are also tested.

1.3 Statement of the problem

The foodservice operations within Australian hospitals have undergone major changes in the past decade. Historically, the provision of food to patients was the responsibility of each individual hospital which had its own kitchen facilities. Food was cooked and plated and served hot, in what is known as the ‘cook-serve’ system. This system required a substantial labour input and has always created tension arising from the necessity of working to tight schedules, and at the same time achieving high quality standards. Since the 1970s, advances have been made in foodservice systems with the introduction of the hybrid and the ‘cook-chill’ systems, in which the cooking of food was followed by rapid chilling or freezing for subsequent reheating and service. Despite the large initial capital investment of these new technologies, their real relevance was in the ‘decoupling’ process by which food production can be carried out separately from foodservice customer demand, either in terms of time, or place or both (Jones and Huelin, 1990a). Bankstown hospital was the first to introduce the cook-chill system in 1971, followed by Lidcome and Royal North Shore hospital in the mid-1970s. Due to technology changes in the late 1980s and early 1990s there has been a significant expansion in the use of cook-chill systems throughout the different states. The 1990s saw further changes with a number of food production units established to centrally prepare meals and have them delivered to hospitals. Today, the Australian Health Departments operate 13 centralized cook-chill production units (CPU) in New South Wales and 38 in Victoria; the majority of Queensland hospitals serve cook-chill meals (Krassie, 2005). Many smaller hospitals, particularly those in rural locations with less than 50 beds and others in more remote locations, continue to provide meals using the cook-serve method.

While many hospitals reported increased efficiency by the use of these new technologies (Krassie, 2005), many other have failed (NSW Health, 2005). The last health service report published by the department of health indicated that inefficiency is still a problem with most health care foodservice operations due to the under-utilisation of production capacity (NSW Health, 2006). Additionally, many area health services such as New South Wales recommended the closure of several central production units due to the increase in production cost and the emergence of external providers of food services. At the time of this study, food services in NSW Health were under review, and in 2007-2008 will transition to a state-wide business unit, ‘Shared Business Services’. The objective of the change is to standardize services to eliminate duplication, maximize resources, increase purchasing power and increase the efficiency and effectiveness of the state-wide business. Additionally, patient needs in public hospitals vary considerably and therefore a ‘one size fits all’ approach is not necessarily the answer to delivering the most cost effective and efficient service. The key challenge for Shared Business Services will be to ensure standardization can be maximised without compromising food safety, nutritional standards and patient satisfaction. Similar suggestions were also recently reported by Victoria Health (Victoria Health, 2005). It was stated that the key impediment to achieving efficiency in most health care foodservice operations is the fact there is no management framework that sets and drives the operations of foodservices (Victoria Health, 2005). Additionally many area health services are operating without financial and benchmarking data which need to be accelerated in a consistent way across the different area foodservices.

Internationally, and especially in the USA, there has been also a quite severe budget cut to foodservices (Sherer, 2004). In cities where there are many hospitals, only the efficient hospitals are surviving. Many state institutions have seen their kitchens close because of low efficiency, and major central production facilities have been built to achieve economy of scale. For example, the State of Tennessee has built a 93.000 square foot CPU at a cost of $20 million to cater for 49 sites and is managed by Marriott Management Services (NSW Health, 2006). This centre uses extended life cook-chill technology and is currently capable of producing 80,000 meals a day (21 million a year). Another significant factor is that many Area Health Services started to buy some of their food from commercial providers; this is to assist foodservice operations to cut operational cost and improve the level of production (ADA, 2005).

In summary, there is currently a major controversy over the efficiency of health care foodservice operations in Australia and the USA. This provides an additional justification for the need of this study. Results could be used to provide a clearer picture about the true level of efficiency, and to assist Area Health Services to take the appropriate corrective actions regarding the future of some foodservice operations.

1.4 Aim and Objectives of the Study

The aim of this study is to assess the level of technical, allocative and cost efficiency of health care foodservice operations.

The specific objectives include the following:

- to estimate and evaluate the production and cost frontier functions using a sample of health care foodservice operations,

- to compute technical, allocative and cost efficiency and their degree of variability among the different health care foodservice operations,
- to identify the variables that have influenced the technical and cost efficiency measures of health care foodservice operations,
- to test the functional form that represents the production and cost frontier models, in order to avoid any specification error in the estimation of the model,
- to test the for the existence of technical and cost inefficiency in the sample.

1.5 Significance of the study

This study uses a stochastic frontier approach to analyse the level of technical, allocative and cost efficiency of health care foodservice operations. The results of this study will be useful in several aspects. First, none of the previous studies that have analysed the productivity of health care foodservice operations have adopted the methodology used in this study. Most studies are outdated and limited to partial productivity measures or restricted statistical techniques. Therefore, the results of this study will add and complement those studies that have approached the productivity of this sector in a limited setting. Additionally, the model used in this study has the advantage of accounting for measurement error in the assessment of efficiency, which provides greater confidence in the interpretation and generalisation of the efficiency results.

Second, the issue of efficiency takes on added significance in the context of health care foodservice operations as they face increasing competition from commercial suppliers, which offer similar food products at a competitive price. Additionally, most hospitals, especially in the public sector operate within a tight budget and receive continuous pressure from the government to decrease operational costs (NSW Health, 2005).

The results of this study should provide foodservice operators with an opportunity to assess their level of performance against other competitors, and to re-evaluate their management practices relative to efficient producers.

Third, the study also identifies the variables that statistically explain total cost. This can provide many hospitals- especially those which are currently going through structural changes and refurbishment to their production departments (e.g. Health Area foodservices reform which is taking place in the States of New South Wales and Victoria in Australia) - with the opportunity to assess those variables that negatively affect total cost, and to take the appropriate corrective actions if necessary.

Finally, and equally important to the estimation of efficiency, the study also identifies the main factors that have bearing on technical and cost efficiency in the health care foodservice sector. This should provide less efficient foodservice operations with additional insights on how to improve their level of efficiency and to emphasise management practices that contribute to higher efficiency.

1.6 Outline of the study

The study is organized in the following manner:

Chapter 2: This chapter provides a review of the literature and gives the proposed study its relevance by including a summary of the existing literature on the productivity of health care foodservice operations. The chapter also provides an introduction to the frontier approach to measure efficiency and reviews the theoretical framework for both technical and cost efficiency.

Chapter 3: This chapter provides a detailed discussion of the empirical methods used in the study, elabourating on models and pertinent methodological issues. The first part elabourates on the parametric measurements of technical, allocative and cost efficiencies. The second part provides a discussion related to the specific stochastic frontier models used in this study.

Chapter 4: This chapter presents the results from the estimation of the frontier models used in this study. The chapter starts with a verification of the functional form adopted in the estimation of the models. The measures of technical, allocative and cost efficiency are then presented, including a discussion of the factors that exogenously influence these different types of efficiency.

Chapter 5: This chapter provides a detailed discussion related to the results reported in Chapter 4. The results of the efficiency estimates are first discussed and analyzed. This is followed by a detailed discussion of the frontier models, including a comparison with related studies in the health care foodservice area.

Chapter 6: This chapter provides a summary the key findings of the study and provides recommendations for further research.

Chapter 2: Literature Review

2.1 Introduction

As was stated in the previous chapter, new incentives and demand for efficiency have necessitated improvement in financial management of health care institutions. Managers of hospital foodservice operations are under increased pressure to compete for dwindling financial resources, to control costs, and to account for extra expenditures. Foodservice managers must seek new approaches to improve the profitability of foodservice departments.

Efficiency measurement, which motivates this study, could be one of the most important tools for identifying areas of cost containment and cost reduction. Before elabourating further on the concept of efficiency, it is important to distinguish at this stage between productivity and efficiency which are two different methods for measuring the performance of a foodservice operation. Productivity is the ratio of outputs over inputs. This ratio yields a relative measurement of performance that may be applied to any factor of production. This ratio can be calculated for a single input and output, or by aggregating multiple inputs and outputs. It is, however, more applied to a single production factor, because of the aggregation problem posed when combining different factors. Since it is relative measurement, managers usually look for external benchmarks to interpret the productivity ratio. Moreover, there are many alternative productivity ratios and choosing from among them is somewhat arbitrary. All of these measurement limitations are overcome by the efficiency concept.

Efficiency can be defined as relative productivity over time, space, or both (Barros, 2005). It relates to the concept of the production possibility frontier and comprises both technical efficiency and allocative efficiency. A production frontier is widely used to define the relationship between inputs and outputs by depicting graphically the maximum output obtainable from the given inputs consumed. It therefore reflects the current status of technology available in the industry. As efficiency is a relative measurement with regard to a production function, a benchmark is included in its definition, i.e. the production frontier. This being the case, an external benchmark is not required.

Despite these advantages of efficiency measurements, performance measurements in the health care foodservice industry were restricted to a limited number of productivity studies. Additionally, most measurement approaches were calculated as simple ratios such as food and labour cost per meal (Clark, 1997; Hong and Kirk, 1995; Mibey and Williams, 2002) or limited parametric techniques such as regression analysis (Clark, 1997). As stated before, these measures of performance are only meaningful when compared to a benchmark, and finding a suitable benchmark (e.g. the number of meals produced per employee that must be obtained before a firm is regarded as performing well) may be difficult. Another problem with these measures is that they are calculated using only a subset of the data available on the firm. This is problematic because a foodservice operation may perform well using one measure (e.g. energy cost per meal) but badly using another (e.g. labour cost per meal). What is needed is a single measure of total performance that is more sensitive than partial ratio measures and that can explicitly consider the mix of inputs and outputs provided.

Efficiency is a performance tool for obtaining such a measure. Two principal approaches have been proposed in the literature to measure efficiency. These include data envelopment analysis and stochastic frontier analysis, which involve mathematical programming and econometric methods, respectively. Both of these approaches are based on the concept of relative efficiency originated by Farrell (1957), and attempt to define variations from an efficiency frontier as sources of inefficiency. In this chapter there will be a short review of these approaches, along with the different types of efficiency proposed by Farrell (1957). The chapter is divided as follows: in the first section, a discussion of the existing productivity studies in the health care foodservice industry is provided. Analytical foundations of efficiency measurement are discussed in the following section. This is followed by a brief discussion of the frontier measurement approaches. The chapter concludes with a review of functional forms used in the estimation of the frontier models.

2.2 Traditional productivity approaches

The measurement of productivity in the health care foodservice sector can be considered as one of the most difficult in all foodservice segments (Reynolds, 1998). This can be particularly illustrated by the multiple inputs and outputs variables which require advanced analytical techniques to measure productivity. For example, studies by (Brown and Hoover, 1990; Clark, 1997; Greathouse and Gregoire, 1988) identified four inputs and two outputs. Inputs were number of full- time employees, energy cost, capital and overheads while outputs were number of meals and patient satisfaction.

Confusion and disagreement over the definition of some of these inputs and outputs has also created further difficulties (ADA, 2005; Clark, 1997). For example, meals are frequently used as an output measurement; however, what constitutes a meal and how meals should be counted has always been an area of debate. There is no industry-wide acceptable method for accounting for the number of meals. In Australia, many hospitals follow the meal unit methodology developed by the Australian Institute of Hospitality in Health Care (www.ihhc.org.au) which defines an average meal by applying different weighting coefficients according to the difference in labour and food costs.

When all inputs and outputs have been identified, the measurements of the so-called environmental variables- the variables that indirectly affect productivity- represent additional challenges. For example, the type of foodservice system can itself affect operational costs. There are mainly four types of foodservice systems in operation today, and each system has certain operational advantages. These are highlighted in Table 2.1.

Low productivity is, for example, inherent within the conventional system due to the peaks and valleys in demand (Green, 1992). Preparation is timed to when the food will be served and eaten, thus more labour needs to be scheduled during peak times, making the cost higher than for any of the other foodservice systems (Glew and Armstrong, 1981). On the other hand, the cook-chill system is expected to provide operational saving as it allows management to allocate staff more accurately as production is designed to meet future rather than immediate needs. It also allows foodservice providers to create a ‘bank’ which eliminates the need to produce additional products during peak hours.

Table 2.1. Advantages and disadvantages of foodservice systems

Foodservice systems	Definition	Main advantages	Main disadvantages
Traditional cook-fresh	Food is prepared hot held for a short period of time and then served to customers	• No need for chilling and reheating • Superior food quality • Less time for temperature abuse • Less energy consumption • Less 'in stock costs'	• Labour- intensive • High skilled chefs required • Potential food safety risks • Affected by level of market demands
Cook-Chill	Food is prepared and chilled for later reheating and service	• Wide menu selection • High productivity and flexibility • Energy savings • Better food quality • Reducing labour costs	• Greater risk of food poisoning • Large capital investment demands • High operational standards from both management and staff • Vitamin loss
Hybrid	Using a combination of two or three systems	• Long shelf life • Wide menu selection • Minimal food safety risks • Recipe modifications	• High energy usage
External	Most cooked menu items are prepared outside the hospital and brought in chilled or frozen	• Cost benefits • Reducing labour cost • Energy savings	• Product limitations • Low food quality

Sources: (Carroll, 1980; Carroll and Montag, 1979; Jones, 1990; Jones and Huelin, 1990b; Jones and Huelin, 1990a; Lindstrom, 1990; Rodgers and Assaf, 2006; Rodgers, 2003; Rodgers, 2005b; Rodgers, 2005c; Rodgers, 2005a)

Jones and Huelin (1990a) maintain that the real relevance of cook-chill is in the decoupling process by which food production can be carried out separately from foodservice customer demand, either in terms of time, or place or both. In empirical studies, Snyder et al. (1987) and Brendel et al. (1985) refer to the use of cook-chill systems to increase productivity with less money being spent on employee salaries and staff hours, because fewer employees are required for production, compared to the traditional cooking systems. Also, less equipment is used; therefore a reduction in capital costs can be achieved with less energy costs also being incurred. Boltman (1975) also proposes the use of technology to improve human resource productivity. She estimates that a cook-fresh system requires one worker per 25-60 meals produced, whereas one worker in a cook-chill system can produce 100-140 meals. Several case studies have also emphasised the advantages of the cook-chill system. The introduction of cook-chill in an Iowa (USA) hospital has allowed foodservice to cut 9.5 full- time equivalent employees (FTE) from its 50.9 FTE, as well as achieve reduction in food costs (King, 1989). The conversion from a conventional to cook-chill system at the University of Wisconsin hospital also resulted in a reduction of staff from twenty- three to four cooks in the production units and nine percent reduction in the cost of producing and serving each patient meal (Kaud, 1972).

Finally, the use of the external and the hybrid systems is also expected to provide some operational saving over the cook-fresh system. The external system allows the downsizing of the central production, and thus provides further savings especially in the area of labour and energy costs, while the main advantage of the hybrid system is that it allows foodservice operations to combine the operational benefits of more than one system and offers great flexibility in the production area (Nettles et al., 1997). In addition to the type of foodservice system, other environmental variables such as the age of equipment (Brown and Hoover, 1990), quality of labour or skill level of employees (Reynolds and Thompson, 2005) and the degree of readiness of materials (Clark, 1997) might also affect the production process and therefore should be considered in the measurement of productivity. To illustrate, the relationship between productivity and age of equipment was addressed by Brown and Hoover (1990) who reported that newer equipment is usually associated with improved productivity. Similar findings were also reported by Hayes and Clark (1986). Similarly, the degree of readiness of raw material was also considered by Clark (1997) as an important factor in improving the productivity of hospital kitchens. Clark (1997) provided a comparison between cook-chill operations (Figure 2.1) that are heavy and medium users of ready food materials and concluded that the use of cook-chill with prepared vegetables can result in significant gains in productivity.

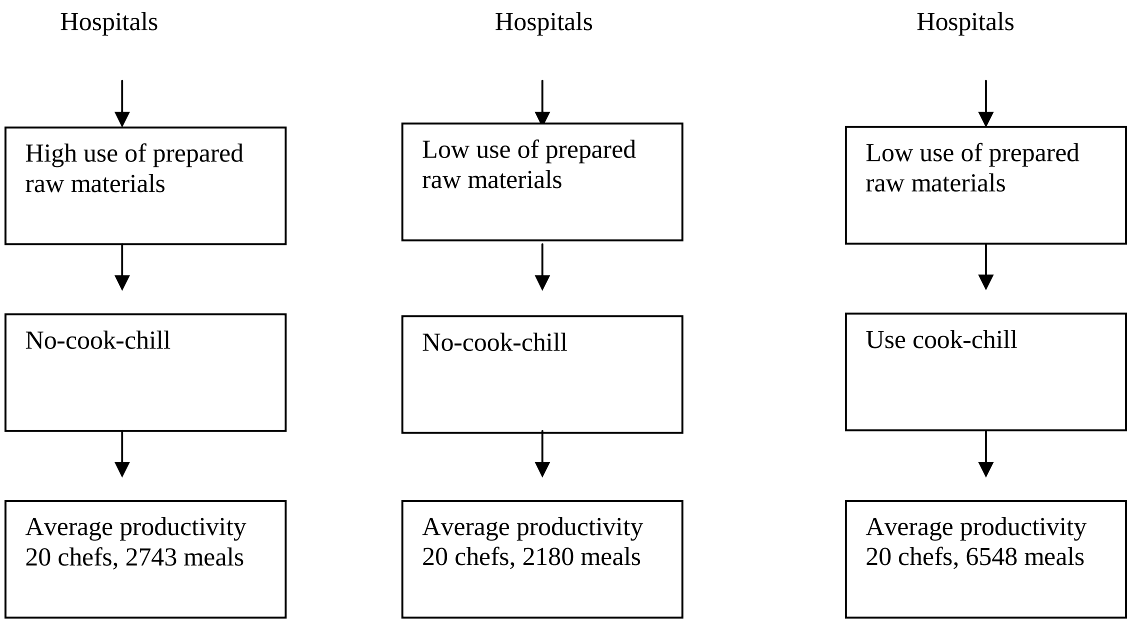

Figure 2.1. The impact of degree of readiness of raw materials on hospital productivity (adapted from Clark, 1997)

Despite all these above mentioned complexities, traditionally most of the measurement approaches have been limited to the use of partial ratios and the key performance indicators (KPIs). Those that are commonly used are meals produced per labour hour and food cost per meal (Brown and Hoover, 1990; Greathouse, 1987). By definition, these measures are always only partial in that they do not account for the relationships and trade-offs between different inputs and outputs. This is a significant limitation in their application to this field, which typically involves multiple inputs and outputs. For example, if labour inputs are replaced by capital inputs, labour inputs are likely to increase while capital productivity declines. Several partial productivity measures may be used collectively to obtain a broad picture of efficiency. However, the presentation of a large number of partial measures will be difficult to comprehend and interpret if some indicators move in opposite directions over a given period of time. This reinforces the values of more comprehensive summary measures of efficiency. Partial measures may provide important information on specific aspects of operations, but it is important to see how firms are performing overall relative to comparable firms using similar outputs (Commonwealth State Service, 1997)

In attempting to address the limitations of the partial productivity ratios, Hong and Kirk (1995) measured the number of meals produced per labour-hours in different hospital kitchens using a labour productivity index ($PI = N_m / N_h$), where N_m represents the adjusted meal equivalents, and calculated using the following formula:

$$N_m = N_p(\text{weekly patient meals}) + (S_t(\text{total turnover}) + S_m(\text{average selling price}))$$

and N_h represents the total foodservice hours worked in the department including all direct and indirect time by paid food service employees plus all hours worked by managers plus all hours worked by part- time employees. They reported mean productivity figures equivalent to 27.6 meals/day/employee, with a range of 16.9 to 46.7. Similar measurement approaches were also used by Ruff (1975) and Mayo et al. (1984). Although it is clear that these approaches provide more accurate and reliable measures than the simple partial productivity measures as they include a larger group of staff in their calculation; they are nevertheless still limited to only one area of the operation (e.g. labour). The integration of multiple inputs/outputs and environmental variables is still disregarded, which means it could be misleading to generalise the results of such studies to all other areas of the foodservice operation.

The application of statistical techniques to this field is limited to the use of regression analysis. It is a parametric method that requires a general production model to be specified. Typically, regression analysis takes into account a single output or multiple inputs or vice versa. It can be used in multiple inputs and outputs settings but requires the estimation of more than one equation. Clark (1997) applied ordinarily least square regression analysis to compare labour productivity between hospitals using the cook-chill and conventional systems. He demonstrated that the use of pre-prepared materials (an environmental factor by nature), coupled with cook-chill, results in substantial productivity gains. There was, however, a high variation of the data around the regression line. The accuracy of the analysis was affected by the fact that other inputs and outputs (such as energy and capital costs) were not taken into account. Additionally, the use of regression as a productivity analysis tool can itself lead to inaccuracy in measurements as it allocates all the source of variations to inefficiency reasons without separating the random noise from the genuine trends in the data set.

This above review highlights the need for a comprehensive approach in measuring productivity in the health care foodservice sector as most of the available methods are simple and limited owing to the complexities involved. In other fields such as education (Casu and Thanassoulis, 2006), banks (Luo, 2003), and hospitality (Bell and Morey, 1994; Reynolds, 2003a), researchers overcame the limitations of the traditional productivity approaches through the use of efficient frontier techniques which have the ability to benchmark the efficiency of similar organisations by explicitly considering multiple inputs and outputs. These techniques are based on the concept of efficiency originated by Farrell (1957) in which the performance of a particular firm is roughly measured by the deviation form the efficiency frontier, and this represents the best practice technology among all observed firms. In the next section, a detailed definition of the concept of efficiency is provided, before briefly discussing the efficiency frontier techniques and their application to the hospitality industry. Note that a detailed discussion of these techniques is provided in Chapter 3.

2.3 Definition of efficiency

Discussion of frontiers and efficiency measurement started formally with the work of Farrell (1957) who provided computational measures for technical, allocative and cost efficiency based on original work by Debreu (1951) and Koopmans (1951). Farrell illustrated his ideas using a simple example involving firms that use two inputs (x_1 and x_2) to produce a single output q (Figure 1), under the assumption of constant return to scale (a proportionate increase in inputs results in the same proportionate increase in output).

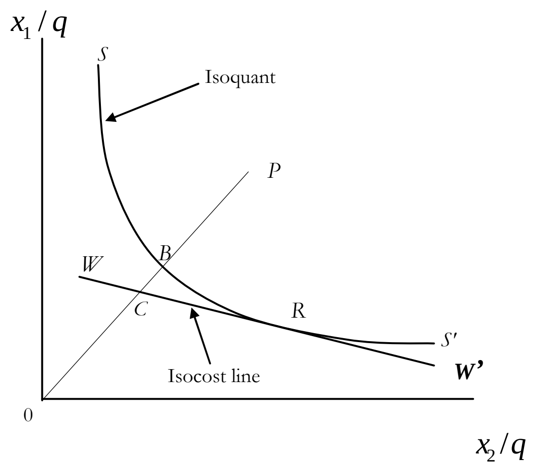

Figure 2.2. Two-inputs Single-Output Production Technology (Source: Coelli et al., 1998)

Knowledge of the isoquant of the fully efficient firm *SS'* (a curve showing the alternative combinations of inputs which can be used to produce a given level of output, thereby representing a production frontier) permits the measurement of technical efficiency. If a given firm uses quantities of inputs, defined by the point *P*, to produce units of output the level of technical inefficiency of that firm could be represented by the distance *BP* which is the proportional reduction in all inputs (i.e. by movement onto the efficient isoquant) that could be theoretically achieved without any reduction in output. This is usually expressed in percentage terms by the ratio *BP/OP*, which represents the percentage by which all inputs need to be reduced to achieve technically efficient production. The technical efficiency (TE) ratio for the firm at point *P* is most commonly measured by the ratio:

$$\text{TE}=OB/OP$$

which is equal to one minus *BP/OP*. It takes a value between zero and one, and hence provides a degree of the technical efficiency of the firm. A value of one implies that the firm is fully technically efficient. Point *R*, for example is technically efficient since it already lies on the efficient isoquant. The technical efficiency ratio of the firm at *R is OR*/*OR* or unity, thereby implying absolute or relative efficiency (depending upon the manner in which the efficient isoquant is constructed). If the input price ratio *WW''* is known (showing the different combinations of inputs that can be purchased with a given cost outlay), then allocative efficiency (AE) at point *P* is measured by the ratio:

$$\text{AE}=OC/OB,$$

where the distance *CB* is the reduction in production costs which would occur if production occurred at *R* – the allocatively and technically efficient point, rather than *B* – the technically efficient, but allocatively inefficient point.

The degree of cost efficiency (CE) for the producer at *P* is given by the ratio:

CE= *OC/OP,*

This measure follows from the interpretation of the distance *CP* as the reduction in cost that would occur if the technically and allocatively inefficient producer at P were to become both technically and allocatively efficient at *R*. Note that the cost efficiency ratio *OC*/*OP* is the product of the technical efficiency ratio *OB*/*OP* and the allocative efficiency ratio *OC*/*OB.*

The measurement of cost efficiency necessitates the use of the indirect cost function which is a dual form of the production frontier. The cost function reflects a behavioral objective (i.e. cost minimisation) and can account for multiple outputs. Mathematically, it can be written as:

$$c(\mathbf{w},\mathbf{q}) = \min_{x} \mathbf{w}'\mathbf{x} \,\big|\, f(\mathbf{x}) \geq \mathbf{q}, \mathbf{x} \geq \mathbf{0}$$

where $\mathbf{w} = (w_1, w_2, ...w_N)'$ is a vector of input prices. The right hand side of this equation says search over all technically feasible input-output combinations and find the input quantities that minimise the cost of producing $\mathbf{q}$. We have used the notation $c(\mathbf{w},\mathbf{q})$ on the left hand side to emphasise that this minimum cost value varies with variations in $\mathbf{w}$ and $\mathbf{q}$.

To be consistent with economic theory, a cost function must satisfy the following properties (see Coelli et al., 1998):

1. $c(\mathbf{w},\mathbf{q}) > 0 \ \forall \ \mathbf{w} > 0$ and $\mathbf{y} > 0$

2. $c(\mathbf{w}',\mathbf{q}) \geq c(\mathbf{w},\mathbf{q})$ for $\mathbf{w}' \geq \mathbf{w}$

3. $c(\mathbf{w},\mathbf{q})$ is concave and continuous in $\mathbf{w}$

4. $c(t\mathbf{w},\mathbf{q}) = tc(\mathbf{w},\mathbf{q})$ for $t > 0$

5. $c(\mathbf{w},\mathbf{q}') \geq c(\mathbf{w},\mathbf{q})$ for $\mathbf{q}' \geq \mathbf{q}$

where:

Property 1 simply states that it is not possible to produce a positive output with no costs, as follows from the assumption that at least one input is required to produce an output.

Property 2 states that cost will increase when at least one input rises and the others do not fall.

Property 3 states that when input prices increase, the cost will increase at most by an amount obtained by multiplying the inputs with the new prices, i.e. in a linear way.

Property 4 is called the linear homogeneity problem (or homogeneity of degree one) and states that, when all prices change proportionally, then total costs will also change in the same manner.

Finally property 5 states that costs cannot decrease as output increases**.**

A firm will fail to achieve a cost minmisation by being technically inefficient, allocatively inefficient or both. If the firm uses an excess amount of inputs without getting maximum output, such a firm is not minimising its cost and it is technically inefficient. If the firm uses its inputs in wrong proportions given input prices, it will fail to achieve total cost minimisation, and will certainly be allocatively and costly inefficient.

2.4 Approaches to measure efficiency

Following Farrell (1957), the measurement of efficiency and the estimation of frontiers have developed extensively over the past two decades. The non-parametric and the parametric approaches are the two most important methodologies used in this respect. The nonparametric approach constructs a frontier and measures efficiency relative to the constructed frontier using linear programming techniques. The approach goes frequently by the descriptive title of 'data envelopment analysis' (DEA) and was first developed by Charnes et al. (1978). It involves the use of linear programming for the construction of the efficiency frontier. The relative efficiencies of firms is assessed by comparing all sets of inputs and outputs into a single measure of productive efficiency, taking a value between zero (indicating poor efficiency) and one (indicating maximum efficiency). Instead of a pre-specified functional form, the frontier is convex shaped and based on the construction of piece-wise linear combinations of the most efficient units.

DEA is popular in the literature as it can readily incorporate multiple inputs and outputs, and it does not require a prior specification of the functional form between inputs and outputs (Banker and Thrall, 1992). However, it also has several limitations that one may encounter in conducting an efficiency analysis. Its main problem is that it is a deterministic rather than a statistical technique and, therefore, is sensitive to measurements error. If one organisation's inputs or outputs are underestimated or overestimated, then that organisation can become an 'outlier' that significantly distorts the shape of the frontier and reduces the efficiency score of other organisations included in the sample. Additionally, DEA scores are sensitive to input and output specification and the size of the sample. Increasing the sample size will tend to reduce the average efficiency scores, because including more organisations provides greater scope for DEA to find similar comparison partners. Conversely, including too few organisations relative to the number of outputs and inputs can artificially inflate the efficiency scores.

These above limitations make the use of DEA unfavorable in many situations, especially in cases where data are heavily influenced by noise and measurement errors. An alternative approach to the solution of these problems has, however, been widely adopted. This is the method known as the stochastic frontier approach (SFA). In contrast to DEA, the great virtue of SFA is that it not only allows for measurement of inefficiency, but also acknowledges the fact that random shocks outside the control of producers can affect the level of output. The essential idea behind SFA is that the error term is composed of two parts; one part of the error is assumed to follow a symmetric distribution (usually the standard normal) and to capture random error; the other part reflects inefficiency and is assumed to follow several common distributions such as half-normal, truncated and exponential distribution. As a result, the SFA-based model yields technical, allocative and cost efficiency that are free from distortion and statistic noise inherent in the deterministic DEA models (Ferrier and Lovell, 1990). Practical illustrations of the conventional stochastic frontier models can be found in Anderson et al. (1999a), Chen (2006), Dolton et al. (2003), Tingley et al. (2005) and Cullinane et al. (2006). The SFA is not however without limitations. One of the major limitations is the need to impose *a priori* sampling distributions on the inefficiency term of the composed error term that characterises the SFA models. Recently, several researchers have overcome this problem (Koop et al., 1997; Van den Broeck et al., 1994) by estimating the stochastic frontier in a Bayesian framework. In doing so, they treat uncertainty concerning which sampling model to use by mixing over a number of inefficiency distributions with posterior model probabilities as weights.

In summary, as has shown above, each technique has its advantages and disadvantages. There is no approach that is strictly preferable to any other. However, the overall agreement, apparent in the literature, is that these (SFA) techniques are more powerful and comprehensive than partial productivity approaches. This study is the first to apply the frontier approach to the area of health care foodservice operation. To the author's knowledge, there is no prior research that adopted these techniques in this area, despite being heavily applied in related industries such as hotels and tourism (see Table 2.2).

Table 2.2 Literature survey of frontier models on hospitality

Study	Approach	Sample	Inputs	Outputs
Bell and Morey (1994)	DEA	31 corporate travel departments	1) Actual level of travel expenditures 2) Nominal level of other expenditure 3) Level of environmental factors 4) Actual level of labour costs	1) Level of service provided qualified as excellent or average
Johns et al. (1997)	DEA	15 hotels over a 12 month period	1) Number of room nights available 2) Total labour hours 3) Total food and beverage costs 4) Total utilities costs	1) Number of room nights
Anderson et al. (1999a)	SFA	48 hotels	1) Number of full- time equivalent employees 2) Number of rooms 3) Total gaming-related expenditures	1) Total revenue

			4) Total food and beverage expenses 5) Other expenses	
Anderson et al. (1999b)	DEA and SFA	31 corporate travel departments	1) Total air expenses 2) Hotel expenses 3) Car expenses 4) Labour expenses 5) Hourly labour 6) Part-time labour 7) Fee expenses 8) Technology costs 9) Building and occupancy expenses	1) Number of trips
Randy et al.(2000)	DEA	48 hotels	1) Full- time equivalent employees 2) Number of rooms 3) Total gaming-related expenditures	1) Total revenue 2) Other revenue

Table 2.2 continued

			4) Total food and beverage expenses 5) Other expenses	
Tsaur (2000)	DEA	53 Taiwan hotels	1) Total operating expenses 2) The number of rooms occupied 3) The total floor space of catering 4) The number of employees in the room division 5) The number of employees in the catering division 6) Catering cost	1) Total operating revenue 2) The number of employees 3) Average daily rate 4) Average production value of employee in the catering division 5) Total operating revenue of the room division 6) Total operating revenue of the catering division 7) Room revenue
Brown and Ragsdale (2002)	DEA	46 US hotels	1) Median price 2) Problems (defined in a 4 point scale) 3) Service 4) Upkeep 5) Rooms	1) Satisfaction (defined on a 100 point scales) 2) Value (defined on a 5 point scale)

Hwang and Chang (2003)	DEA	45 hotels equivalent	1) Full- time equivalent employees 2) Guest rooms 3) Total space 4) Operating expenses	1) Room revenues 2) Food and beverage Revenues 3) Operating revenues
Barros (2004)	SFA	43 hotels	1) Price of labour 2) Price of capital 3) Price of food	1) Sales 2) Number of nights occupied
Reynolds Thompson (2005)	DEA	62 restaurants	1) Server wage 2) Seats 3) Square footage 4) Server count 5) Server hours 6) Parking	1) Sales 2) Tips 3) Turnover

Table 2.2 continued

Barros (2005)	DEA	43 hotels	1) Full-time workers 2) Cost of labour 3) Rooms 4) Surface area of the hotel 5) Book value of property 6) Operational costs 7) External costs	1) Sales 2) Number of guests 3) Nights spent
Sigala et al. (2005)	DEA	93 hotels	1) Rooms division payroll 2) Rooms division total expenses 3) Front office payroll 4) Administrative material and other expenses 5) Total demand variability beverage total	1) Non food and Lock beverage revenue 2) Average room rate 3) Room nights 4) Non- room-nights revenue
Reynolds and Thompson (2005)	DEA	38 restaurants	1) Front of house hours worked per day during lunchtime 2) Front of house hours worked during dinner per day 3) Uncontrollable input 4) Number of competitors 5) Seating capacity	1) Sales 2) Customer satisfaction
Fei-Ching et al. (2006)	DEA	25 Taipei hotels	1) Rooms 2) Food	1)Yielding index 2) Food revenue

			3) Beverages 4) Number of employees 5) Total cost	3) Beverage revenue 4) Miscellaneous revenue
Perez-Rodriguez and Gonzalez (2006)	SFA	237 hotels and apartments	1) Annual cost 2) Annual depreciation 3) Annual financial expenses	1) Operating annual revenue
Chen (2006)	SFA	55 Hotels	1) Price of labour 2) Price of food and beverage 3) Price of materials	1) Total revenue 2) Occupancy Rate 3) Production value of unit catering space
Koksal and Aksu (2007)	DEA	155 group travel agencies	1) Number of staff 2) Annual expenses 3) Having service potential	1) Number of customers served

2.6 Functional forms

In the previous section, different concepts of efficiency were introduced and as discussed, the measurement of efficiency is based on the theory of production and cost function. It is, therefore, important to review of the functional forms used in the estimation of the production and cost frontier models before discussing the methodological aspects of the study in Chapter 3.

There are varieties of functional forms in the current literature and the selection of the correct functional form is critical before the estimation of the model. The functional form differ in many features and the selection criteria is sometimes difficult, since the true shape of the production or cost function is unknown and can only be approximated. Many of the proposed functions have restrictive properties which mean they can not be tested. The Cobb-Douglas cost function, for example, possesses the property of a constant elasticity of scale. Therefore, it is not possible to test within the Cobb-Douglas framework whether different firms possess different values of scale economies. Consequently, less restrictive functional forms have been proposed. Unfortunately, the increased flexibility is almost always linked to a greater need for information. The translog, for example, is a more flexible form than the Cobb-Douglas, but for proper estimation more observations are needed because of the increased number of parameters to be estimated. Even when such observations are available there is no guarantee that advantages can be drawn from estimating a more flexible form, due to the problem of multicollinearity.

In the following sections, the Cobb-Douglas and the translog functional forms, two of the most common functional forms currently used, are discussed. Table 2.3 provides further details about functional forms. Varian (1992) discusses and highlights common functional forms. The Cobb-Douglas is introduced because it is relatively easy to estimate and the results are easy to interpret. The translog is a generalisation of the Cobb-Douglas form, where less restrictive assumptions about the production technology are made. Amongst other things, it allows us to estimate first-specific scale economies.

2.6.1 Cobb-Douglas functional form

The Cobb-Douglas functional form has been popular in the empirical estimation of the frontier model. This is due to the fact that the Cobb-Douglas function is easy to estimate and a logarithmic transformation makes the model linear in logarithm of the inputs. Also, the Cobb-Douglas form is self- dual which means that associated function form has the same functional form (Varian, 1999). The cost function has the following functional form:

$$C = \alpha_0 \prod_{i=1}^{M} q_i^{\delta_i} \prod_{i=1}^{N} w_i^{\beta_i} \quad , \qquad \delta_i , \beta_i > 0 \ \forall i, \tag{2.1}$$

or when taking the natural logarithm it is written as:

$$\ln C = \ln \alpha_0 + \sum_{i=1}^{M} \delta_i \ln q_i + \sum_{i=1}^{N} \beta_i \ln w_i$$

where C stands for cost, q_i for the different outputs, w_i for the input prices, and the δ_i and β_i symbolise the parameters to be estimated.

The Cobb-Douglas is only homogenous of degree one in input prices if $\sum_{i=1}^{N} \beta_i = 1$. This restriction can be imposed in the estimation of the cost function by dividing the input prices and the cost by one of the input prices or by imposing some linear restriction in the estimation (Greene, 2000). One last feature of the Cobb-Douglas form is that is exhibits a constant value of economies of scale, which can be expressed as $R_s = 1/\sum_{i=1}^{M} \delta_i$. Depending on the value of $\sum_{i=1}^{M} \delta_i$, the underlying technology exhibits increasing, constant or decreasing return to scale depending on the sample under consideration.

2.6.2 Translog functional form

Another class of logarithmic functional forms is the translog class. This class generalises the Cobb-Douglas functional form by adding quadratic terms to the log-linear terms that are in the Cobb-Douglas function. The addition of quadratic terms is an approach used by flexible functional forms. The idea of flexible functional forms is to specify functions that have as many free econometric parameters as there are independent economic parameters that need to be estimated. In general, a translog cost function can be expressed as follows:

$$\ln C(q,w) = \alpha_0 + \sum_{i=1}^{N} \beta_i \ln w_i + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \beta_{ij} \ln w_i \ln w_j + \sum_{i=1}^{M} \gamma_i \ln q_i + \frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M} \gamma_{ij} \ln q_i \ln q_j + \sum_{i=1}^{N}\sum_{j=1}^{M} \delta_{ij} \ln w_i \ln q_i \tag{2.2}$$

where C stands for cost, q_i for the different output characteristics, w_i for the input prices and the Greek letter represents the parameters to be estimated.

Table 2.3. Some Common Functional Forms

Linear	$y = \beta_0 + \sum_{n=1}^{N} \beta_n x_n$
Cobb-Douglas	$y = \beta_0 \prod_{n=1}^{N} x_n^{\beta_n}$
Quadratic	$y = \beta_0 + \sum_{n=1}^{N} \beta_n x_n + \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N} \beta_{nm} x_n x_m$
Normalised quadratic	$y = \beta_0 + \sum_{n=1}^{N-1} \beta_n \left(\frac{x_n}{x_N}\right) + \frac{1}{2}\sum_{n=1}^{N-1}\sum_{m=1}^{N-1} \beta_{nm} \left(\frac{x_n}{x_N}\right)\left(\frac{x_m}{x_N}\right)$
Translog	$y = \exp\left(\beta_0 + \sum_{n=1}^{N} \beta_n \ln x_n + \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N} \beta_{nm} \ln x_n \ln x_m\right)$
Generalised Leontief	$y = \sum_{n=1}^{N}\sum_{m=1}^{N} \beta_{nm} \left(x_n x_m\right)^{1/2}$
Constant Elasticity of Sub-stitution (CES)	$y = \beta_0 \left(\sum_{n=1}^{N} \beta_n x_n^{\gamma}\right)^{1/\gamma}$

Compared to the Cobb-Douglas form, it can be seen that this functional form uses many more parameters, and this might cause some problems of multicollinearity. The function also needs an increased amount of observations to maintain the same degree of freedom. Note as well that the translog is a special case of the Cobb-Douglas cost function in which:

$$\beta_{ij} = 0$$

$$\delta_{ij} = 0$$

$$\gamma_{ij} = 0$$

Because these are just restrictions on the coefficients of the translog model, it is possible to test whether the specialisation to the Cobb-Douglas is supported by the data.

As it is the case with the Cobb-Douglas cost function, linear homogeneity must be imposed on the translog model. The restrictions can be written as:

$$\sum_{i=1}^{N} \beta_i = 1$$

$$\sum_{i=1}^{N} \beta_{ij} = 0$$

$$\sum_{i=1}^{N} \delta_{ij} = 0$$

will ensure a translog function is linearly homogenous in input prices. These restrictions are implemented by either dividing the costs and the prices by one price or estimating the function by enclosing the linear restriction in the estimation.

2.6.3 Criteria for selecting a functional form

The different functional forms have been introduced and discussed in the previous section. A researcher with no *priori* knowledge about the true functional form of the model being estimated needs to develop a good understanding of the functional form that can satisfy the required conditions. The selection of the appropriate functional form should also be tested after estimation. In the econometric literature, several statistical tests have been developed which can further assist in selecting the most preferred functional form. To further clarify the above, we review in this section a set of conditions which should be met by a potential functional form.

Coelli et al. (1998) emphasised the importance of finding a functional form, and highlighted a set criteria which should be met prior to choosing a suitable functional form. According to them, a functional form should meet the following conditions:

- theoretical consistency
- flexibility
- parsimony

Theoretical consistency means that a functional form should be able to display the theoretical properties required by economic theory. In the case of a cost function, these conditions are that homogeneity is of degree one, non-decreasing and concave in inputs and non-decreasing in output. All the functional forms in Table 2.3 with the exception of quadratic meet this requirement.

The next criterion is flexibility; a functional form is said to be first-order flexible if it has enough parameters to provide a first-order differential approximation to an arbitrary function at a single point. Second-order flexible has enough parameters to provide a second-order approximation. The linear and Cobb-Douglas forms are first-order flexible, while the remaining functions listed in Table 2.3 are second orders flexible. Usually, a second-order flexible form is preferred. However, increased flexibility comes at a cost, there are more parameters to estimate, and this may give rise to problems of multicollenearity.

The principle of parsimony implies that the simplest functional form that "gets the job done adequately" should be chosen. Particularly, this means that its unknown parameters should be easy to estimate from the data. This requires that the functional form is linear in the parameters (possible after taking the logarithm), and if there are restrictions on the parameters they too should be linear. Both the Cobb-Douglas and translog can be transformed to linear functions after taking the logarithms of both sides of these functions.

Sometimes, the adequacy of a functional form can be assessed prior to the estimation. For example, the Cobb-Douglas functional form is inadequate for situations where elasticities may vary across data points (the Cobb-Douglas elasticities are constant), and both the Cobb-Douglas and the tanslog functions are problematic when the data contains zero because this make it impossible to construct the logarithm of the variables. However, model adequacy is often determined after estimation by conducting residual analysis (i.e. assessing whether residuals exhibit any systematic patterns that are indicative of a poorly chosen function), hypothesis testing, and calculating measures of goodness-of-fit.

2.7 Summary

This chapter highlights the need for a comprehensive approach in assessing the efficiency of health care foodservice operations. Despite the complex setting of these operations, efficiency measurement approaches have been limited to partial ratios or limited parametric techniques. These traditional approaches cannot capture the interaction of numerous parameters affecting efficiency. On the other hand, efficiency frontier techniques offer the total measure of performance. They can account for the multiple input and output settings for the health care foodservice operations and allow a comprehensive productivity evaluation. These techniques can be divided into two categories, DEA and SFA. The former uses linear programming to derive an aggregate productivity score, while the latter is a parametric technique that takes into account the measurement error in the estimation of efficiency.

In the next chapter, a detailed explanation of the efficiency frontier techniques including their advantages and disadvantages is provided. This is followed by a description of the specific frontier models used in this study.

Chapter 3: Methodology

3.1 Introduction

Following the review of efficiency in the previous chapter, this chapter provides a detailed discussion of the frontier techniques used in the estimation of efficiency. In contrast to the traditional productivity approaches, these techniques benchmark the efficiency of similar organisations by explicitly considering multiple inputs and outputs. Coelli (1995) presents two reasons to estimate frontier functions, rather than average functions, which are conventionally estimated by the ordinary least square (OLS) method. First, the frontier function is consistent with a theoretical representation of production activities which is derived from an optimization process. For example, the production function consists of a series of outputs attainable, given different combination of inputs, while a cost function is represented by a frontier derived from optimisation. Second, the estimation of frontier function provides a tool for measuring the efficiency level of each firm within a given sample.

In estimating frontiers, researchers have taken either a parametric or non-parametric approach, using either deterministic or stochastic estimation methods. The parametric and non-parametric approach differs in three respects. First, the non-parametric approach does not impose a functional form on the data. Second, it does not make assumptions about the distribution of the error term representing inefficiency. Lastly, the estimated non-parametric frontiers have no statistical properties on which to be gauged. The overall agreement in the literature is that there is no approach that is strictly preferable to any other. A careful consideration of them, of the data set utilised, and of the intrinsic characteristics of the industry under analysis, will help the researcher in the correct implementation of these techniques. In the subsequent sections, an overview of both approaches is provided. A more detailed discussion is, however, given to the parametric approach as it was selected for the estimation of the frontier model used in this study, for reasons described later in the chapter.

The chapter is organized as follows: the first section provides a brief overview of the non-parametric approach. This is followed by a detailed discussion of the parametric approach and its extension to accommodate for environmental variables. The available methods to estimate allocative efficiency are also discussed. A detailed discussion of the application of the frontier approach to the model used in this study is then provided. Coupled with this discussion is an analysis of the functional form used for the estimation of the production and cost frontier models and an overview of the sources and construction of data used in this study.

3.2 Nonparametric approach to frontier analysis

The nonparametric approach constructs a frontier and measures efficiency relative to the constructed frontier using linear programming techniques. The most used non-parametric approach is known as 'data envelopment analysis' (DEA) and was first developed by Charnes et al. (1978). The first DEA model proposed by Charnes et al. (1978) assumed constant return to scale (CRS) so that all observed production combinations can be scaled up or down proportionally (see Figure 3.1). Subsequent papers have considered alternative set of assumptions such as Fare et al. (1983) and Banker et al. (1984), in which variable return to scale (VRS) models are proposed.

A DEA model can be written as a series of K linear programming problems with the constraints differentiating between the DEA-CRS and DEA-VRS models as shown in

(3.1) to (3.5):

$$\max_{\phi\lambda}\phi \qquad (3.1)$$

Subject to $-\phi\mathbf{q}_{\mathrm{i}} + \mathbf{Q}\lambda \geq 0$ (3.2)

$\mathbf{x}_i - \mathbf{X}\lambda \geq 0$ (3.3)

$\lambda \geq 0$ (DEA-CRS) (3.4)

$\mathrm{I}1\lambda = 1$ (DEA-VRS) (3.5)

where ϕ is a scalar, λ is a $I \times 1$ vector of constants, $\mathbf{q}_i$ is an output vector for the i-th firm, $\mathbf{Q}$ is the matrix of outputs for all I firms, $\mathbf{x}_i$ is an input vector for the *i*-th firm, and $\mathbf{X}$ is the matrix of inputs for all I firms. The value of ϕ obtained is the efficiency score for the *i*-th firm where $1 \leq \phi < \infty$, and ϕ-1 is the proportional increase that could be achieved by the *i*-th firm, with input quantities held constant. Note that $1/\phi$ defines a technical efficiency score which varies between zero and one. In case ϕ has a value equal to one, the firm lies on the frontier and is considered fully efficient. Essentially the optimization process maximizes the proportional increase in the output vector while remaining within the envelopment space or efficient frontier.

The shape of the frontier will differ depending on the scale assumptions that underline the model. The restriction $\mathrm{I}1\lambda = 1$ imposes variable returns to scale. In contrast, excluding this constraint implicitly imposes constant returns to scale. The difference is that the model with VRS creates the frontier as a convex hull of interesting planes, in contrast to the model with CRS which forms a conical hull. Thus, the VRS model envelops the data more tightly and provides efficiency scores that are greater or equal than those of the CRS model (Banker et al., 1984). Note that the VRS model also ensures that an inefficient firm is only ‘benchmarked’ against hospitals of similar size.

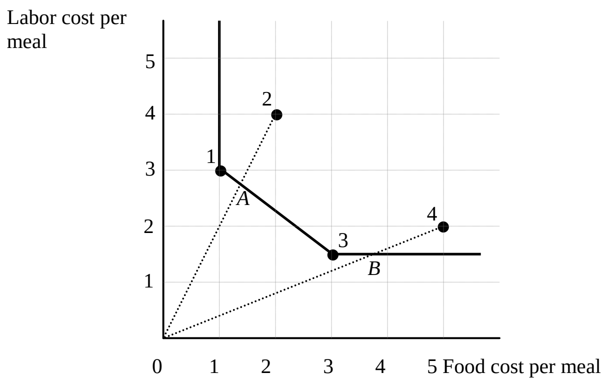

Figure 3.1. CRS DEA model

Note: Figure 3.1 plots the efficiency frontier which is the set of all points (hospitals) that are fully efficient; e.g. hospitals 1 and 3 are fully efficient (because they lie on the frontier); however, hospitals 2 and 4 lie to the northeast of the frontier and are regarded as inefficient. Hospital 2 could reduce its both inputs by about 30% before it would reach the efficient frontier at point A.

In general, the main advantages of DEA are that it can readily incorporate multiple inputs and outputs, and it does not require a prior specification of the functional form between inputs and outputs (Banker and Thrall, 1992). This makes it suitable for several applications including healthcare such as hospitals (Giokas, 2001), education such as schools, universities (Abbott et al., 1998), banks (Luo, 2003), and the hospitality industry such as hotels and tourism organisations (Bell and Morey, 1994; Reynolds, 2003b). However, like any empirical technique, DEA is also based on a number of simplifying assumptions that need to be acknowledged when interpreting the results of DEA studies. DEA's main limitations include the following (Banker and Thrall, 1992, Cooper et al., 2000):

- It is a deterministic rather than a statistical technique and, therefore, is sensitive to measurements error. If one organisation's inputs or outputs are underestimated or overestimated, then that organisation can become an 'outlier' (a data point that is located far from the rest of the data) that significantly distorts the shape of the frontier and reduces the efficiency score of other organisations included in the sample.

- It does not provide the means for hypothesis testing regarding the presence of inefficiency or the structure of the production technology. This is because mathematical programming techniques have estimators with unknown statistical properties.
- DEA scores are sensitive to input and output specification and the size of the sample. Increasing the sample size will tend to reduce the average efficiency scores, because including more organisations provides greater scope for DEA to find similar comparison partners. Conversely including too few organisations relative to the number of outputs and inputs can artificially inflate the efficiency scores.

These above limitations make the use of DEA unfavourable in many situations, especially in cases where data are heavily influenced by measurement errors. An arguably better approach is to estimate the frontier parametrically as this would account for source of variations in the data and therefore provides additional evidence on the true structure of the efficiency frontier.

3.3 Parametric frontier techniques: cross sectional framework

In terms of a cross-sectional production function, a parametric frontier can be represented as:

$$\ln q_i = \mathbf{x}_i^{'}\beta - u_i \qquad (3.6)$$

where q_i represents the output of the *i*-th firm; $\mathbf{x}_i$ is a $K \times 1$ vector containing the logarithms of inputs, β is a vector of unknown parameters, and u_i is a non-negative random variable associated with technical inefficiency. This restriction imposed on u_i ($u_i \geq 0$) guarantees that technical efficiency is less or equal to one.

Once the production function has been parameterized; both goal programming and econometric techniques can be used to either calculate or estimate the parameters of this model and to obtain estimates of u_i and so of technical efficiency. Goal programming techniques calculate the technology parameter vector by solving deterministic optimization problems. Aigner and Chu (1968) and Timmer (1971) are some of the most relevant references in this area. The major problem with this approach is that the parameters are calculated (using mathematical programming techniques) rather than estimated (using regression techniques) which complicates the statistical inference concerning the calculated parameter values (Kumbhakar and Lovell, 2000).

Due to these problems, econometric analysis of frontier functions became popular in the estimation of efficiency (Kumbhakar and Lovell, 2000). A wide literature related to the estimation of frontier functions has proliferated over the last three decades. These attempts can be classified into two main groups according to the specification of the error term, namely deterministic and stochastic econometric approaches.

The deterministic econometric approach employs the technological framework previously introduced by mathematical programming approaches. With the econometric formulation, parameters are estimated rather than calculated so it is possible to draw statistical inferences. Several techniques such as ‘Corrected Ordinary Least Squares’ (Afriat, 1972), ‘Modified Ordinary Least Squares’ (Richmond, 1974) and ‘Maximum Likelihood

Estimation' (Greene, 1980) have been developed to estimate these deterministic frontier models.

Unlike the mathematical programming approaches, the deterministic econometric model accommodates economic efficiency as an explicative factor for the output variation, but still does not account for the measurement and other sources of statistical noise. Therefore, a problem with both the deterministic approach and the linear programming is that they assume that all deviations from the frontier are a result of technical inefficiency. This might consequently lead to an inaccurate measure of the productive structure. An obvious solution to this problem is to introduce to equation 3.3 another random variable that accounts for statistical noise. The resulting frontier is known as 'stochastic frontier', and it will be discussed in detail in the next section.

3.3.1 Stochastic frontier production models

Aigner et al. (1977) and Meeusen and van Den Broeck (1977) simultaneously proposed the stochastic frontier production model that, besides incorporating the efficiency term into the analysis (as do the deterministic approaches), also captures the effects of exogenous shocks beyond the control of producers. Moreover this type of model also covers errors in the observations and in the measurement of outputs.

The model was called stochastic frontier because the output values is bounded from above by the stochastic (i.e. random) variable $\exp(x_i\beta + v_i)$ rather than $\exp(x_i\beta)$ the deterministic frontier. These important features of the stochastic frontier can be illustrated graphically. To do so it is convenient to restrict attention to firms that produce output q_i using only one input.

For the Cobb-Douglas case and in logarithmic terms, the single output stochastic frontier (Coelli et al., 2005) can be represented as:

$$\ln q_i = \beta_0 + \beta_1 \ln x_i + v_i - u_i \tag{3.7}$$

or $$q_i = \exp(\beta_0 + \beta_1 \ln x_i + v_i - u_i) \tag{3.8}$$

or $$q_i = \exp\underbrace{(\beta_0 + \beta_1 \ln x_i)}_{\substack{\text{determnistic} \\ \text{component}}} \times \underbrace{\exp(v_i)}_{\text{noise}} \times \underbrace{\exp(u_i)}_{\text{inefficiency}} \tag{3.9}$$

The frontier is depicted in figure 3.2. The term $v_i - u_i$ is a composed error term where v_i represents randomness (or statistical noise) and u_i represents technical inefficiency. The error representing statistical noise is assumed to be identically independent and identically distributed. Values of the inputs are measured along the horizontal axis and values of outputs on the vertical axis. Firm A uses the input level x_A to produce the output q_A, while firm B uses the input level x_B to produce the output q_B (the observed values are indicated by the points marked with $\times$). "If there were no inefficiency effects (i.e., if u_A=0 and u_B=0) the so called frontier output would be:

$q_A^* \equiv \exp(\beta_0 + \beta_1 \ln x_A + v_A)$ and $q_B^* \equiv \exp(\beta_0 + \beta_1 \ln x_B + v_B)$

for firms A and B respectively" (Coelli et al., 2005, p.243). These frontier values are indicated by the points marked with $\otimes$ in figure 3.2. The values of the observed outputs will be above the deterministic frontier if $v_i > u_i$ and below the frontier if $v_i < u_i$, (i.e. $q_i > \exp(x_i\beta)$ if $v_i > u_i$ and $q_i < \exp(x_i\beta)$ if $v_i < u_i$).

With this specification of the production frontier, one can derive an output-oriented measure of technical efficiency. The most common measure is the ratio of the observed output to the corresponding stochastic frontier output:

$$TE_i = \frac{q_i}{\exp(x_i^{'}\beta + v_i)} = \frac{\exp(x_i^{'}\beta + v_i - u_i)}{\exp(x_i^{'}\beta + v_i)} = \exp(-u_i) \tag{3.10}$$

This measure of technical efficiency can take a value between zero and one q_i takes its maximum value if, and only if, TE_i =1. Otherwise, TE_i <1 provides a measure of the shortfall of maximum output to observed output in an environment characterised by stochastic elements that vary across producers.

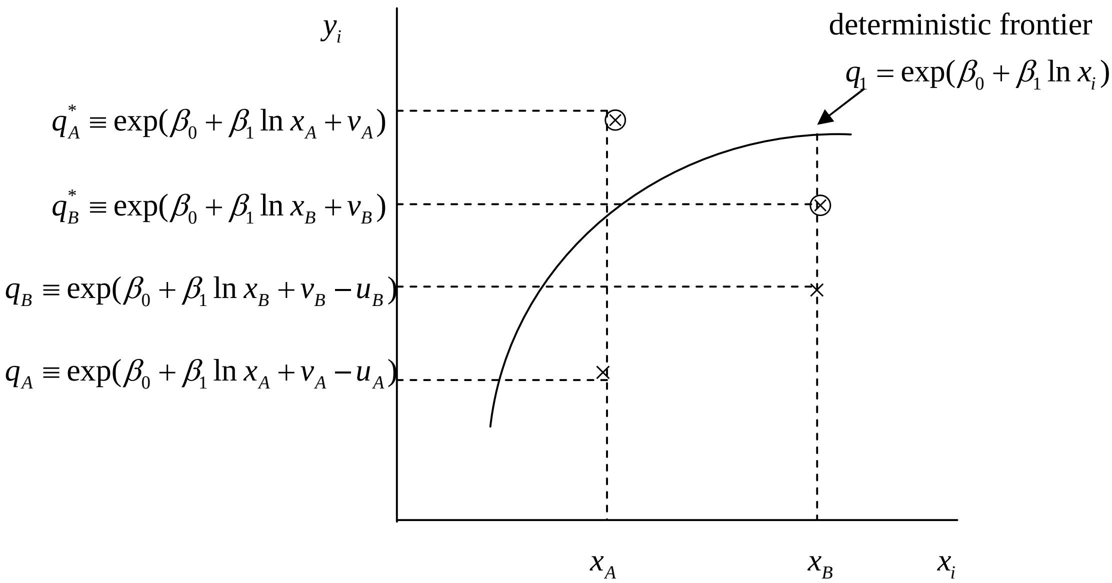

Figure 3.2. The Stochastic Production Frontier (Adapted from Coelli et al., 1998)

As described above, the estimation the technical efficiency TE_i should first start with the estimation of the stochastic production frontier model 3.7. In addition, there is a need to obtain estimates of the u_i term representing inefficiency. To achieve this objective it is required that separate estimates of statistical noise v_i and technical inefficiency u_i are extracted from estimates of $\varepsilon_i = v_i - u_i$ for each producer. This requires distributional assumptions on the two error components. The error representing statistical noise is generally assumed to be normally distributed. With respect to the inefficiency error, a number of distributions have been assumed in the literature- the most frequently used are the half-normal, exponential and truncated normal.

In general, the main assumptions of the stochastic frontier model described in equation 3.7 are:

$$E(v_i) = 0 \qquad \textit{(zero mean)} \tag{3.11}$$

$$E(v_i^2) = \sigma_v^2 \qquad \textit{(homoscedastic)} \tag{3.12}$$

$$E(v_i v_j) = 0 \textit{ for all } i \neq j \qquad \textit{(uncorrelated)} \tag{3.13}$$

$$E(u_i^2) = constant \qquad \textit{(homoscedastic)} \tag{3.14}$$

$$\textit{and } E(u_i u_j) = 0 \textit{ for all } i \neq j \qquad \textit{(uncorrelated)} \tag{3.15}$$

Given these assumption, the parameters of the stochastic frontier can be estimated using either the maximum-likelihood (ML) method or using a variant of the corrected ordinary least square method (COLS), suggested by the Richmond (1974) method, which requires numerical maximization of the likelihood function. The ML estimator is, however, asymptotically more efficient than the COLS estimator. The finite sample properties of the half-normal frontier model were investigated in the Monte Carlo experiment in Coelli (1995), in which the ML estimator was found to be significantly better than the COLS estimator. Coelli (1995) advises that the ML estimator should be used in preference to the COLS estimator when possible.

The basic elements for obtaining the ML estimator for the parameters of the stochastic frontier model are now discussed. As described above, the stochastic frontier is composed of two error terms. The random error term v_i which usually follows a normal distribution and the inefficiency error term u_i which can follow a number of different distributions (half-normal, truncated and exponential). In this discussion only the truncated-normal distribution is discussed for reasons described later in the chapter. For details of other distributions, see Appendix 1.

Stevenson (1980) introduced the truncated formulation of the frontier model. In his formulation the following assumptions are made:

i) $v_i \sim iidN(0, \sigma_v^2)$

ii) $u_i \sim iidN^+(\mu, \sigma_u^2)$, that is non-negative half normal

iii) v_i and u_i are distributed independently of each other and of the repressors.

The truncated normal distribution assumed for u_i generalizes the one-parameter half normal distribution (See Appendix 1), by allowing the normal distribution, which is truncated from below at zero, to have a non-zero mode. Thus, the truncated distribution has an additional parameter to be estimated (its mode) and consequently provides a more flexible representation for efficiency in the data.

The density function for v_i is given by:

$$f(v) = \frac{1}{2\pi\sigma_v} \exp\left\{ \frac{-v^2}{2\sigma_v^2} \right\} \tag{3.16}$$

The truncated normal density function for $u_i \geq 0$ is given by:

$$f(u_i) = \frac{1}{\sqrt{2\pi}\Phi(\mu/\sigma_u)} \cdot \exp\left\{ -\frac{(u-\mu)^2}{2\sigma_u^2} \right\} \tag{3.17}$$

where μ is the mode of the normal distribution which is truncated from below at zero. In contrast to the normal distribution, the truncated normal distribution is a two- parameter distribution depending on placement spread μ and σ_u. The joint density function of u_i and v_i is the product of their individual density function:

$$f(u,v) = \frac{1}{2\pi\sigma_u\sigma_v\Phi\left(-u/\sigma_u\right)}.\exp\left\{-\frac{\left(u-\mu\right)^2}{2\sigma_u^2}-\frac{v^2}{2\sigma_v^2}\right\} \tag{3.18}$$

and the joint density of u and ε is given by:

$$f(u,\varepsilon) = \frac{1}{2\pi\sigma_u\sigma_v\Phi\left(-u/\sigma_u\right)}.\exp\left\{-\frac{\left(-u-\mu\right)^2}{2\sigma_u^2}-\frac{\left(\varepsilon+u\right)^2}{2\sigma_v^2}\right\} \tag{3.19}$$

Hence, the marginal density of ε is given by

$$f(\varepsilon) = \frac{1}{\sqrt{2\pi}\sigma\Phi\left(\mu/\sigma_u\right)}.\Phi\left(\frac{\mu}{\sigma\lambda}-\frac{\varepsilon\lambda}{\sigma}\right).\exp\left\{-\frac{\left(\varepsilon+\mu\right)^2}{2\sigma^2}\right\}$$

$$= \frac{1}{\sigma}.\phi\left(\frac{\varepsilon+u}{\sigma}\right).\Phi\left(\frac{\mu}{\sigma\lambda}-\frac{\varepsilon\lambda}{\sigma}\right).\left[\Phi\left(-\frac{\mu}{\sigma_u}\right)\right]^{-1} \tag{3.20}$$

where $\sigma = (\sigma_u^2+\sigma_v^2)^{1/2}$, $\lambda = \sigma_u/\sigma_v$, and $\Phi\left(.\right)$ and $\phi(.)$ are the standard normal cumulative distribution and density functions. Thus, in addition to the standard deviation parameters σ_u and σ_v, the truncated normal distribution for the stochastic frontier has a placement parameter, μ, that signifies the difference between the truncated-normal and half-normal marginal density functions. If μ =0, its marginal density function reduces to the half-normal marginal density function (See Appendix 1).

The marginal density function $f(\varepsilon)$ is asymmetrically distributed with mean and variance

$$E(\varepsilon_i) = -E(u_i) = -\frac{\mu a}{2} - \frac{\sigma_u a}{\sqrt{2\pi}} \cdot \exp\left\{-\frac{1}{2}\left(\frac{\mu}{\sigma_u}\right)^2\right\} \tag{3.21}$$

$$V(\varepsilon_i) = \mu^2 \frac{a}{2}\left(1-\frac{a}{2}\right) + \frac{a}{2}\left(\frac{\pi - a}{\pi}\right)\sigma_u^2 + \sigma_v^2 \tag{3.22}$$

respectively, where $a = \left[\Phi\left(\mu/\sigma_u\right)\right]^{-1}$

The normal-truncated normal contains three parameters, a placement parameter μ and two spread parameters σ_u and σ_v.

The log likelihood of a sample of I producers is given by:

$$\ln L = constant\ \text{-}I \ln\sigma - I\ln\Phi\left(\frac{\mu}{\sigma_u}\right) + \sum_i \Phi\left(\frac{\mu}{\sigma_u} - \frac{\varepsilon_i\lambda}{\sigma}\right) - \frac{1}{2}\sum_i\left(\frac{\varepsilon_i + \mu}{\sigma}\right)^2 \tag{3.23}$$

Where $\sigma_u = \lambda\sigma\sqrt{1+\lambda^2}$

Employing the first-order conditions of the log likelihood maximization enables an estimation of the frontier parameters. These estimates are consistent as $N \to +\infty$.

Once the parameters are estimated, the interest centers on the estimation of inefficiency u_i. The estimate of $\varepsilon_i = v_i - u_i$ obviously contains information on u_i. However, the problem is to extract the information that ε_i contains on u_i. A solution to this problem is obtained from the conditional distribution of u_i given ε_i, which contains whatever information ε_i contains concerning u_i.

The conditional distribution $f(u_i/\varepsilon_i)$ is given by

$$f(u_i/\varepsilon_i) = \frac{f(u_i,\varepsilon_i)}{f(\varepsilon_i)}$$
$$= \frac{1}{\sqrt{2\pi}\sigma_*\left[1-\Phi\left(-\tilde{\mu}/\sigma_*\right)\right]} \cdot \exp\left\{-\frac{\left(u-\tilde{\mu}\right)}{2\sigma_*^2}\right\} \tag{3.24}$$

where $\tilde{\mu}_i = (-\sigma_u^2 \varepsilon_i + \mu \sigma_v^2) / \sigma^2$ and $\sigma_*^2 = \sigma_u^2 \sigma_v^2 / \sigma^2$. Since $f(u_i \mid \varepsilon_i)$ is distributed

as $N^+(\tilde{\mu}_i, \sigma_*^2)$, the mean of this distribution can be used as a point estimator for u_i. This is

given by:

$$E(u_i / \varepsilon_i) = \sigma_* \left[\frac{\tilde{\mu}_i}{\sigma_*} + \frac{\phi(\tilde{\mu}_i / \sigma_*)}{1 - \Phi(-\tilde{\mu}_i / \sigma_*)} \right] \tag{3.25}$$

Finally, points of estimates of technical efficiency can then be obtained from:

$$TE_i = \exp\left\{ -E(u_i / \varepsilon_i \right\} \tag{3.26}$$

3.3.2 Stochastic frontier cost models

The previous section showed how technical efficiency can be estimated by estimating a production function. If price data are available and it is reasonable to assume firms minimise costs, the Aigner et al. (1977) model can be extended to estimate the economic characteristics of the production technology and to predict the cost efficiency using a cost frontier. In the case of cross-sectional data, the cost frontier model can be written in the general form:

$$\ln c_i = \ln c(q_i, w_i) + v_i + u_i \tag{3.27}$$

where c_i is the observed cost for firm i ($i = 1....N$), q_i is a vector of output; w_i is a vector of input prices for firm i, u_i is a one-sided error term (i.e., positive for cost frontiers) representing cost inefficiency , v_i is a two-sided random error accounting for variation in costs due to stochastic factors, $c\left(q_i, w_i\right)$ is the deterministic part of the cost equation, and $c\left(q_i, w_i\right) e^{v_i}$ is the stochastic cost frontier.

If it is assumed again that the above equation takes the log linear Cobb Douglas functional form, then the stochastic frontier model can be written as:

$$\ln c_i = \beta_0 + \sum_{n=1}^{N} \beta_n \ln w_{ni} + \sum_{m=1}^{M} \phi_m \ln q_{mi} + v_i + u_i \tag{3.28}$$

This cost frontier must be linearly homogenous in input prices i.e.

$c(q_i, \lambda w_i; \beta) = \lambda c(q_i, w_i; \beta)$ for λ >0 (for details see Coelli et al., 1998, 2005). In the case of

the Cobb-Douglas functional form, this can be achieved by restricting the sum of input prices coefficients to be equal to one:

$$\sum_{n=1}^{N} \beta_n = 1 \tag{3.29}$$

Substituting this constraint into the model in 3.25 yields the homogeneity constrained cost frontier model:

$$\ln(c_i / w_{Ni}) = \beta_0 + \sum_{n=1}^{N-1} \beta_n \ln(w_{ni} / w_{Ni}) + \sum_{m=1}^{M} \phi_m \ln q_{mi} + v_i + u_i \tag{3.30}$$

Alternatively, in a compact form this model can be written as:

$$\ln(c_i / w_{Ni}) = \mathbf{x}_i^{'} \beta + v_i + u_i \tag{3.31}$$

or, since the distribution of v_i is symmetric, the model can be written as:

$$-\ln(c_i / w_{Ni}) = -\mathbf{x}_i^{'} \beta + v_i - u_i \tag{3.32}$$

From a statistical viewpoint, this equation is statistically indistinguishable from the production frontier model given by equation 3.7. Thus, apart from sign changes, the entire analysis in section 3.3.1 applies exactly to the estimation of a stochastic cost frontier. A measure of cost efficiency can be provided by:

$$CE_i = \exp\left(-u_i\right) \tag{3.33}$$

Thus, firms' specific cost efficiency can also be predicted using the equations discussed in section 3.3.1

3.3.3 Estimating allocative efficiency

As was described in the literature review, cost efficiency is composed of two elements: technical efficiency and allocative efficiency. In the previous two sections the estimation process of technical and cost efficiency was discussed. If the goal is to estimate technical or cost efficiency, one can estimate the production or cost frontier in equations 3.7 and 3.27. However, to obtain measures of allocative efficiency, the process is slightly more complicated. Different approaches have been proposed in the literature. One model developed by Greene (1976) involves estimating a stochastic cost frontier together with a subset of cost- share equations in what is known by a seemingly unrelated regression framework:

$$\ln c_i = \ln c(q, w_i; \beta) + v_i + u_i \tag{3.34}$$

$$S_{ni} = S_{ni}(q_i, w_i; \beta) + \eta_{ni} \tag{3.35}$$

where $\ln c(q_i, w_i; \beta)$ is the deterministic kernel of the stochastic cost frontier, $S_{ni}(q_i, w_i; \beta)$ are the deterministic kernels of the stochastic cost share equations, β represents the set of all parameters appearing in the cost frontier model, u_i is an error component representing cost inefficiency, and η_{ni} is an error component introduced to represent allocative inefficiency, which represents a violation of the first order condition of the cost function. A problem with this model has to do with the fact that the cost frontier contains an error representing the combined effects of both technical and allocative inefficiency (because both types of inefficiency lead to increased cost) while the cost shares equation involves an error representing allocative inefficiency only (because technical inefficiency involves a radial expansion of the input vector and this leaves cost shares unchanged). It is difficult to explicitly model the relationship between these different error terms without making the system highly non-linear and extremely difficult to estimate. This dilemma was first noted by Greene (1980) and is known in the literature as the 'Greene Problem' (Kumbakhar and Lovell, 2000).

An alternative method for estimating allocative efficiency was proposed by Kopp and Diewert (1982) and refined by Ziechang (1983). The implementation of this method involves estimations of a cost function in a single equation framework, followed by numerical estimation of many sets of $N-1$ non linear equations (one set for every data observation). Although this approach is analytically correct, it does not provide a solution to the 'Greene Problem' as it fails to incorporate statistical noise in an econometrically consistent fashion (Kumbakhar and Lovell, 2000).

Schmidt and Lovell (1979) solved the 'Green problem' by estimating a production function together with a subset of the first order condition for cost minimisation. Their approach exploits the self-duality of the Cobb-Douglas production functional form. The stochastic Cobb-Douglas production frontier is:

$$\ln q_i = \beta_0 + \sum_{n=1}^{N} \beta_n \ln x_{ni} + v_i - u_i \tag{3.36}$$

Minimizing cost subject to (3.36) involves writing out the langrangean, taking the first order derivatives and setting them to zero. Taking the logarithm of the ratio of the first and n-th order condition yields:

$$\ln\left(\frac{w_{1i}x_{1i}}{w_{ni}x_{ni}}\right) = \ln\left(\frac{\beta_1}{\beta_n}\right) + \eta_{ni} \qquad \text{for } n=2,\ldots, N \tag{3.37}$$

where η_{ni} is a random error introduced to represent the allocative inefficiency for the input pair x_{1i} and x_{ni}. This error can be positive, negative or zero depending on whether the firm over-utilizes, under-utilises, or correctly utilises input 1 relative to input *n*. A producer is allocatively efficient in input use if, and only if η_{ni} =0 for all n. As shown in 3.37 the inputs appear in ratio form, thus a "radial expansion in the input vector (i.e., an increase in technical efficiency) will not cause a departure from the first order condition. However, a change in the input mix (i.e. allocative efficiency) will clearly cause a departure from the first order condition" (Coelli et al., 205, p. 270).

The systems of *N* equations (3.36) and (3.37) can be estimated by the method of maximum likelihood under the assumption that $v_i s$, $u_i s$ and the $\eta_{ni} s$ are identically and independently distributed as univariate normal, half-normal and multivariate normal random variables respectively, i.e.:

$$v_i \sim iidN \ (0, \sigma_v^2)$$

$$u_i \sim iidN^+ (0, \sigma_u^2)$$

and $\quad \eta_i = (\eta_{2i}, \eta_{3i}, \ldots\ldots \eta_{ni})' \sim iidN(0, \Sigma)$

With these distributional assumptions, the log likelihood function is:

$$\ln L = I\ln(2r) - \frac{IN}{2}\ln\left(2\pi\right) - \frac{I}{2}\ln\left(\sigma^2\right) - \frac{I}{2}\ln\left|\Sigma\right|$$
$$+\sum_{i=1}^{I}\ln\Phi\left(-\frac{\varepsilon_i}{\sigma}\sqrt{\frac{\gamma}{1-\gamma}}\right) - \frac{1}{2}\sum_{i=1}^{I}\left[\eta_i^{'}\Sigma^{-1}\eta_i + \varepsilon_i^2/\sigma^2\right] \quad (3.38)$$

where $\varepsilon_i = v_i - u_i = \ln y_i - \beta_0 - \sum_{n=1}^{N}\beta_n \ln x_{ni}$ (3.39)

$$\eta_{ni} = \ln\left(\frac{w_{1i}x_{1i}}{w_{ni}x_{ni}}\right) - \ln\left(\frac{\beta_1}{\beta_n}\right) \quad (3.40)$$

and $r = \sum_{i=1}^{N}\beta_n$ is a measure of return to scale (3.41)

This log likelihood function can be maximised to obtain maximum likelihood estimates of all parameters in the model. Schmidt and Lovell (1979) used these parameter estimates to obtain an equation of the dual-cost frontier associated with equation 3.36 (See Coelli et al., 2005 for details), which was used then to decompose the allocative efficiency elements of the overall cost efficiency using the following equation:

$$CAE_i = \exp(\ln r - A_i)$$

where $A_i = \frac{1}{r}\sum_{n=2}^{N}\beta_n\eta_{ni} + \ln\left[\beta_1 + \sum_{n=2}^{N}\beta_n\exp\left(-\eta_{ni}\right)\right]$ (3.42)

3.3.4 Extension of the stochastic frontier model: accounting for the production environment

The estimation of production efficiency has, or at least should have, two components. The first is the estimation of a stochastic production or cost frontier that serves as a benchmark against which to estimate the technical or cost efficiency of the producers.

Thus, the objective of the first component is to estimate efficiency with which producers allocate their inputs and outputs under some maintained hypothesis concerning behavioral objectives. This first component is by now discussed in the previous sections of this chapter.

The second component, which is equally important, is the incorporation of environmental variables in the estimation of the frontier. These variables are neither inputs nor outputs to the production process but exert an influence on producer performance. Consequently, a failure to account for them may result in an inaccurate estimation of the frontier function (Coelli et al., 1998)

The simplest way to account for environmental variables is to incorporate them directly into the non-stochastic component of the production or cost frontier. In the case of a cross-sectional data this leads to a model of the form:

$$\ln q_i = \mathrm{x}_i^{'}\beta + \mathrm{z}_i^{'}\gamma + v_i - u_i \qquad (3.43)$$

where z_i is a vector of environmental variables and γ is a vector of unknown parameters. The model has the same error structure as the conventional stochastic frontier model discussed in section 3.3.1. Thus, all the estimators and testing procedures discussed in the previous sections are applicable to this model.

Some authors explore the relationship between the environmental variables and the predicted efficiencies using a two-stage approach. In the first stage, a stochastic frontier function is used to obtain estimates of the inefficiencies. The estimated inefficiencies are then regressed on a vector of exogenous variables in a second stage of general form:

$$E(u_i \mid v_i) = g\left(z_i;\gamma\right) + \varepsilon_i, \qquad (3.44)$$

where $\varepsilon_i \sim iidN(0,\sigma_\varepsilon^2)$ and γ is a vector of parameters to be estimated.

Unfortunately, this two-stage formulation poses significant estimation problems. First, it must be assumed that there is no correlation between the elements of z_i and x_i, otherwise the maximum likelihood estimates of $(\beta, \sigma_v^2, \sigma_u^2)$ are biased due to the omission of the variables z_i in the first stage stochastic frontier model. This will consequently to inaccurate estimates of efficiencies.

A second problem with this approach is that, in the first-stage, the inefficiencies are assumed to be independently and identically distributed, while in the second stage they are assumed to be a function of firm specific factors, contradicting the assumption that u_i are independent (Kumbakhar and Lovell, 2000).

More recently, models for inefficiency effects in stochastic frontier function have been proposed by S. C. Kumbhakar, Ghosh, & McGuckin (1991), Reifschneider & Stevenson (1991), and Huang and Liu (1994). They all assume that the inefficiency effects are explicit functions of various explanatory variables, and estimate the parameters of both the stochastic frontier and the model for the inefficiency effects in a single-stage procedure. Battese and Coelli (1995) formulated a stochastic frontier model that is essentially the same as that of Huang and Liu (1994) and specified for longitudinal or panel data.

For a cost frontier example, the model would consist of equation 3.45 and 3.46. The first equation illustrates the stochastic frontier cost function. The second component which captures the effects of cost inefficiency (u_i) has a systematic component $\gamma' z_i$ associated with the exogenous and a random component ε_i:

$$LnC_i = Lnf(w_i, q_i, k_i; \beta) + v_i + u_i \tag{3.45}$$

$$u_i = \gamma' z_i + \varepsilon_i \tag{3.46}$$

where C_i denotes the total cost of the ith firm, w_i is a vector of input prices, q_i is a vector of outputs, k_i is a vector of fixed input levels and β is a vector of unknown parameters to be estimated. The non-negativity requirement $u_i = (\gamma' z_i + \varepsilon_i) \geq 0$ is modeled as $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$ with the distribution of ε_i being bounded below by the variable truncation point $(-\gamma' z_i)$. Finally, the $v_i's$ are identically and independently random errors having $N(0, \sigma_v^2)$ distribution and independent of u_i.

The advantage of using this type of model is that the inefficiency variables and the explanatory variables of the stochastic frontier model can be estimated simultaneously, i.e. allowing interaction between firm-specific variables and the right-hand-side variables of the frontier function. Allowing this interaction emphasises the possibility of non-neutral shifting of average response functions, in which case OLS is not capable of determining the shape of the boundary function, which weakens its analytical ability even further.

3.4 Empirical application

This section discusses the empirical application of the frontier approach to the model used in this study. All the discussions are based on the stochastic frontier approach, as it was selected in this study for the estimation of both the production and cost frontier models. This is due to its many advantages over the DEA approach (refer to section 3.2), especially as it takes into account the measurement errors, so allowing for additional evidence in the estimation of the frontier.

This section is organised to address the research objectives raised in the introductory part of this study:

- to estimate and evaluate the production and cost frontier functions using a sample of health care foodservice operations,
- to compute technical, allocative and cost efficiency and their degree of variability among the different health care foodservice operations,
- to identify the variables that have influenced the technical and cost efficiency measures of health care foodservice operations,
- to test the functional form that represents the production and cost frontier models, in order to avoid any specification error in the estimation of the model
- to test the for the existence of technical and cost inefficiency in the sample.

In the first part, technical efficiency is examined, this is followed by a discussion of cost and allocative efficiency. A discussion of the selection of functional form used in the estimation of the frontier models is then presented. The section concludes with a detailed overview of the input/output and environmental variables used in this study.

3.4.1 Examining technical inefficiency and its determinants

In this sub-section, technical inefficiency is considered as part of the total error term for the stochastic production frontier (see section 3.3.1). Stochastic frontier analysis is used to separate technical inefficiency from the error attributable to random factors. The process entails estimating a production frontier and technical efficiency of hospital foodservice operations.

If the only objective is to estimate technical efficiency, one could estimate the traditional product frontier described in section 3.3.1. However, as the objective of this study is to also account for the factors that exogenously influence technical efficiency, it was necessary to estimate an extended frontier model that allows for this estimation (see Section 3.3.4). The Battese and Coelli (1995) model was used. This model extends further the framework of estimating the production frontiers and technical inefficiency independently proposed by Aigner et al. (1977) and Meusen and van den Broek (1977). The Battese and Coelli (1995) model was appealing for the present task because, first, it allows the simultaneous estimation of the inefficiency variables and the explanatory variables of the stochastic frontier model. This has the advantage of overcoming the statistical shortcomings that could be caused by assuming the model in a two-stage formulation (see section 3.3.4). Second, it assumes that Stevenson's (1980) general distribution of firm effect applies to the stochastic frontier production function. The half-normal and exponential distribution both have a mode at zero. This causes conditional technical efficiency scores, especially in the neighbourhood of zero that can involve artificially high technical efficiency levels. Moreover, these distribution specifications fix a pre-determined shape for the distribution of the disturbances that can also be considered a shortcoming. Stevenson (1980) argued that the zero mean assumed in the Aigner et al. (1977) model was an unnecessary restriction, and favoured the use of use of the truncated distribution to estimate efficiency as opposed to the half-normal and exponential distributions.

A discussion of the functional form and specification of the stochastic frontier model used in this study is presented in the next section. In general the stochastic frontier is given as:

$$q_i = f(x_{1i}, x_{2i}, x_{3i}, x_{4i}, x_{5i}, x_{6i}, dum_{1i}, dum_{2i}, dum_{3i}, dumc_i, \beta_i)\exp(v_i - u_i) \qquad (3.47)$$

where, for the i^{th} firm,

q_i = the number of meal produced per year

x_{1i} = the number of full- time equivalent employees

x_{2i} =the amount of energy

x_{3i} = the total square area of the department

x_{4i} =the age of equipment

x_{5i} =the skill level of employees

x_{6i} =the degree of readiness of raw materials

dum_{1i} = dummy variable representing the cook-chill system

dum_{2i} =dummy variable representing the hybrid system

dum_{3i} =dummy variable representing the external system

$dumc_i$ =dummy variable representing the country code

β_i = parameters to be estimated.

The criteria for selecting these above variables drew mainly from previous studies in the literature (Freshwater, 1980; Greathouse et al., 1989). In general, these variables constitute factor inputs and environmental variables that influence the amount of meals produced. A greater usage of any inputs should lead to an increase in size of meal production, which would be indicated by a positive relationship between the dependent variables and the explanatory variables. Different relationships are expected between the number of meals produced and each of the environmental variables as will be described later in this chapter (Section 3.4.5.4).

The $v_i^{'}s$ are assumed to be *iid* random errors having $N(0,\sigma_v^2)$ distribution, and the $u_i^{'}s$ are *iid* non-negative random variables, representing the effect of technical inefficiency of the hospitals involved. In the Battese and Coelli (1995) model, these u_i variables are obtained by truncation (at zero) of an *iid* normal distribution with unknown mean, μ and unknown variance σ^2. The variance of the parameters is given as:

$$\sigma^2 = \sigma_u^2 + \sigma_v^2$$

$$\gamma = \sigma_u^2 / \sigma^2$$

where γ takes on a value between zero and one.

The technical inefficiency latent model is given by:

$$u_i = \delta' z_i + \varepsilon_i$$

where z_i is a vector of explanatory variables associated with the technical inefficiency effects, δ is a vector of unknown parameters to be estimated, and the $\varepsilon_i^{'}s$ are unobservable random variables, which are assumed to be independently distributed, obtained by the truncation of the normal distribution with mean of zero and unknown variance σ^2 such that u_i is non-negative (i.e. $\varepsilon_i \geq -z_i\delta$).

Specifically:

$$u_i = \delta_0 + \delta_1 edu + \delta_2 exp + \varepsilon_i \qquad (3.48)$$

where:

edu = Level of a manager's education

exp = Years of a manager's experience

The variables used to statistically explain technical inefficiency are well established in the literature (Battese and Coelli, 1993) and relate to factors that affect the manager's ability to improve the efficiency of their operation.

The random variable ε_i is defined by the truncation of the normal distribution (with zero mean and variance σ^2) such that the point of truncation is $-z_i\delta$, i.e., $\varepsilon_i \geq -z_i\delta$. These assumptions are consistent with the u_i's being non- negative truncation of the $N(z_i\delta, \sigma^2)$ distribution. Thus the technical efficiency of production for the i^{th} firm is defined by:

$$TE = \exp(-u)$$

$$= \exp(-z_i\delta - \varepsilon_i) \quad (3.49)$$

In equation 3.49 a positive sign for the estimated δ coefficient implies that the associated variables have a negative impact on efficiency, and vice versa. For each explanatory variable there was *a priori* expectation concerning the sign of the coefficients as explained below:

- **Level of a manager's education**

Higher level of manager education is hypothesized to be associated with lower level of inefficiency (i.e. negative sign for the parameter estimate). This is based on the supposition that managers with higher education are more experience in the use of the new technology in the efficiency utilisation of their resources.

- **Years of a manager's experience**

Similarly, the higher level of manager experience is hypothesised to be associated with lower level of inefficiency. This is based on the assumption that managers will learn from their mistakes and improve on their production with time, leading over time to a reduction in technical inefficiency.

Finally, the mean technical efficiency for the whole sample was obtained as a simple average of individual hospital efficiency. To obtain this mean, technical efficiency of hospitals was gauged on the production of best performing hospitals; that is, hospitals for which output is located on the estimated frontier. Average technical efficiency for the whole sample is the proportion of output by which the 'average' producer falls short of full technical efficiency. This is measured as the difference between full and mean efficiency; that is, a proportion of output not realized by the hospitals, on average, because the inputs that went into producing its outputs were not fully utilised.

3.4.2 Examining cost efficiency (CE) and its determinants

Cost efficiency was estimated from the estimated stochastic cost frontier. The Battese and Coelli (1995) framework was again used to estimate the cost frontier model simultaneously with the model explaining cost inefficiency. The methods used and the procedure followed to obtain cost inefficiency were the same as those used in the case of technical efficiency.

The stochastic cost frontier of hospital foodservices is given by:

$$C_i = f(w_{1i}, w_{2i}, x_{1i}, x_{2i}, x_{3i}, x_{4i}, q_i, dum_{1i}, dum_{2i}, dum_{3i}, dumc_i, \beta_i)\exp(v_i + u_i) \qquad (3.50)$$

where for the i^{th} firm

C_i = total operational cost

w_{1i} =the price of labour

w_{2i} =the price of energy

x_{1i} = the total square area of the department

x_{2i} =the age of equipment

x_{3i} =the skill level of employees

x_{4i} =the degree of readiness of food raw materials

dum_{1i} = dummy variable representing the cook-chill system

dum_{2i} =dummy variable representing the hybrid system

dum_{3i} =dummy variable representing the external system

$dumc_i$ =dummy variable representing the country code

u_i = one sided error term (i.e. positive for cost frontiers)

v_i = a two-sided random error accounting for variation in costs due to stochastic factors

β_i = parameters to be estimated.

The above variables in the stochastic frontier constitute input prices, fixed inputs (capital) and environmental variables that influence the total operational cost. An increase in any of the input prices should lead of an increase in total cost (Coelli et al. 1998), which would be indicated by a positive relationship between the dependent variables and the explanatory variables. The expected relationships between the total cost and each of the environmental variables are described later in this chapter (Section 3.4.5.4).

The cost inefficiency in the latent model, as in the case of technical inefficiency, is given by:

$$u_i = z_i\xi + r_i$$

where z_i is a vector of explanatory variables associated with the cost efficiency effects, ξ is a vector of unknown parameters to be estimated, and the $r_i^{'}s$ are random variables with $N(0,\sigma^2)$ truncated at $-z_i\xi$, i.e., $r_i \geq -z_i\xi$.

Specifically:

$$u_i = \xi_0 + \xi_1 edu + \xi_2 exp + r_i \tag{3.51}$$

where the variables and the parameters are the same as described and discussed in section 3.4.1. The signs of the coefficients are also as hypothesised in the technical inefficiency model. This is because technical efficiency is a part of cost efficiency, so consequently what affects technical inefficiency will also affect cost efficiency in the same direction.

3.4.3 Estimation of allocative efficiency (AE)

Another contribution to this study is the estimation of allocative efficiency. In section 3.3.3 the approaches used in the literature to obtain estimates of allocative efficiency were discussed. The estimation is relatively simple with the DEA approach. The process involves estimating two DEA models, one to estimate technical efficiency and another to estimate cost efficiency. Allocative efficiency can then be estimated from the ratio $AE = CE/TE$. The process is, however, more complicated when stochastic frontier is used. Different approaches were proposed in the literature. The one proposed by Schmidt and Lovell (1979) has some advantages over the other approaches as it provides a solution to the 'Greene' problem proposed by Greene (1980) (see section 3.3.3).

Their approach involves estimating a production frontier together with a subset of the first order conditions for cost minimisations. In this study this approach is used; however, the frontier is estimated in a single equation framework. This is due to two reasons. First, it is less computationally complicated that the system of equations framework. Second, when deriving the log-likelihood of their model, Schmidt and Lovell (1979) based their calculation on the assumption that the inefficiency term follows a half normal distribution, which is inconsistent with the estimation of the production frontier used in this study where a truncated normal distribution is assumed for the inefficiency term (see section 3.3.4).

Specifically, the calculation of allocative efficiency involved taking the first order condition of cost minimization associated with the production frontier in equation 3.47 and then using equations 3.39 to 3.42 in order to derive the allocative efficiency measures.

3.4.4 Functional forms

The choice of functional form in an empirical study is of prime importance, since the functional form can significantly affect the results. Most efficiency studies focus solely on determining the degree of inefficiency and do not examine alternative specifications of the technology. However, if researchers choose a form that it incorrect, this model will potentially predict responses in a biased and inaccurate way (Griffin et al., 1987).

Some common functional forms were discussed in section 2.6 of the literature review. Those that are most popular are the Cobb-Douglas and the translog forms (Coelli et al. 1998). In this study the Cobb-Douglas functional form was selected for the estimation of the stochastic frontier model. However, to avoid any mispecification problem, the 'translog' was also tested in comparison to the selected Cobb-Douglas form.

The Cobb-Douglas form is a considered a special case of the translog functional form (for example, it can be obtained from the translog by setting all $\beta_{mn} = 0$. see Table 2.3) and is used mainly because of its simplicity and parsimony (Richards and Jeffrey, 1996). Moreover, by transforming the model into logarithms, one can obtain a model that is linear in inputs and easier to estimate (Coelli et al., 1998). Some studies justify using the

Cobb-Douglas form by referring to Kopp and Smith's (1980) conclusion that the functional form has limited effect on empirical efficiency measurement.

The translog functional form is in its turn one of the most popular flexible functional forms. One of its advantages is that it can provide a second order approximation to an arbitrary twice-differential linearly homogenous function (Chambers, 1988). The main drawbacks associated with this function, however, are its susceptibility to multicollinearity and the potential problem of insufficient degrees of freedom due to the presence of interaction terms.

3.4.5 Source and construction of data

The data for this study were collected by means of a questionnaire (See Appendix 2). The questionnaire was first discussed with foodservice managers through a focus group and then piloted with eight hospitals from both the private and public sectors to ensure its clarity and reliability. After data collection was completed, the entire data set was reviewed and assessed for the presence of any missing data and outliers that can distort the results. The questionnaire was sent to 200 Australian hospitals and 50 American hospitals. All hospitals were randomly selected. We received reply from 90 Australian hospitals, representing the different states of Australia (response rate 45%) and 11 American hospitals (response rate 22%). All models were estimated with and without the American sample and no significant differences on the results were noticed, so the decision was to keep the American sample in the data.

Respondents to the questionnaire involved mainly the foodservice manager(s). The hospitals surveyed were heterogeneous in terms of size, ranging from 60 to 900 beds, and including hospitals from both the private and public sectors. The hospitals were also heterogeneous in terms of the type of foodservice systems used, with each of the four systems- cook-fresh, cook-chill, hybrid, and external. The distribution of the data by each of the three characteristics (type of systems, number of beds, and type of hospitals) is represented in Table 3.1.

Table 3.1. Data characteristics

Distribution by hospital type		
Type	Number	Percentage
Private	33	32.67%
Public	68	67.33%
	N=101	
Distribution by number of beds		
No of Beds	Number	Percentage
50-150	33	32.67%
150-250	43	42.57%
250-400	11	10.89%
400+	15	14.85%
	N=101	
Distribution by type of system		
Type of System	Number	Percentage
Cook-fresh	40	39.60%
Cook-chill	20	19.80%
Hybrid	19	18.81%
External	22	21.78%
	N=101	

The focus of the questionnaire was on the various production costs (labour, energy) rather than the service and delivery costs. Data collected consisted mainly of input and output quantities and input prices. Additionally, data were collected on a set of environmental variables which were also included in the estimation of the production and cost frontier models.

The selection of input/output quantities, input prices and environmental variables, used in the estimation of the production frontier model, is in line with previous studies from the literature (ADA, 2005; Battese and Coelli, 1995; Brown and Hoover, 1990; Clark, 1997; Hong and Kirk, 1995; Light and Walker, 1990; Mcproud, 1982). Table 2.3 provides a summary of all variables used in the model estimation, their classification, and references to studies in the related literature where these variables have previously been used.

3.4.5.1 Input quantities

On the inputs side, three input quantities were collected: the number of FTEs, amount of energy, and total square meters of the production area. The number of FTEs was selected as a proxy for labour input; while total square meters of the production area was used as a proxy for capital input (using proxies for inputs is a common approach in efficiency studies).

All these inputs are well established in the literature (Clark, 1997; Greathouse et al., 1989; Hong and Kirk, 1995; Mibey and Williams, 2002), and have been selected in previous productivity studies in the health care foodservice area. Labour input is a major component of the total expenditure of foodservice departments (Nettles et al., 1997) and can be considered as one most important factors in improving the overall level of production (Clark, 1997).

Table 3.2. Selection of input and output variables

Variable	Input/ Output/ Environmental	Measured as	Reference(s)
FTE	Input	Number of full-time equivalent employees	Greathouse (1987) Brown and Hoover (1990) Clark (1997)
Energy	Input	Amount of electricity and gas used	McProud (1982) Brown (1987)
Capital	Input	Total square meters of production area	Mibey and Williams (2002)
Number of Meals	Output	Meals produced/year	ADA (2005) Clark (1997) Hong and Kirk (1995)
Age of Equipment	Environmental	Average age of equipment	Brown and Hoover (1990)
Skill level of employees	Environmental	Percentage of qualified employees	Walker (1988)
Degree of readiness of raw materials	Environmental	Percentage of raw materials bought ready prepared	Clark (1997)
Type of foodservice system	Environmental	Dummy variables with 1 for cook-chill, 2 for hybrid and 3 for external	Light and Walker (1991) Greathouse (1987) Clark (1997)
Level of manager's education	Environmental	1 if holds a qualification 0 if non	Battese and Coelli (1995)
Years of managers'experience	Environmental	Years of working experience in the industry	Lachaal et al. (2005)

Similarly, energy input is also considered as an important input in health care foodservice operations (Brown and Hoover, 1990; Mcproud, 1982; Nettles and Gregoire, 1993), as most of these operations produce food in bulk quantities and require additional equipment for chilling, storing and reheating of the food**.** The third input, capital input, is usually included in any efficiency study (Coelli et al., 2005). It has also a major importance in health care foodservice operations (Clark, 1997; Greathouse, 1987) and, therefore, should not be ignored. The variable selected to represent capital input (total square meters of the production area) in this study is an indicator of the relationship between the size of the kitchen and the capacity of production. The trend in hospital foodservice seems to be towards smaller kitchens (Bertagnoli, 1996). Vast kitchens and unrestricted equipment usage may no longer be acceptable or feasible, and may be giving way to more compact and energy-efficient systems. In many instances, it has become necessary to fit kitchens into much smaller spaces than it was a decade ago (Light and Walker, 1990). Additionally, owners, operators, and designers have linked reducing the size of hospital kitchens with more efficient and profitable operations. Moreover, where space is limited (and expensive), owners may find it more desirable to reduce non-sales areas such as the kitchen, and to enlarge the dining area (Bertagnoli, 1996; Ghiselli et al., 1998).

Data on all these inputs were collected from the questionnaire. The number of FTEs and total square meters of the production area were determined directly from the participants' answers. The process was, however, slightly more difficult with the amount of energy. It was clear from the pilot study that it is difficult for managers to separate the energy consumption of the foodservice department from the energy consumption of the entire hospital, especially where there is only one utility meter reading available for the entire hospital.

A second method developed by Messermith et al. (1994) has then been adopted. The method consists of manually multiplying the equipment rating by the actual time the equipment is operating. For this purpose, the questionnaire was redesigned with the help of three equipment suppliers. The final list included 18 different types of equipment divided into three categories: short-order cooking equipment, cooking equipment and service equipment. For each type of equipment different capacities were specified. The energy consumption of refrigerated storage was also assessed by asking respondents to identify the number and total square meters of each of their cool rooms and freezers.

The data recorded in the equipment list were used to calculate the energy consumption of foodservice production in each hospital according to the following equation:

$$\textit{Time Operating} \times \textit{Equipment Rating} = \textit{Energy Consumption} \tag{3.54}$$

where *Equipment Rating* is a value of power used per hour of operation

This equation was slightly modified with some other equipment. Ovens, for example, do not run continuously even when they are still turned on. Once the proper temperature is reached, the internal thermostat shuts off to avoid overheating. The amount of time the equipment actually operates divided by the total time it is turned on is known as the duty cycle as shown in the following equation:

$$\textit{Duty Cycle} = \textit{Time Operating/Time on} \tag{3.55}$$

For this study an approximate of the duty cycle was determined from the equipment suppliers and then energy for this equipment was calculated as power multiplied by the amount of time the equipment operated:

$$KWh = KW \times time\ on \times Duty\ Cycle \tag{3.56}$$

where KWh equals kilowatt hours.

Finally, the 'Kirby' software (www.kirbyjn.com.au) developed by 'Kirby' manufacturers (a wholesaler for refrigeration and air conditioning equipment in Australia) was used to provide a proximate of energy consumption of the cool rooms and freezers in the different hospitals. The data needed were the size and number of cool rooms and freezers, which were collected directly by the questionnaire, in addition to a proximate of the average temperature in each area based on the hospital location.

3.4.5.2 Output

The number of meals was selected as the output in this study, following previous studies in the literature (Clark, 1997; Greathouse, 1987; Mibey and Williams, 2001). To ensure consistency in the way respondents address this question, the suggestions of the pilot group were followed, and a meal was defined as a complete menu item for breakfast, lunch or dinner, and not a snack or afternoon tea.

3.4.5.3 Input Prices

Two input prices are used in the estimation of the cost frontier model: the price of labour and the price of energy. The price of labour was obtained by dividing the total labour cost (collected directly from the questionnaire) by the number of FTE while the price of energy was obtained from the main energy suppliers in each of the States surveyed (e.g. Integral Energy and AGL). The criteria for selecting these variables follow that of the production frontier discussed in the previous section, as what affects the level of production should also affect total cost (Coelli et al., 1998; Kumbakhar and Lovell, 2000)

The total cost of production which acts as a dependent variable in the cost frontier model, consisted of two components: labour cost and energy cost. The labour cost was obtained directly from the questionnaire, while the energy cost was obtained by multiplying the total amount of energy by the respective prices of energy (gas and electricity).

3.4.5.4 Environmental variables

Data for all environmental variables were collected from the questionnaire. Four environmental variables (age of equipment, skill level of employees, type of foodservice system and type of country) were included directly in the non-stochastic component of the production and cost frontier models, while those reflecting management characteristics (level of managers' education and years of managers' experience) were included in the inefficiency component of the frontier.

The use of the systems was assessed with four questions asking respondents to classify their operation as being cook-holding, cook-chill, hybrid or external. The degree of readiness of prepared vegetables was assessed by three questions asking what percentage of potatoes, meat and fresh vegetables used were purchased pre-prepared. The responses to these questions were then added for each hospital. The skill level of employees was measured by three questions asking respondents to classify their employees into the following three categories: apprentices, trade certificate and non-trade certificate. Finally, the level of managers' education and years of managers' experience were computed directly from the questionnaire.

Different relationships are expected between each of these environmental variables and the level of output, which is the number of meals in this case. The age of equipment, for example, is expected to decrease the number of meals produced as older equipment tends to have a negative impact on the level of production (Brown and Hoover, 1990). On the other hand, a higher degree of readiness of raw materials is expected to improve the level of production and to allow for more flexibility in the production area (Clark, 1997). The same applies for the skill level of employees. It is an indicator of the quality of labour inputs. Employees with higher skills are expected to positively impact the level of output produced (Reynolds and Thompson, 2005).

The relationship between the type of foodservice system and the level of output is also *a priori* expected for some systems. The use of batch cooking systems such as the cook-chill, for example, is expected to have a better impact on the efficiency of production in comparison with the traditional cook-serve system (Clark, 1997). The use of the hybrid system should in its turn lead to some advantages in the production site, as it allows the combination of more than one system, so offering more flexibility in the selection of menu items (Nettle et al., 1997). Lastly, it is difficult to establish any prior hypothesis for the external system as it has not been previously evaluated in any of the related studies despite its widespread use, especially in Australia.

Different relationships can as well be hypothesized between each of the environmental variables and the total cost of production- the dependent variable in the cost frontier model. The age of equipment, for example, is expected to increase total cost as the capacity of production might decrease with total cost as this would require extra labour to produce the required capacity. Similarly, the degree of readiness of raw materials is expected to have a positive impact on the total cost but not significantly so as it leads to a decrease in the labour time needed for meal preparation (Clark, 1997).

The relationship between the total cost, and type of foodservice system has been an area of debate in the literature (Freshwater, 1980; Light and Walker, 1990). For example, while some studies reported cost savings of the cook-chill system in comparison to the cook-fresh system (Light and Walker, 1990), other studies failed to support these savings (Greathouse et al., 1989). Also, it is difficult to establish any prior hypothesis for the impact of the 'hybrid' and 'external systems' on the total production cost, as none of these systems has been addressed before in the literature. However, some cost savings from these systems is expected, due to their many operational advantages over the traditional cook-fresh system (See Table 2.1).

3.4.6 Estimation of the stochastic frontier and inefficiency functions

The parameters of the stochastic frontier and the inefficiency functions are estimated simultaneously by the method of maximum likelihood using the computer program, Frontier Version 4.1 (Coelli, 1992).

The estimation is carried out in three steps. First, ordinary least squares (OLS) estimation of the stochastic frontier function yields estimates of the β coefficients. All the estimates except the one of intercept, β_0, are unbiased. Second, a grid search finds γ, using the OLS estimates of the β coefficients and the estimates of β_0 and σ^2 which are adjusted according to the corrected ordinary least squares formula presented in Coelli (1995). The coefficients δ are set to zero and γ is limited between zero and one, and is defined as:

$$\gamma = \frac{\sigma_u^2}{\sigma^2}$$

The frontier model is then estimated using the values selected in the grid search as starting values in an iterative procedure to obtain the final maximum likelihood estimates of the coefficient β and δ together with a variance parameter which are expressed as:

$$\sigma^2 = \sigma_u^2 + \sigma_v^2$$

Finally, to obtain estimates of allocative efficiency a two-stage approach was adopted. As the decomposition option is not automatically available in the 'Frontier' program, the frontier estimates of the coefficients of the production frontier were first taken, and then decomposition equations were programmed in the Shazam econometric program (Version 9).

3.5 Summary

This chapter provided a detailed discussion of the empirical methods used in the study, elabourating on models and pertinent methodological issues. The first part discussed the data envelopment analysis and its limitations. This was followed by a detailed discussion of the stochastic frontier approach and its methodological extensions. Between the two methodologies, stochastic frontier was selected in this study due to its many advantages over data envelopment analysis, especially as it accounts for statistical noise, making it more suitable in the health care foodservice application where data is usually characterized by a high level of variation.

The last part of the chapter provided a discussion of the specific stochastic frontier models used in this study. Additionally, the methods of data collection were discussed, and the selection criteria of the different input/output and environmental variables used in estimation of the stochastic frontier was presented and justified.

In the next chapter, the results from the estimation of the stochastic frontier models are presented and checked for significance and reliability. Additionally, the measures of technical, allocative and cost efficiency are presented, including a detailed discussion of the factors that exogenously influence these different types of efficiency.

Chapter 4: Empirical Analysis and Results

4.1 Introduction

This chapter presents the results of both the stochastic cost and production frontier models discussed in Chapter 3. The Battese and Coelli (1995) formulation is adopted for both models. This formulation has the advantages of simultaneously estimating the parameters of the stochastic frontier model and the factors affecting efficiency, given appropriate distributional assumptions associated with the error terms.

The chapter starts with a verification of the functional form adopted in the estimation of stochastic cost frontier (SCF) model. The estimation of the cost function and the derived cost efficiencies are then presented in the following section which also includes a detailed analysis of the cost efficiency latent model which was estimated simultaneously with the SCF.

In a similar way, the estimation of the stochastic production frontier (SPF) is presented. The functional form is first verified and then the estimation of the production function and the derived technical efficiencies are presented. The technical efficiency latent model which was estimated along the production frontier is also presented. Finally the results of allocative efficiency are presented and summarized. The chapter concludes with a short summary of the main findings of the study.

4.2 Stochastic cost frontier (SCF)

This section reports results from the estimation of the SCF. In section 4.2.1 the selection of the functional form used in the estimation of the frontier is presented. In section 4.2.2 the maximum likelihood estimates are reported and discussed. This follows with a discussion of the results from testing of the presence or absence of cost efficiency in our sample. The results of the cost inefficiency latent model, which was estimated simultaneously with the SCF, are discussed in section 4.2.3. Section 4.2.4 presents and discusses measures of cost efficiency.

4.2.1 Selection of Functional Form

In order to avoid any specification error related to the functional form of the SCF, an F - test was conducted. The purpose of the test was to determine whether the functional form of the frontier function is of Cobb-Douglas technology against the alternative hypothesis, which has the following translog functional form:

$$\ln C_i = \beta_0 + \sum_{n=1}^{6} \beta_n \ln x_{ni} + \beta_q \ln q_i + 0.5 \sum_{n=1}^{6}\sum_{m=1}^{6} \beta_{nm} \ln x_{ni} \ln x_{mi} + \sum_{n=1}^{6} \beta_{qn} \ln q_i \ln x_{ni} + \beta_{qq} \ln q_i^2 + \sum_{\mathrm{m}=1}^{3} \beta_{\mathrm{m}} dum_{\mathrm{mi}} + \beta_c dumc_i + u_i + v_i \tag{4.1}$$

where for the i^{th} firm:

C_i = the total operational cost

x_{1i} = the price of labour

x_{2i} = the price of energy

x_{3i} = the total square area of the department

x_{4i} = the age of equipment

x_{5i} = the skill level of employees

x_{6i} = the degree of readiness of raw materials

q_i = the number of meals

dum_{1i} = cook-chill system dummy variable

dum_{2i} = hybrid system dummy variable

dum_{3i} = external system dummy variable

$dumc_i$ = country dummy variable

u_i = one-sided error term

v_i = a two-sided random error term

Under the null hypothesis: $H_0 : \beta_{nm} = \beta_{qn} = \beta_{qq} = 0$, If this hypothesis is not rejected, then this means that it favours the simple Cobb-Douglas functional form which is a special case of the above model.

Since the F statistic was equal to 1.39, rejection of the null hypothesis at any conventional level of significance failed, and hence the following Cobb-Douglas technology was adopted:

$$\ln C_i = \beta_0 + \beta_1 \ln x_{1i} + \beta_2 \ln x_{2i} + \beta_3 \ln x_{3i} + \beta_4 \ln x_{4i} + \beta_5 \ln x_{5i} + \beta_6 \ln x_{6i} + \beta_7 \ln q_i$$
$$+ \beta_8 dum_{1i} + \beta_9 dum_{2i} + \beta_{10} dum_{3i} + \beta_{11} dumc_i + u_i + v_i \tag{4.2}$$

Equation 4.2 was estimated. It contains two input prices (labour and energy prices), one fixed input (capital input), one output (number of meals), three environmental variables (skill level of employees, age of equipment and degree of readiness of raw materials) and three dummy variables representing the different types of foodservice systems, with dum_1 representing the cook-chill system, dum_2 representing the hybrid system and dum_3 representing the external system. To avoid perfect multicollinearity, the traditional system was not included and it will be serving as the base system against which all the other systems are compared. The descriptive statistics for all these variables are presented in Table 4.1.

The linear homogeneity of the Cobb-Douglas function was imposed on the estimated equation by restricting the sum of all input prices' coefficients to be equal to 1. Again, the Cobb-Douglas function specified above fits the data well as the R-squared from the original least square estimation- which was used to obtain the starting values for the maximum likelihood in both the production and the cost frontier estimation- is in excess of 89.00% and the overall F-statistic is 67.791

Table 4.1. Data Description

Variables	Mean	Min	Max	St.Dev
$\ln C$	3.30	1.29	5.26	0.96
$\ln x_1$	-13.71	-15.47	-12.53	0.89
$\ln x_2$	10.48	9.78	10.78	0.17
$\ln x_3$	5.30	4.11	7.31	0.82
$\ln x_4$	5.52	4.38	5.99	0.44
$\ln x_5$	2.20	0	3.63	0.82
$\ln x_6$	-1.08	-2.94	0	0.83
$\ln q$	11.76	8.98	13.99	1.26
edu	0.56	0	1	0.49
yoe	26.02	5	43	7.95

4.2.2 Maximum likelihood estimates of the stochastic cost frontier

Table 4.2 illustrates the estimated parameters and their asymptotic t-ratios along with measures of overall goodness of fit. Since the logarithmic specification of the cost functions is being used, the estimated parameters represent the elasticities of total cost with respect to the estimated coefficients (i.e. the percentage change response in the dependent variable to a 1% change in the dependent variable). For example, as shown in Table 4.2, the percentage change in total cost as a result of a change of the quantity produced is 0.386. Thus, if total meals are to increase by 100%, then total cost will increase by 38.6% assuming all the other factors remain constant.

As for input prices, the energy price coefficient is 0.067 indicating that, if price of energy is to increase by 100%, then total cost will increase by 6.7%. The coefficient of the degree of readiness of raw materials is positive and significant (0.143) indicating the significant impact of this variable on total cost. Similarly, the coefficient of the age of equipment is also positive and significant indicating the negative impact that older equipment might have on total cost.

The dummy systems coefficients indicate that both the hybrid and the cook-chill systems are significantly more cost-effective than the traditional system. Similarly, the use of the external system would lead to a significant reduction in total cost but to a less extent than the hybrid and the cook-chill systems. Finally, regarding the dummy country coefficient, the result shows that there is no significant difference in total cost between foodservices in the two countries. The return to scale derived from the inverse of the differential of the cost frontier with respect to output shows that the cost frontier exhibits increasing return to scale. This means that in order to operate at the most productive scale size (MPSS), hospital foodservices have to expand both their inputs and outputs.

Table 4.2. Estimated coefficients for the Cobb-Douglas Cost Frontier

Variable	Coefficient	Standard-error	T-Ratio
Intercept	-2.635	1.207	-2.194**
$\ln x_2$	0.067	0.048	1.395
$\ln q$	0.386	0.100	3.843**
$\ln x_3$	0.134	0.113	1.187
$\ln x_4$	0.373	0.215	1.737*
$\ln x_5$	0.121	0.084	1.445*
$\ln x_6$	0.143	0.081	1.766*
dum_1	-0.473	0.203	-2.332**
dum_2	-0.652	0.213	-3.050**
dum_3	-0.346	0.187	-1.846*
$dumc$	-0.042	0.197	-0.214
σ^2	0.346	0.092	3.763**
$\gamma = \frac{\sigma_u^2}{\sigma^2}$	0.184	0.019	9.684**

Symmetry and homogeneity were imposed, utilizing the price of labour ($\ln x_1$)
** Coefficients are significant at the 5% level
* Coefficients are significant the 10% level

4.2.3 Cost efficiency effects

To investigate if there is significant cost inefficiency, the maximum likelihood estimates of the γ-parameter were used in a log- likelihood ratio (*LR*) test. The γ -

parameter is the ratio of the variance of the inefficiency error term (σ_u^2) to the sum of variance of the error term (σ_v^2) (see Table 4.2). Specifically the test was to determine if $H_0 : \gamma$ =0; that is, the health care foodservice operations are perfectly efficient against the alternative hypothesis, $H_A : \gamma \neq 0$, which indicates that the hospital foodservice operations are not perfectly efficient.

Cost inefficiency is said to be negligible the closer the γ-parameter is to zero. In the absence of cost inefficiency, all deviations are random and the average cost function (e.g. ordinary least squares (OLS) estimates) may be used to estimate the frontier. On the other hand, as γ approaches one, the model tends to be more deterministic, but whether the deterministic frontier is appropriate depends on whether or not γ is significantly different from one.

The LR test for this hypothesis was conducted using the log-likelihood function values of the estimated cost-frontiers and the values of the corresponding OLS cost functions. More specifically the test is formulated as:

$$LR = -2(LLF_R - LLF_U) \tag{4.3}$$

where LLF_U and LLF_R are the log-likelihood function values of the unrestricted (i.e. stochastic frontier and the restricted (i.e. OLS) function respectively.

From this test, the γ parameter for the cost frontier estimation was determined to be significantly different from zero (Table 4.3). This implies that hospital foodservices are not 100% percent cost-efficient and the cost function estimated by OLS does not provide an adequate representation of the data.

Table 4.3 Likelihood Ratio (LR) Tests of hypothesis for the Parameters of the SCF and SPF

Hypothesis	SCF		SPF
a) $H_0 : \gamma = 0$ Estimated frontier not different from OLS (average response function)	$LLF_U{}^a$	-82.57	-48.39
	$LLF_R{}^a$	-92.28	- 55.71
	LR^b	19.43	14.62
	Critical value (5% level)	8.76	8.76
	Decision	Reject H_0	Reject H_0
b) $H_0 = \delta_1 = \delta_2 = 0$ (All parameters on the variables explaining technical and cost efficiency are simultaneously equal to zero)	$LLF_U{}^a$	-82.57	-48.39
	$LLF_R{}^a$	-91.89	-55.71
	LR^b	18.64	14.64
	Critical value (5% level)	5.13	5.13
	Decision	Reject H_0	Reject H_0

- Critical values are obtained from Kodde and Palm (1986). These values entail a mixed χ^2 distribution.
- $^a LLF_u$ and LLF_R are the log-likelihood function values of the unrestricted and the restricted function, respectively.

$^b LR$ is the computed Likelihood ratio value.

4.2.4 Estimated cost efficiency (CE)

This sub-section assesses the extent of cost efficiency by considering the mean and the distribution (in percentage of firms) among the different hospital kitchens. The mean of cost efficiency shows the extent of cost efficiency of hospitals on average. Table 4.4 shows the mean cost efficiency is 77%.

Table 4.4. Descriptive statistics of cost efficiency scores

Minimum	0.2462
Maximum	0.9176
Mean	0.7658
Median	0.7692
St.Dev	0.1775
Variance	0.0315

This suggests that hospitals could reduce their input costs by 23% without decreasing their total output, which is the number of meals in this case. The cost efficiency scores of hospital foodservice operations are presented in Table 4.5. They range from a minimum value of 24.62% to a maximum value of 91.76%. In terms of percentage distribution of cost efficiency levels, Figure 4.1 shows that most of the hospitals are operating within 70 to 90% efficiency levels. A reasonable percentage is operating within 50 to 70% efficiency levels (Figure 4.1). In addition to efficiency measures being predominantly in the 70 to 90% percent range, the distribution of cost efficiency is characterized by low variance (i.e. around 3.15%), which is an indication of a high degree of homogeneity of performance among hospitals in the sample.

Table 4.5. Individual Cost Efficiency (CE) Scores

Hospitals	CE	Hospitals	CE
1	0.7825	52	0.8478
2	0.9603	53	0.6573
3	0.9368	54	0.8363
4	0.9558	55	0.2462
5	0.7458	56	0.3591
6	0.8497	57	0.7447
7	0.7610	58	0.4659
8	0.5705	59	0.6557
9	0.5808	60	0.7646
10	0.9557	61	0.9527
11	0.6808	62	0.7568
12	0.7626	63	0.7501
13	0.9702	64	0.6921
14	0.9553	65	0.8590
15	0.9336	66	0.9486
16	0.3235	67	0.9603
17	0.9716	68	0.9593
18	0.9614	69	0.5665
19	0.4997	70	0.8814
20	0.7692	71	0.8553
21	0.6601	72	0.7532
22	0.5908	73	0.9716
23	0.9462	74	0.8759
24	0.6971	75	0.8532
25	0.6434	76	0.8560
26	0.9265	77	0.7487
27	0.9434	78	0.5297
28	0.4091	79	0.7970
29	0.9142	80	0.4199
30	0.9577	81	0.9112
31	0.9532	82	0.6852
32	0.7868	83	0.8569
33	0.6093	84	0.3608
34	0.6121	85	0.7819
35	0.8250	86	0.8561
36	0.8607	87	0.7578
37	0.8134	88	0.9711
38	0.9577	89	0.9588
39	0.9540	90	0.4903
40	0.5291	91	0.7517
41	0.8544	92	0.7510
42	0.8701	93	0.6556
43	0.7473	94	0.9496
44	0.9558	95	0.7119
45	0.5930	96	0.9484
46	0.9547	97	0.7518
47	0.7546	98	0.8713
48	0.3631	99	0.7595
49	0.5190	100	0.7411
50	0.6490	101	0.6250
51	0.9625		

4.2.5 Cost inefficiency latent model (CILM)

To understand potential sources of cost inefficiency, both the overall significance of the model explaining cost efficiency and the significance of the coefficients for the explanatory variables of the model were examined (equation 3.51). The overall significance of the model involved testing the null hypothesis $H_0 : \delta_i = 0$. In other words, the coefficients of the variables (level of a manager's education, years of a manager's experience) explaining cost inefficiency in the CILM are simultaneously zero.

The above hypothesis was tested using a likelihood ratio (LR) test, in which the restricted CILM has only the constant term. The restricted model implies that the combined effect of the explanatory variables on cost efficiency is insignificant. The results of the estimation are shown in Table 4.3. The null hypothesis was rejected, indicating that the CILM model is statistically significant in explaining the causes of cost inefficiency in the sample. Following the verification of the existence of cost inefficiency, the signs and the significance of the coefficients were also checked (Table 4.6). Both variables are significant and negatively signed, indicating the positive impact of these two variables on cost efficiency.

Table 4.6. Coefficient estimates for the model explaining cost efficiency

Variable	Coefficient	Standard-error	T- ratio
Intercept	1.490	0.329	4.521**
exp	-0.267	0.134	-1.979*
edu	-0.053	0.018	-2.942**

**Coefficient significant at the 5% level
* Coefficient significant at the 10% level

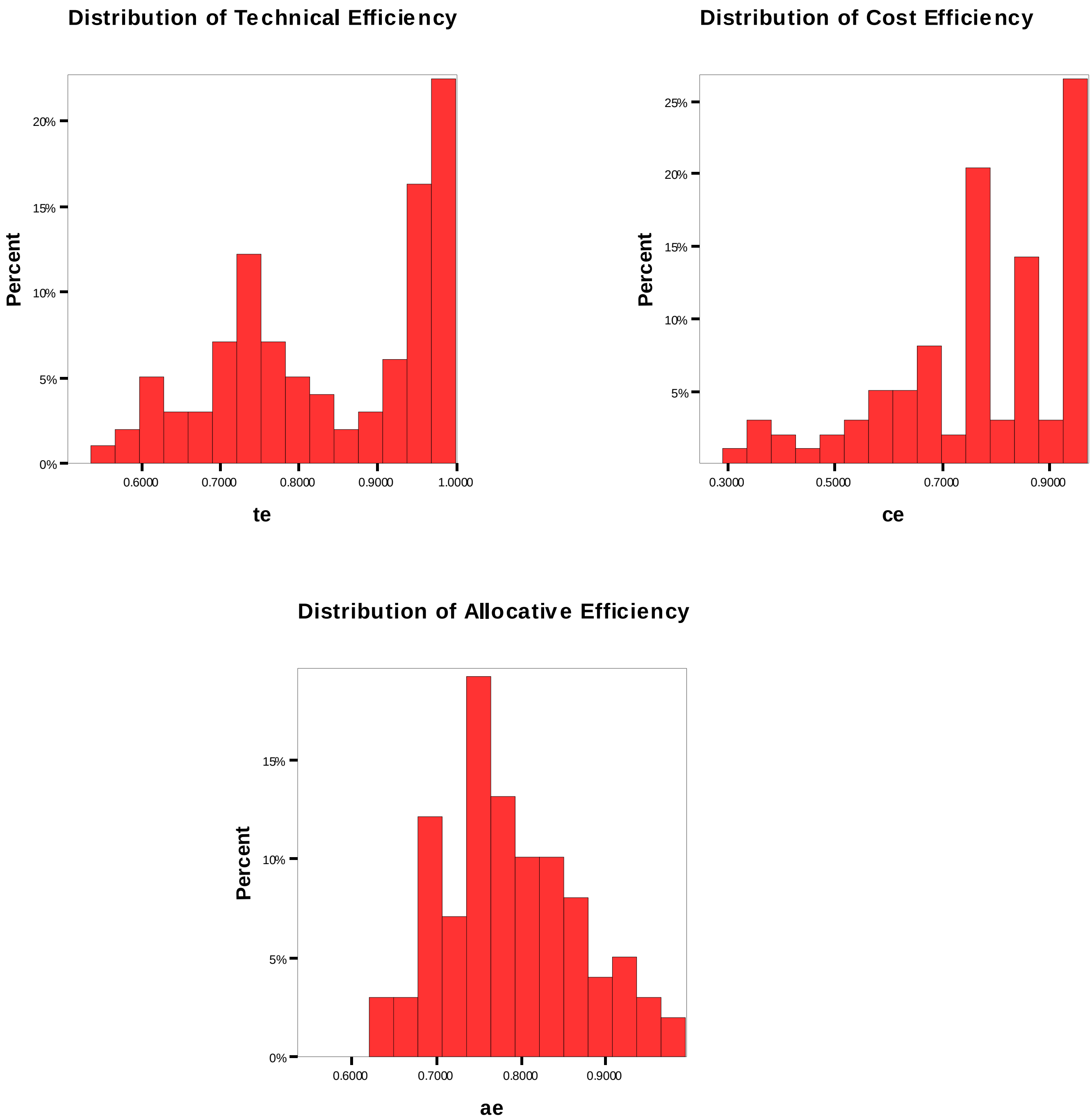

Figure 4.1 Distribution of efficiency by percentage of health care foodservice operations

4.3 Stochastic production frontier (SPF)

This section analyses results from the SPF, in the same way as those from the SCF estimation in the previous section. In section 4.3.1 the test of the functional form is presented. The estimated coefficients are reported and discussed in section 4.3.2. This is followed in section 4.3.3 with a discussion of the results from testing for the presence or absence of technical inefficiency in the sample. Section 4.3.4 presents measures of technical efficiency (TE). The results of the technical efficiency latent model (TILM) estimated simultaneously with the frontier are discussed in section 4.3.5.

4.3.1 Selection of the functional form

Similar to the process used prior to the estimation of the SCF, an F - test was also used to determine the appropriate functional form of the SPF. The purpose of the test was to determine whether the functional form of the SPF is of Cobb-Douglas technology against the alternative hypothesis, which has the following translog functional form:

$$\ln q_i = \beta_0 + \sum_{n=1}^{6} \beta_n \ln x_{ni} + 0.5 \sum_{n=1}^{6} \sum_{m=1}^{6} \beta_{nm} \ln x_{ni} \ln x_{mi} + \sum_{\mathrm{m}=1}^{3} \beta_{\mathrm{m}} dum_{\mathrm{mi}} + \beta_c dumc_i + v_i - u_i \quad (4.4)$$

where, for the i^{th} firm,

q_i = the number of meals

x_{1i} = the number of full-time equivalent employees

x_{2i} =the amount of energy

x_{3i} = the total square area of the department

x_{4i} =the age of equipment

x_{5i} =the skill level of employees

x_{6i} =the degree of readiness of raw materials

dum_{1i} = dummy variable representing the cook-chill system

dum_{2i} =dummy variable representing the hybrid system

dum_{3i} =dummy variable representing the external system

$dumc_i$ =dummy variable representing the country code

The null hypothesis of the test can be formulated as follows: $H_0 : \beta_{nm} = 0$. If this hypothesis is not rejected, then this means that it favours the simple Cobb-Douglas functional form which is a special case of the above model. The estimated F -statistic was equal to 1.65, which indicates that the null hypothesis cannot be rejected at any conventional level of significance.

Hence the following Cobb-Douglas technology was adopted:

$$\ln q_i = \beta_0 + \beta_1 \ln x_{1i} + \beta_2 \ln x_{2i} + \beta_3 \ln x_{3i} + \beta_4 \ln x_{4i} + \beta_5 \ln x_{5i} + \beta_6 \ln x_{6i} + \beta_7 dum_{1i} + \beta_8 dum_{2i} + \beta_9 dum_{3i} + \beta_{10} dumc_i + v_i - u_i \tag{4.5}$$

Equation 4.5 was estimated. It contains three inputs (number of FTE, amount of energy and total square area of the production department representing capital input) and six environmental variables (skill level of employees, age of equipment, degree of readiness of raw materials, three dummy variables for the type of systems and one dummy variable for the type of country). The descriptive statistics for all variables in 4.5 are presented in Table 4.7.

Table 4.7. Data description

Variables	Mean	Minimum	Maximum	St.Dev
$\ln q$	11.766	8.98	13.99	1.26
$\ln x_1$	2.66	0.69	4.89	0.95
$\ln x_2$	13.25	9.51	15.98	1.49
$\ln x_3$	5.30	4.11	7.31	0.82
$\ln x_4$	5.52	4.38	5.99	0.44
$\ln x_5$	2.20	0	3.63	0.82
$\ln x_6$	-1.08	-2.94	0	0.83
edu	0.56	0	1	0.49
exp	26.02	5	43	7.95

4.3.2 Maximum likelihood estimates of the SPF

The estimated coefficient of the log-linearized SPF represents the elasticities for the Cobb-Douglas specification. Table 4.8 presents the results from the estimation of the production frontier.

The coefficient estimates of the labour, energy and capital inputs are all positive. This implies that a greater usage of any inputs should lead to an increased size of meal production, as theory postulates for rational producers (Coelli et al., 1998). Similarly, the increased use of ready raw materials has also a positive impact on the level of output but insignificantly so, which means the results are inconclusive as to whether an excessive use of ready raw materials will lead to an increase in the output produced.

As expected, the coefficient of the age of equipment is negative and significant; indicating that older equipment tends to decrease the level of output that can be produced. The dummy variables coefficients for the types of systems show significant differences between each of the hybrid, cook-chill and cook-serve systems. No significant difference was, however, found between the external and the cook-serve system. The dummy country coefficient is again insignificant indicating that there is no significant difference in the level of output produced between the two countries (Australia and United States).

The return to scale derived by summing all of the individual output elasticities for the SPF estimation is higher than one, which implies that firms are operating in an increasing return to scale. As it is ordinarily assured by theory, this result is also consistent with the result obtained from the cost function in Section 4.2.2.

4.3.3 Technical efficiency effects

To investigate if there is significant technical inefficiency, the maximum likelihood estimated of the γ-parameter was used as in the cost frontier to assess the presence of technical efficiency. A positive statistically significant value of the γ-parameter is needed to reject the null hypothesis that there is no presence of technical inefficiency. From the estimation of the production frontier, the γ parameter estimates were found to be statistically significant at the 5% level (Table 4.8), an indication that technical inefficiency effects are very significant in the analysis. The results of the t-test were further confirmed with the LR-test for the presence of technical inefficiency in the sample. In this test the unrestricted log was obtained from the estimation of the full production frontier while the restricted log was obtained from the OLS estimation of the average production function. The result of the test (Table 4.3) also led to the conclusion that the hospital foodservice in our sample is not fully technically efficient.

Table 4.8. Estimated coefficients for the Cobb-Douglas Production Frontier

Variable	Coefficient	Standard-error	T-Ratio
Intercept	6.467	1.100	5.870**
$\ln x_1$	0.564	0.101	5.571**
$\ln x_2$	0.202	0.047	4.298**
$\ln x_3$	0.186	0.084	2.211**
$\ln x_4$	-0.184	0.074	-2.479**
$\ln x_5$	0.061	0.013	4.692**
$\ln x_6$	0.147	0.059	2.492**
dum_1	0.037	0.153	-0.245
dum_2	0.279	0.157	1.773*
dum_3	0.244	0.147	1.664*
$dumc$	-0.010	0.158	-0.065
σ^2	0.153	0.021	7.242**
$\gamma = \frac{\sigma_u^2}{\sigma^2}$	0.712	0.073	9.753**

** Coefficients are significant at the 5% level
* Coefficients are significant at the 10% level

4.3.4 Estimated technical efficiency

This sub-section assesses the extent of technical efficiency by considering the average and the distribution (in percentage of hospitals) of hospitals among the sample. These results were computed from results on technical efficiency of hospitals on average. Table 4.9 shows that the mean technical efficiency for the 101 observations is around 83%.

Table 4.9. Descriptive statistics of technical efficiency scores

Minimum	0.5055
Maximum	1
Mean	0.8348
Median	0.8399
St.Dev	0.1396
Variance	0.0190

This implies that hospitals, by utilising the same amount of inputs more efficiently, could improve the average output of meals by up to 17%. The individual technical efficiency scores are presented in Table 4.10. The median of technical efficiency is very close to its mean, implying than more than half of the firms are technically more efficient than the average firm. These results, in general, point to the homogeneity of performance among hospitals in the sample, which is further evidenced by a small variance in the mean of technical efficiency that is in the order of less than 0.01. Regarding the percentage distribution of technical efficiency level, Figure 4.1 shows that most of the hospitals are within the 0.7 to 0.9 efficiency levels, indicating again a high degree of homogeneity between hospitals in the sample, which is further evidenced by the median and the small variance reported in Table 4.9.

Table 4.10. Individual Technical Efficiency (TE) Scores

Hospitals	TE	Hospitals	TE
1	0.7194	52	0.9408
2	0.9641	53	0.6572
3	0.8909	54	0.8251
4	0.9814	55	0.8256
5	0.7857	56	0.5092
6	0.7445	57	0.9190
7	0.9846	58	0.6027
8	0.7196	59	0.9596
9	0.6252	60	0.7059
10	0.9807	61	0.9811
11	0.8265	62	0.6234
12	0.9927	63	0.9639
13	0.9962	64	0.6009
14	0.7823	65	0.7844
15	0.8481	66	0.9222
16	0.8563	67	0.7371
17	0.9960	68	0.9814
18	0.9956	69	0.7628
19	0.7453	70	0.5055
20	0.8399	71	0.9662
21	0.7741	72	0.9660
22	0.6439	73	1.0000
23	0.9272	74	0.8130
24	0.6809	75	0.9428
25	0.7766	76	0.9666
26	0.8016	77	0.9240
27	0.8906	78	0.5918
28	0.5694	79	0.7338
29	0.7765	80	0.5598
30	0.9870	81	0.9877
31	0.7425	82	0.7578
32	0.7154	83	0.9804
33	0.6683	84	0.6921
34	0.6023	85	0.7423
35	0.7428	86	0.9965
36	0.9874	87	0.7838
37	0.7714	88	0.7461
38	0.9662	89	0.9879
39	0.9848	90	0.7168
40	0.6576	91	0.9391
41	0.9551	92	0.9253
42	0.9933	93	0.7332
43	0.9535	94	0.9649
44	0.9752	95	0.7290
45	0.9665	96	0.9963
46	0.9941	97	0.9649
47	0.7171	98	0.9527
48	0.7384	99	0.9940
49	0.7302	100	0.8919
50	0.9256	101	0.6808
51	0.9925		

4.3.5 Technical inefficiency latent model (TILM)

Given that the LR -test has indicated the presence of technical inefficiency, the discussion in this section addresses the technical efficiency model. In particular, is the technical efficiency model significant, and if so, what factors are individually significant in explaining the inefficiency? The overall significance of the model involved testing the null hypothesis $H_0 : \delta_i = 0$. In other words, the coefficients of the variables (level of manager's education, years of manager's experience) explaining technical inefficiency in the TILM are simultaneously zero.

The LR -test used values for the log likelihood functions for stochastic frontiers estimated simultaneously with the full TILM (LLF_U) and the corresponding values for the frontiers when estimated with the TILM including only the constant term (LLF_R). From the results for this test, the hypothesis was rejected for all estimations (Table 4.3). This implies that the technical efficiency model has statistical merit in modeling the cost efficiency.

Most of the results are consistent with those of the cost efficiency model. Both variables (education and experience) have the same signs and are both significant, indicating a positive relationship between these two variables and technical efficiency. It was expected that factors that influence cost efficiency will also influence technical efficiency as technical efficiency is a component of cost efficiency. The values and the significance of the coefficients are summarized in Table 4.11.

Table 4.11. Coefficient estimates for the model explaining technical efficiency

Variable	Coefficient	Standard-Error	T- Ratio
Intercept	0.772	0.072	10.594**
exp	-0.253	0.084	-3.019**
edu	-0.017	0.004	-4.232**

** Coefficient significant at the 5%level
* Coefficient significant at the 10% level

4.4 Allocative efficiency

To obtain estimates of allocative efficiency the Schmidt and Lovell (1979) approach was adopted (see Section 3.3.3). However, the frontier was estimated in a single equation framework. This is due to two reasons. First, it is less computationally complicated than the system of equations framework. Second, to derive the log-likelihood of their model, Schmidt and Lovell (1979) made the assumption that the inefficiency term follows a half normal distribution. This is inconsistent with the estimation for the SPF used in this study where a truncated distribution was assumed for the inefficiency term. This approach is, however, limited to the use of functional forms for which the implied production function can be explicitly derived (self–dual), such the Cobb-Douglas form. Once a more flexible functional form such as the translog form is specified, where the implied cost function can not be derived, this method is no longer possible.

4.4.1 Allocative efficiency effects

The average allocative efficiency was found to be equal to 78% (Table 4.12). This implies that the average hospital would reduce its cost by 22% if it were to allocate the inputs in an optimal fashion, according to their relative prices.

Table 4.12. Descriptive statistics of allocative efficiency scores

Minimum	0.5535
Maximum	0.9946
Mean	0.7873
Median	0.7749
St.Dev	0.0878
Variance	0.0077

The distribution of allocative efficiency among hospitals (Figure 4.1) indicates that many of the hospitals operate within the 70% and 80% allocative efficiency level. The individual allocative efficiency score are presented in Table 4.13.

Table 4.13. Individual allocative efficiency scores

Hospitals	AE	Hospitals	AE
1	0.6950	52	0.8380
2	0.7696	53	0.7625
3	0.8127	54	0.8412
4	0.8878	55	0.6360
5	0.7302	56	0.8379
6	0.7146	57	0.7053
7	0.7391	58	0.6894
8	0.7481	59	0.6629
9	0.7871	60	0.7680
10	0.9633	61	0.9417
11	0.7740	62	0.6824
12	0.7645	63	0.7379
13	0.7486	64	0.7181
14	0.6757	65	0.7553
15	0.7470	66	0.7659
16	0.6234	67	0.8480
17	0.8040	68	0.9946
18	0.7131	69	0.8359
19	0.8188	70	0.7376
20	0.6832	71	0.7766
21	0.7516	72	0.7862
22	0.8038	73	0.8671
23	0.9248	74	0.8626
24	0.7401	75	0.8384
25	0.9051	76	0.8318
26	0.6570	77	0.7485
27	0.9173	78	0.6949
28	0.6821	79	0.9111
29	0.8261	80	0.6337
30	0.7927	81	0.8962
31	0.7710	82	0.8573
32	0.6867	83	0.8426
33	0.8201	84	0.8580
34	0.7953	85	0.7481
35	0.8883	86	0.7897
36	0.8604	87	0.8724
37	0.8663	88	0.9293
38	0.8377	89	0.8156
39	0.9513	90	0.6988
40	0.7253	91	0.7396
41	0.8200	92	0.7052
42	0.7923	93	0.7056
43	0.7166	94	0.8123
44	0.8082	95	0.7584
45	0.7866	96	0.9794
46	0.7681	97	0.7151
47	0.9337	98	0.7438
48	0.5353	99	0.8517
49	0.7436	100	0.6906
50	0.7547	101	0.7524
51	0.9786		

4.5 Summary

The main objectives of this chapter were to investigate the technical, allocative as well cost efficiency for hospital foodservices. Because the foodservice sector is facing continuing changes in technological, structural and economic environments, which are likely to continue in the future, hospitals will be exposed to more competition. Hence, emphasis on improving efficiency and management practices is a key to success. In order to do this, they need to have an indication on how efficient their operation is now and what factors influence this efficiency.

4.4.1 Summary of model:

Cost and technical efficiency were examined using SCF and SPF respectively. The data from the sample were fitted to the Battese and Coelli (1995) model using econometric techniques to generate estimates of the frontier and efficiency measures. While cost efficiency was estimated as part of the total error term of the SCF, technical efficiency was estimated as part of the total error term of the SPF. Cost and production frontiers were, respectively, gauged on the output and cost of production of best performing hospital foodservices.

The mean cost and technical efficiency values were computed as simple averages of individual foodservice operations' efficiency. The efficiency results revealed that the average levels of technical, allocative and cost efficiency were equal to 83 %, 78 %, and 76% respectively. These figures suggest that substantial gains in output and/or decreases in cost can be attained if hospital foodservice operations were to improve their current performance.

In addition, the estimated frontiers were used to compute the elasticities of output relative to inputs and the elasticities of cost relative to input prices. Results of model estimation showed that all input/output and environmental variables used in the estimation of the stochastic production and cost frontiers satisfy the theoretical requirement, and are generally in line with related studies from the literature. This estimation was also coupled with determination of potential sources of cost and technical efficiency of hospital foodservices, by empirically examining and elabourating on the influence factors in the model explaining either the cost inefficiency or technical inefficiency of hospitals. The estimation of these efficiency models involved regressing on the estimated inefficiency (CILM and TILM), a set of variables (years of manager's experience and level of manager's education) hypothesized to explain the level of inefficiency in health foodservice operations. These models were estimated simultaneously with the corresponding frontiers. Results showed that both these models are statistically significant in explaining the sources of inefficiency.

Chapter 5: Discussion of Results

5.1 Introduction

The results presented in Chapter 4 are further analysed in this chapter on two levels. The first level is the analysis of relative performance of hospital foodservices represented in the sample. The second level is the comparison with other studies on efficiency in this area. However, comparison at the second level should be taken with caution because it can only be justified if the methodology used, and the variables included in the previous studies and their definitions, are the same. The literature review in Chapter 2 clearly indicated the limitations of the previous methodologies applied in this area which ranged from partial ratios to simple parametric techniques. In contrast, the methodology applied in this thesis is the first to use a stochastic frontier approach in measuring and analyzing efficiency of hospital foodservices. Consequently, it is difficult to make a direct comparison of the results of this study with any of the previous studies. Future research using a similar quantitative approach could be conducted to validate and confirm the findings of this study.

This chapter is structured as follows: the first section presents the analysis of the efficiency results. This follows with the analysis of both the cost and the production frontier models. The chapter concludes with a short summary of the main findings and limitations of the study.

5.2 Efficiency results

The findings suggest that both the average level of technical and cost efficiency are generally acceptable. The average technical efficiency (TE) which reflects the ability of hospital foodservices to obtain maximum output (number of meals in this case) from its given set of inputs was around 83%, and for more than 60% of the hospitals it is greater than 70%. These hospitals are close to the efficiency frontier, where technical efficiency reaches its maximum value of 1. The findings in general suggest that hospitals could reduce their inputs by up to 17% while keeping their level of output constant. These efficiency scores are in line with what is found in similar industries such as hotels and restaurants (Table 5.1).

Table 5.1. Empirical estimates of efficiency from related studies in the literature

Study	Units analyzed	TE (%)	AE (%)	CE (%)
Anderson et al. (1999b)	48 Hotels	----	----	89
Barros and Mascarenhas (2005)	43 Hotels	86.8	27.5	24.8
Reynolds and Thompson (2005)	62 Restaurants	82	----	----
Chen (2006)	55 Hotels	----	----	80
Anderson et al. (2000)	48 Hotels	81	51	81
Barros (2004)	43 Hotels	----	----	21.6
Fei-Ching et al. (2006)	58 Hotels	74.2	83.2	62.2

The average cost efficiency (CE) score was around 76%, which suggests that hospitals could reduce their input cost by 24% without decreasing their output which is the number of meals produced. More than 75% of hospitals scored over 70% with the maximum efficiency score 97%, while the minimum efficiency score was 24%. Having reasonably high technical and cost efficiency scores, it was also expected to get acceptable scores for allocative efficiency (AE). The average was around 78% which means that most of hospital foodservices are generally using the right mix of inputs (given their prices) to produce their output. A comparison of these efficiency scores to the findings of similar industries such as hotels and restaurants are also presented in Table 5.1.

In summary, these results should direct the attention of hospital foodservice directors to implement strategies that can improve their level of operational activities. A case-by-case basis is, however, necessary to validate the results and to determine the appropriate corrective actions to be taken. Additionally, there are several issues that need be considered in order to improve the accuracy of the efficiency results. First, a common finance system has to be adopted for all foodservices so that accurate comparison can be made in the knowledge that measuring tools will contain similar and comparable data (NSW Health, 2005). The problem of not having a uniform system of accounts was actually clearly noticed in the process of data collection as it took some hospitals two months to gather the financial information that was requested for the analysis. Second, the full computarisation of the foodservice department can also improve the accuracy of the data collected. For example, the 'CBORD' computer system which entered into a contract with the New South Wales Health Department in 1994 is installed today in many hospitals around NSW. However, there are still some hospitals which are yet to adopt a computerised food service system because of its financial outlay. According to the foodservice manager at Westmead hospital, the advantage of having a computerised system is that it provides managers with a powerful tool to assist them in tasks which range from managing stock, to getting suitable meals to each patient, to sophisticated menu cost and forecasting. It will also decrease the labour time spent on collecting measurement data and makes the measurement consistent across the different hospitals.

5.3 Inefficiency latent models

This section analyses the results of the inefficiency latent models which were estimated simultaneously with both the cost and production frontier models. The purpose was to determine the potential sources which have contributed to the existence of technical and cost inefficiency of health care foodservice operations represented in the estimated sample. Studies of sources of technical and cost efficiency are concerned with managers' characteristics and their ability to run their operations in an efficiency manner. In this study, two variables, well established in the literature and usually selected as proxies for managers' characteristics, were selected.

5.3.1 Years of managers' experience

The results show that the coefficient of 'years of manager's experience' is significant and negative (Table 4.6) in both the technical and cost inefficiency model, indicating that managers with more experience tend to have a positive impact on increasing efficiency. This result was *a priori* expected. Ordinarily, it would be expected that more years of work in the foodservice industry would lead managers involved to learn by experience and improve on their production (Battese and Coelli, 1995).

5.3.2 Level of managers' education

The coefficient of 'education level of managers' is also statistically significant and negative (Table 4.6), indicating a positive relationship between the education of managers and the increase in efficiency. This result was also intuitively expected, as increase in education is usually expected to be positively correlated to the adoption of improved technology and techniques of production.

The importance of these two factors on efficiency should urge hospitals to search for highly qualified and experienced managers. In the United States, it has been recommended that a bachelor degree should be a minimum qualification for managers of hospitals' food and nutrition services (Dowling et al., 1990). In Australia, the Australian Council on Heath Care Standards requires that services should be directed by persons appropriately qualified by education, training and experience, and that sufficient numbers of qualified personnel and support staffs are employed to allow for the efficient operation of the service (Australian Council on Healthcare Standards, 1992). Catering or foodservice management qualifications are desirable (Institute of Hospital Catering-NSW, 1997) but not mandated. A study by the NSW Health Department in 2005, for example, indicated that only 78% of foodservice managers in NSW are qualified at all (NSW Health, 2005). Mibey and Williams (2002) also assessed the qualifications of the heads of the foodservice department in NSW hospitals. Their results showed that 60% of managers were without formal qualifications in the smaller hospitals (less than 100 beds) and only 44% of managers had qualifications in larger hospitals. The result of this study is similar as only 54% of the managers from the hospitals surveyed had formal qualifications.

Some area health services started to compensate for the lack of education by developing area training systems and providing supervision and management courses. For example, a course in management skills is currently required by all senior managers at the 'Western Sydney Area Health Service' as part of an internal training and development program. Similar types of course are also being employed in other states such as Victoria and Queensland.

In summary, the identification of these two factors as determinants for both technical and cost efficiency is another contribution by this study. Food service is a complex industry, particularly in the health care sector. Experienced and educated managers are needed to ensure a proper working environment and to facilitate the proper use of technology.

5.4 Stochastic cost frontier discussion

This section discusses the results of the stochastic cost frontier based on the estimated coefficients reported in Table 4.2. The final model included two input prices (labour and energy prices), one fixed input (capital input), one output (number of meals), three environmental variables (skill level of employees, age of equipment and degree of readiness of raw materials) and three dummy variables representing the different types of foodservice systems, with dum_1 representing the cook-chill system, dum_2 representing the hybrid system and dum_3 representing the external system. The relationship between the variables of the model is illustrated in Figure 5.1 and discussed in the following subsections.

5.4.1 Inputs/output

The coefficients for the input prices, fixed input and output are all positive, which implies that any increase in input prices or outputs would lead to an increase in total cost, as is expected by economic theory (Coelli et al., 1998). Additionally, the results are also in line with the specific characteristics of the health care foodservice sector. For example, labour cost is a major component of the total expenditures of this sector, constituting up to 60% (Brown, 2005) of the total operational budget, and was found in several studies to be a strong predictor of total cost (Freshwater, 1980; Greathouse et al., 1989). Therefore, it is expected that any change in labour price would have a significant effect on total cost.

The positive but non-significant relationship between energy price and total cost also supports findings from previous studies which examined the energy consumption of different foodservice operations in hospitals (Mcproud, 1982; Messermith et al., 1994). Finally, the positive but non-significant impact of space of production on total cost indicates that larger kitchens are not experiencing any waste in cost in comparison with smaller kitchens. This can be particularly encouraging for health care foodservice operations that are considering an extension to their production areas.

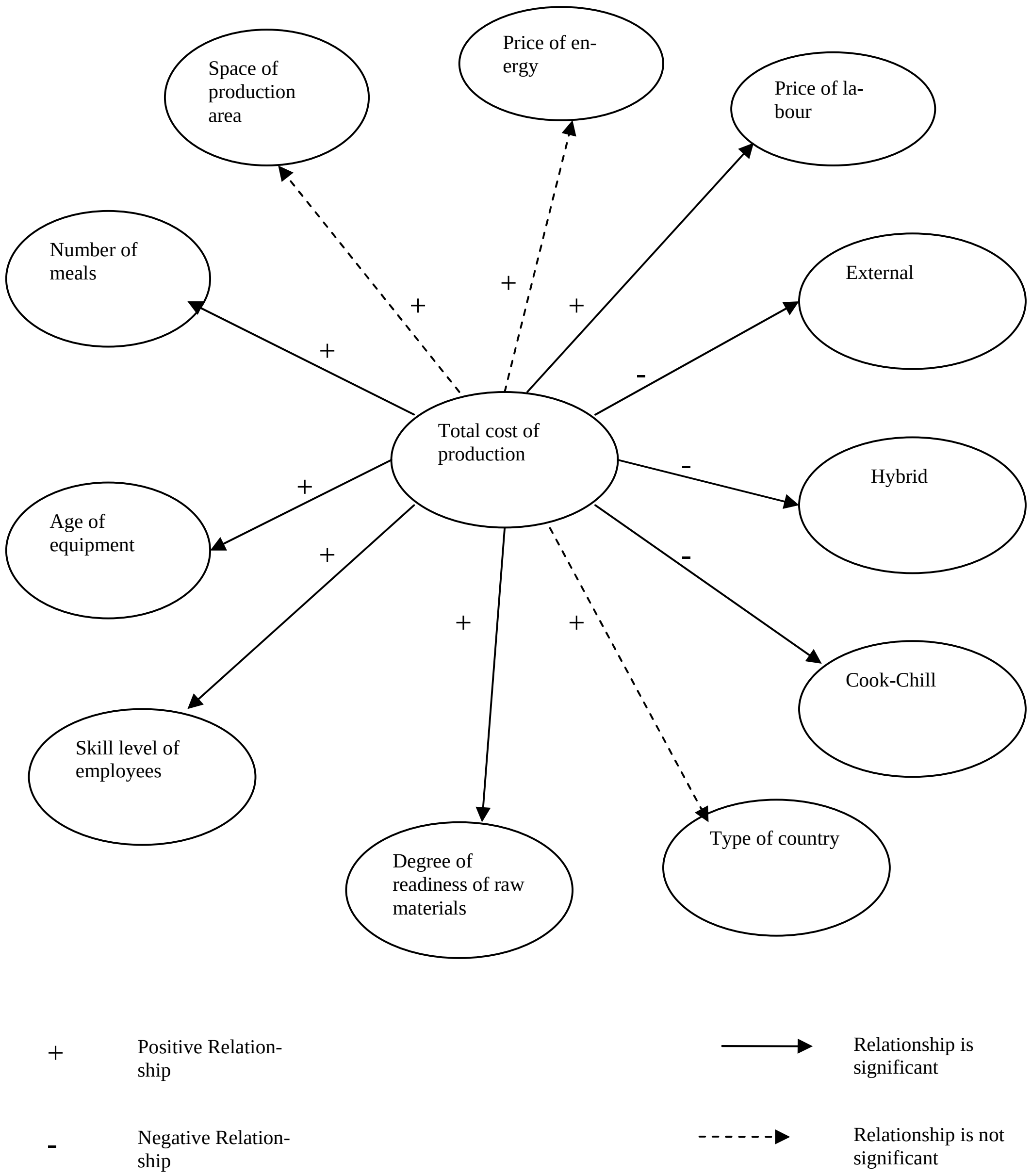

Figure 5.1. Graphical representation of the relationship between total cost and each of the inputs/output and environmental variables

5.4.2 Skill Level of Employees

The coefficient of the skill level of employees is positive and significant. The correlation between total cost and skilled workers is well established in the literature (Bayard and Troske, 1999). It is a common practice to pay higher wage for high-skilled employees; although this might not always be the case in the foodservice industry as it is usually characterized as a low paid industry (Reynolds and Thompson, 2005). However, the extra cost that a foodservice operation might pay for skilled employees might be absorbed by the positive and significant impact of skilled employees on the capacity of production as will be described later in this chapter. Additionally, it is important to note here, that the need for skilled employees can also be affected by the type of foodservice system that a health care foodservice operation is using. For example, a cited advantage of the cook-chill system in comparison with the traditional system is the reduction in the number of skilled employees (Byers et al., 1994; Nettles et al., 1997; Spears, 1995). This is because food services using this system typically operate a production unit for fewer hours in a week than conventional operations. The need for skilled employees is also probably least in operations using the external system. Such a system requires only limited preparation, usually only reheating of food, and as a result does not require the high level of skills needed for the operation of cooking and preparation equipment.

5.4.3 Degree of readiness of raw materials

The coefficient of degree of readiness of raw materials is also positive and significant, indicating that the increased use of ready food materials tends to have a significant impact on total cost. This disagrees with the findings of Clark (1997) who indicated that the cost of purchasing these is only marginally higher than fresh food and reduces as well the number of staff required. Foodservice managers are encouraged to carefully address this issue, and especially those of small health foodservice operations, where the level of production cannot sometimes absorb the extra cost needed to purchase ready food materials.

5.4.4 Age of equipment

Total cost is also expected to increase with the increased age of equipment. This was *a priori* expected as the capacity of production might decrease with older equipment and this would require extra labour hours to produce the required capacity. Additionally, more energy usage is usually attributed to older equipment as new equipment incorporate updated technology that requires less energy (Mcproud, 1982). This finding can be particularly important to health care foodservice operations using old equipment in their kitchens, as it is the case with most Australian hospitals (NSW Health, 2006). These operations are encouraged to reassess the additional cost associated with this equipment and to consider some replacements when necessary.

5.4.5 Dummy Variables

The dummy variable representing the type of country is not significant indicating that there is no difference in cost between health care foodservices in the two countries. Regarding, the dummy systems coefficients, the results show that both the hybrid and the cook-chill systems are significantly more cost effective than the traditional system. The cost effectiveness of the hybrid system has not been addressed in any of the previous studies, but intuitively high cost savings are expected from this system as it allows hospitals to combine the operational benefits of more than one system. It also allows more flexibility in the production area as more menu items that cannot be prepared in a cook-chill system- can be prepared using a supporting system such as the traditional cook-hot-hold. The total cost savings of this system suggest that hospitals considering a shift toward a new technology have a viable alternative option of keeping their traditional system and combining it with another system such as the cook-chill system. This might be a better option than a complete shift towards a new system due to the savings that could occur in the area of capital cost.

The result of the cook-chill system also shows that there is a significant difference between the total cost of this system and the traditional system. The findings of this study are in line with previous studies by Light and Walker (1990), King (1989), Clark (1997) and Mibey and William (2002), and it also supports theories by Snyder (1987) and Brendel (1985) who stressed the importance of cook-chill production systems to increase productivity. The results, however, are not consistent with those from the study by Greathouse (1987) which found that managers of traditional and cook-chill systems are employing similar resources to achieve their objectives.

The study also addressed the use of the external system. Table 4.2 shows that the use of this system could lead to a significant reduction in total cost in comparison to the cook-serve system. This finding can be of particular interest for hospitals which are incapable of shifting to batch cooking systems such as the cook-chill due to the initial capital investment needed to install such a system (Greathouse and Gregoire, 1988). A different option might be to contract-in their foodservice department without the need to invest large amounts of money in a particular system in order to realise operational savings. This will also eliminate the burden of food production as the duties of employees will only be restricted to the reheating and service of food. Finally, as expected, the total cost of the traditional system was relatively larger than all the other systems in the sample. The problem with the traditional system is that preparation is timed in relation to when the food will be served and eaten; thus, this system is more affected by the peaks and valleys of demand for food than any of the other systems (Freshwater, 1980; Nettles et al., 1997). More labour will need to be scheduled during peak times, making the cost of labour higher for this system than for any of the other foodservice systems.

5.5 Production frontier discussion

This section discusses the results of the production frontier function in the same way as cost frontier estimation was described in the previous section. The final model for the production frontier included three inputs (number of FTE, amount of energy and total square area of the production department, representing capital input) and six environmental variables (skill level of employees, age of equipment, degree of readiness of raw materials, three dummy variables for the type of systems and one dummy variable for the type of country). The results of the estimated model are presented in Table. 4.8 and displayed graphically in Figure 5.2.

5.5.1 Inputs

All the inputs coefficients are positive. This implies that using more of any of the inputs (number of FTE, energy input and space of production) would lead to increased output, as theory postulates for rational producers (Coelli et al., 1998). In fact, it would expected that when the numbers of staff are increased and more energy is used, foodservice operations will produce larger amounts of meals. The positive and significant impact of the space of production on the level of production also suggest that larger kitchens tend to be more productive than smaller kitchens, and that an increase in space would not lead to any wastage on the production site.

5.5.2 Age of equipment

The coefficient for the age of equipment is negative and significant, indicating that older equipment tends to decrease the maximum level of output that can be produced. From Section 5.4.4, it was also shown that this variable has a negative impact on the total cost of production. This should alert hospitals that are still using old equipment in their kitchens to consider some refurbishment or replacement of this equipment.

5.5.3 Skill level of employees

The results showed that the number of meals produced tends to increase with the increase in the skill level of employees, which again confirms that the extra cost needed for skilled employees can be absorbed by an increase in the production level. It was *a priori* expected to obtain this positive relationship, as skilled employees are usually better trained and more efficient in their job than non-skilled employees (Reynolds and Thompson, 2005). This finding is also in line with previous studies assessing the importance of skilled employees in hospital kitchens. For example, a research study conducted in the United Kingdom (Walker, 1988) compared the most successful hospital operations with the least successful. The results indicated that the most successful operations increased their employees' level of skill through training in and implementing practices such as recipe development and microbiological control.

5.5.4 Degree of readiness of raw materials

Similarly, the coefficient of the degree of readiness of raw materials is positive but not significant, which means the results are inconclusive as to whether an excessive use of ready raw material will lead to an increase in the output produced. This again disagrees with the results reported by Clark (1997) who stressed the importance of using ready food materials in improving the level of production. According to him, this leads to a decrease in labour time needed to prepare each meal.

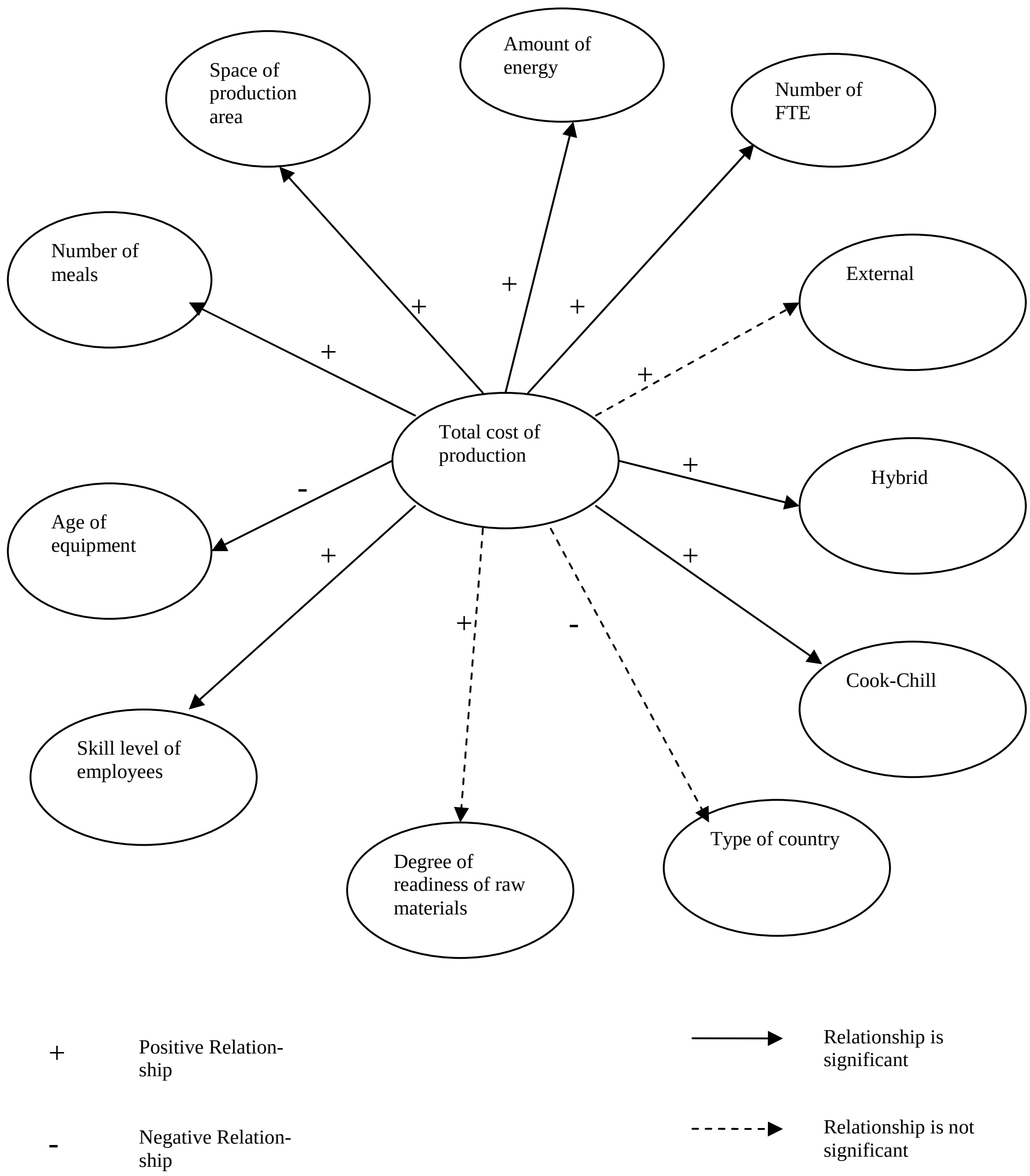

Figure 5.2. Graphical representation of the relationship between the number of meals and each of the inputs/output and environmental variables

5.5.5 Dummy variables

When it comes to the dummy variables coefficients for the types of systems, the cook-serve system was again used as the base system against which all the other systems were compared. The results show that both the hybrid and the cook-chill system are more productive than the cook-serve system. The results of the hybrid system indicate again the importance of using this system. Its main advantage is that it enables hospitals to expand their list of choices on the patient menu, with some items that can not be prepared with a particular system such as cook-chill being suitable for preparation with an accompanying system such as cook-serve. This advantage will be consequently reflected in the production area as, with more flexibility on the menu, hospitals should be able to maximize the use of their equipment and reduce the waste on the labour side. A user of cook-serve in Western Australia, for example, considers that the shift toward a hybrid preparation of chilled and fresh foods is the way to go for the future. According to him, this system would enable hospitals to exploit the advantages from both batch cooking and flexibility in production. Sandwiches, salads and snacks can be produced at facility level. The benefit of this would be the centralisation and standardisation of nearly 80% of food production, which would considerably reduce staff and material costs in the long term.

The results of the cook-chill system are not surprising; it was *a priori* expected that this system would allow hospitals to improve their production capacity. This relates to the idea of batch cooking technique where food can be produced in advance and stored for several days before being reheated and served to customers. Certainly, with this process the demands placed on staff are lessened, since the ‘peaks’ are removed from the production operation. This allows a longer production process to be developed, as food produced is not for immediate consumption (Jones, 1990). The results from this study again confirm the findings of Clark (1997) and Light and Walker (1990) who indicated that substantial gains can be obtained in the number of meals produced per full-time equivalent employees when switching from the cook-serve to the cook-chill system.

Finally, when it comes to the external foodservice system, the estimated coefficient shows that there is no significant difference between the level of production of this system and the cook-serve system. In general, it is difficult to compare this system to any other system as hospitals using this system are not producing internally as is the case with the remaining systems. Instead, they are buying food from commercial suppliers. What can be discussed, however, is the limitation that this system could have on the hospital menu. A recent feasibility study assessing the performance of different hospitals in Victoria, Australia (Victoria Health, 2005) indicated that before switching to this particular system hospitals should be aware that the commercial suppliers do not usually have the capability to provide the full range of products required by hospitals. The study further indicated that production on site is still the more feasible option for the future as it gives more flexibility in expanding the level of production and does not leave hospitals in the control of their commercial suppliers.

5.6 Summary

The purpose of this chapter was to discuss the results of the efficiency frontier models developed in this study. The discussion started with an analysis of the estimates of technical, allocative and cost efficiency scores, derived from the estimation of the stochastic frontier production and cost functions. Efficiency was further examined by comparing the results of this study to those of similar and related sectors.

The chapter then discussed the potential sources of technical and cost inefficiency in health care foodservice operations. The estimations of both technical and cost inefficiency latent models have led to the conclusion that the education and level of experience of foodservice managers have a direct impact on improving the level of efficiency in these operations. This indicates that foodservice operations have the potential for improving on their performance, on average, both in terms of utilisation of inputs and reduced costs, by paying more attention to developing training and educational programs for their management and supervisory team.

The chapter continued with a discussion of the relationship between the input/output and environmental variables selected for the estimation of the frontier models in this study. Different implications were derived. It was determined that health care foodservice managers could decrease the level of waste in their operations by reassessing several factors such as the skill level of employees, the degree of readiness of raw materials, the age of equipment and the type of foodservice system. Also, it was shown that variables such as the space of production do not have a significant impact of total cost, and could benefit health foodservice operations in achieving higher capacity of production.

In summary, the benefit of using the stochastic frontier approach is that it provided a surrogate score for the overall competence and capability of health care foodservice operations, which cannot be easily and cost-efficiently obtained through the company's audited accounts. Using audits is an expensive, time-consuming means of gathering, analysing and evaluating. The methodology proposed in this study overcomes some of these difficulties, allowing hospital foodservices to gather useful data cost-efficiently and swiftly. Further, since multiple dimensions are simultaneously considered in evaluating the overall performance of the hospitals, it is more comprehensive and robust than any of the typical productivity ratios commonly used in financial analysis. The results of the study may help to indicate how hospital foodservices fare in comparison with potential competitors. In addition, none of the previous studies that have analysed efficiency in this field has adopted the methodology of this study. Therefore, the results of this study will add to and complement those studies that have approached the hospital foodservices efficiency in a limited setting.

Chapter 6: Conclusions

6.1 Summary of the main findings

This thesis introduced an original framework for the evaluation of efficiency and its determinants in the health care foodservice sector. The measurement of efficiency in this study was based on a stochastic frontier approach which allowed for the incorporation of multiple inputs/outputs and environmental variables in assessing the level of efficiency. The approach has the advantages of overcoming the limitations of the traditional partial productivity approaches, previously used in this sector.

It was clearly shown throughout this thesis that there is a need for a comprehensive study that addresses questions regarding the current level of performance and the future existence of some health care foodservice operations. Results from this study aim to address all these questions and provide additional evidence on the true level of performance of these operations. Each health care foodservice operation participated in this study will be provided with its efficiency score, which can be used for various reasons. In terms of strategic reasons, efficiency measurement can compare the global performance of health care foodservice operations with competitors or similar firms. In terms of tactical reasons, efficiency measurement enables the performance control of these operations (Chen, 2006). Many 'Area Health Services' in Australia have expressed interest in the results and the methodology of this study, which they considered was needed in the current competitive environment of the health care foodservice industry.

This chapter is structured as follows: the first section addresses the main objectives of the study and how they have been achieved in terms of both, the methodology and the derived results. The second section addresses the limitations of the study and provides guidance for future research.

6.2 Main objectives of the study and how they have been achieved

In this section the main objectives are first stated, and then analyzed in terms of both the results and the methodology used.

Objective 1: to estimate and evaluate the production and cost frontier functions

This study used the Battese and Coelli (1995) model for the estimation of the production and cost frontier functions, using maximum likelihood techniques. The estimation started with verification of the functional form used in the formulation of the stochastic frontier models. A log-likelihood ratio test was conducted. The purpose of the test was to determine whether the functional form of the frontier model is of Cobb-Douglas form against the alternative hypothesis which has a translog functional form. The result of the test showed that the Cobb-Douglas form was an adequate representation of the data.

The estimation proceeded by examining the signs and significances of the coefficients of each of the inputs/ outputs and environmental variables included in these models. In the stochastic cost frontier model, three inputs (price of labour, price of energy, and total square area of the department), one output (number of meals), and six environmental variables (age of equipment, skill level of employees, degree of readiness of raw materials, cook-chill system dummy variable, hybrid system dummy variable, external system dummy variable and country dummy variable) were included in the estimation of the model. Results showed that the estimated coefficients for input prices/fixed input and output were as expected, with total cost increasing with both input prices (the price of labour and price of energy), the fixed input (capital input) and the level of output (number of meals). The environmental variables coefficients were also as expected. This was first illustrated with the positive and significant relationship between the degree of readiness of raw materials, age of equipment and total cost. Second, also as expected, results from the impact of the different types of foodservice systems on total cost indicated that the hybrid and the cook-chill system are still a viable option for foodservice operators.

Similarly, in the stochastic production frontier model, three inputs (the number of full time equivalent employees, the amount of energy ,the total square area of the department), six environmental variables (age of equipment, skill level of employees, degree of readiness of raw materials, cook-chill system dummy variable, hybrid system dummy variable, external system dummy variable and country dummy variable) and one output (number of meals) were included. Results showed that the estimated coefficients for the three inputs variables were as expected. This was indicated by the positive relationship between each of the input variables and the number of meals produced. The environmental variables coefficients were also as expected. This was first illustrated by the positive relationship between the number of meals, the skill level of employees and the degree of readiness of raw materials, and second by the negative relationship between the number of meals produced and the age of equipment. Results of the dummy variables coefficient were also as expected, where it was shown that both the hybrid and the cook-chill system were more productive than the cook-serve system.

In summary, results from both the stochastic production and cost frontier functions indicate that health care foodservice managers could decrease the level of waste in their operations by paying more attention to several factors such as the skill level of employees, the degree of readiness of raw materials, the age of equipment and the type of foodservice system. Also, it was shown that variables such as the space of production do not have a significant impact of total cost, and could benefit health foodservice operations in achieving higher capacity of production.

Objective 2: to compute technical, allocative and cost efficiency and their degree of variability among the different health care foodservice operations

After verifying that the estimated coefficients of both models were correctly signed and satisfy the theoretical requirements, the different type of efficiency scores were then estimated and analysed. The estimated stochastic cost frontier model was used to derive estimates cost efficiency, while a stochastic production frontier was used to derive estimates of technical efficiency. In addition to estimating cost and technical efficiency, the study assessed the level of allocative efficiency of health care foodservice operations using the Schmidt and Lovell (1979) decomposition approach.

Results showed that the average cost efficiency score was around 70%, which suggest that hospitals could reduce their input cost by up to 30% without decreasing their output-which is the number of meals produced in this case. Average technical efficiency was around 80%, and for more than 60% of the hospitals it is greater than 70%. This suggests that hospitals, by utilising the same inputs more efficiently, could improve the level of output by up to 20%. The average allocative efficiency was around 88%, which means that on average, hospitals can achieve cost savings of 12% by using the right mix of inputs. In sum, it is evident from these results that health care foodservice operations could improve cost efficiency substantially, and that technical inefficiency constitutes a more serious problem for these operations than allocative inefficiency.

Objective 3: to identify the variables that influence the technical and cost efficiency measures of health care foodservice operations

The estimations of efficiency were coupled with a determination of potential sources of technical and cost inefficiency of health care foodservice operations, by empirically elabourating on factors that influence either the technical or cost efficiency of these operations. This required the estimation of a technical and cost efficiency latent models, which mainly involved regressing on the estimated efficiency (technical or cost efficiency) a set of variables hypothesized to explain the level of inefficiency. These models were estimated simultaneously with the corresponding frontier models.

In analysing the potential sources of technical and cost inefficiency of the health care foodservice operations, two variables reflecting management characteristics (years of manager's experience, and level of manager's education) were identified and added to the inefficiency latent models, which were estimated simultaneously within the frontier model. Results showed that the coefficient of the 'years of managers' experience' was significant and negative on both the cost and technical efficiency latent models, indicating that managers with more experience tend to have a positive impact on increasing cost and technical efficiency. Ordinarily, this was expected, as more years of work in the foodservice industry would lead managers involved to learn by experience and improve on their production. The coefficient of the 'level of manager's education' was also statistically significant and negative in both models, indicating a positive relationship between the education of managers and the increase in efficiency. This result was also intuitively expected as increase in education is usually expected to be positively correlated to the adoption of improved technology and techniques of production. In summary, the identification of these two variables as potential sources of technical and cost inefficiency for health care foodservice operations represented additional implications. The results should demonstrate to these operations that investing more money and resources on training and improving the level of managers experience and education has a potential for improving on the performance, on average, both in term of utilization of inputs and reduced cost.

6.2 Limitations and direction of further research

The stochastic frontier model used in this study has also the advantage of accounting for measurement error in the assessment of efficiency. This provided greater confidence in the interpretation and generalization of the efficiency results. The primary contribution of this study was that it presented a technique for evaluating the performance of health care foodservice operation that would not suffer from the same disadvantages as the existing techniques available to the health care foodservice professionals. The study also identified the variables that statistically explain the total cost and level of production in health care foodservice operations, therefore providing foodservice managers with additional guidance to areas where improvements can be made, both, in terms of minimizing cost and maximizing the level of production.

However, there are number of directions in which the research of this study can be improved and extended. The main problem related to the quality of some data reported. For example, some data like energy cost could not be collected directly from the questionnaire. Therefore, a proxy for energy cost was used in this study. The use of a questionnaire in the data collection could have, as well, itself affected the quality of data reported. In fact, it is not guaranteed that all foodservice managers addressed all answers in a similar way, or also answered accurately what was required from each question. Future research should collect data when possible from more reliable sources such as the ‘Australian Bureau of Statistics, or other government agencies. Unfortunately, this was not possible in this study, as in Australia, methods used by ‘Area Health Services’ in collecting data from health care foodservice operations are different between each States, making it therefore unwise to draw conclusions from such data.

Another limitation of this study is that it used only cross-sectional data when comparing the efficiency of the different firms. Future research is encouraged when possible to collect data on more years of observation and compare the efficiency change of each hospital across time. The advantage is that foodservice managers would have further indication on the impact of some policy changes on efficiency over the years.

Finally, future studies might concentrate on estimating efficiency using different approaches and methods. Few studies which have compared the efficiency between different frontier approaches, such as stochastic frontier and data envelopment analysis have indicated that the level of efficiency was not the same across the different approaches, even though the ranking of firms’ performance is maintained (Kumbakhar and Lovell, 2000). Therefore, it would be useful to provide further evidence that the level of efficiency score is consistently maintained when a new measurement approach is adopted.

Also, when possible, future research should also support the efficiency results with some qualitative case studies, in order to provide inefficient operations with additional insights on the appropriate corrective actions to be taken. It is true that stochastic frontier provides an indication to where inefficiency exists; however, it does not answer all questions as to why inefficiency exists and what are the strategies that need to be adopted to improve the level of efficiency.

Appendix 1

Half-normal and exponential stochastic frontier

Half-normal distribution

Aigner et al. (1977) obtained the maximum likelihood estimates under the assumption:

i) $v_i \sim iidN(0, \sigma_v^2)$

ii) $u_i \sim iidN^+(0, \sigma_u^2)$, that is nonnegative half normal

iii) v_i and u_i are distributed independently of each other and of the repressors.

In computing the estimates, Aigner et al. (1977) expressed the likelihood function in terms of the variance parameters,

$$\sigma^2 = \sigma_v^2 + \sigma_u^2$$

and $\lambda^2 = \sigma_u^2 / \sigma_v^2$

With the half normal distribution of u_i and the assumed symmetric distribution for v_i, and using the above parameterization, the likelihood function is given as:

$$\ln L = \frac{N}{2}\ln(\pi / 2) - N\ln\sigma + \sum_{i+1}^{N}\ln\left[1 - \phi(-\frac{\varepsilon_i\lambda}{\sigma}\right] - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\varepsilon_i^2$$

The density function of $u \geq 0$, illustrated for three different values for the standard deviations parameter is given by.

$$f(u) = \frac{2}{\sqrt{2\pi}\sigma_u}\exp\left\{\frac{-u^2}{2\sigma_u^2}\right\}$$

The density function of v_i is:

$$f(v) = \frac{1}{2\pi\sigma_v}\exp\left\{\frac{-v^2}{2\sigma_v^2}\right\}$$

Given the independence assumption the joint density function of u_i and v_i is the product of their individual density functions and is given by as:

$$f(u,v) = \frac{2}{2\pi\sigma_u\sigma_v}\exp\left\{-\frac{u^2}{2\sigma_u^2} - \frac{v^2}{2\sigma_v^2}\right\}$$

Since $\varepsilon \equiv v_i - u_i$, the joint density function of u_i and ε_i is

$$f(u,\varepsilon) = \frac{2}{\sqrt{2\pi}\sigma_u\sigma_v}\exp\left\{-\frac{u^2}{2\sigma_u^2} - \frac{(\varepsilon+u)^2}{2\sigma_v^2}\right\}$$

The marginal density function of ε is obtained by integrating u out of $f(u,\varepsilon)$ which yields

$$f(\varepsilon) = \int_0^{\infty} f(u,\varepsilon)du$$

$$= \frac{2}{\sqrt{2\pi}\sigma}.\left[1 - \Phi\left(\frac{\varepsilon\lambda}{\sigma}\right)\right].\exp\left\{-\frac{\varepsilon^2}{2\sigma^2}\right\}$$

$$= \frac{2}{\sigma}.\phi\left(\frac{\varepsilon}{\sigma}\right).\Phi\left(-\frac{\varepsilon\lambda}{\sigma}\right)$$

where $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$, $\lambda = \sigma_u / \sigma_v$, and $\Phi(.)$ and $\phi(.)$ are the standard normal cumulative distribution and density functions. Hence the same standard deviation parameters σ_u and σ_v determine the shape of the half-normal distribution, as in the case of the exponential model.

The conditional distribution of u given ε is:

$$f(u/\varepsilon) = \frac{f(u,\varepsilon)}{f(\varepsilon)}$$

$$= \frac{1}{\sqrt{2\pi}\sigma_*}.\exp\left\{-\frac{(u-\mu_*)^2}{2\sigma_*^2}\right\}\Big/\left[1 - \Phi\left(-\frac{\mu_*}{\sigma_*}\right)\right]$$

where $\mu_* = -\varepsilon\sigma_u^2/\sigma^2$ and $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$

Exponential distribution

For the Exponential Distribution the following distributional assumptions are made:

1) $v_i \sim iid\ N(0, \sigma_v^2)$

2) $u_i \sim iid$ Exponential

3) v_i and u_i are distributed independently of each other and of the repressors

The joint density function of u_i and v_i, $f(u,v)$, is the product of their individual density functions:

$$f(u,v) = \frac{2}{2\pi\sigma_u\sigma_v} \cdot \exp\left\{ -\frac{u}{\sigma_u} - \frac{v^2}{2\sigma_v^2} \right\}$$

From $\varepsilon = v - u$ (production frontier), v is expressed in term of u and ε as

$v = u + \varepsilon$

Hence, $f(u,\varepsilon) = \dfrac{1}{\sqrt{2\pi}\sigma_u\sigma_v} \cdot \exp\left\{ -\dfrac{u}{\sigma_u} - \dfrac{1}{2\sigma_v^2}(u+\varepsilon)^2 \right\}$

Thus the marginal density of ε for the exponential distribution is given by:

$$f(\varepsilon) = \left(\frac{1}{\sigma_u}\right) \cdot \Phi\left(-\frac{\varepsilon}{\sigma_v} - \frac{\sigma_v}{\sigma_u} \right) \cdot \exp\left\{ \frac{\varepsilon}{\sigma_u} + \frac{\sigma_v^2}{2\sigma_u^2} \right\}$$

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