THE ADMINISTRATIVE EFFICIENCY OF HOSPITALS AND THE EFFECT OF ELECTRONIC DATA INTERCHANGE:

A Critical Evaluation of the Stochastic Frontier and the Data Envelopment Analysis Models to Efficiency Measurement

by

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Abstract

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Dimitrios Tsaprounis

Adviser: Professor Michael Grossman

The investigation and measurement of administrative efficiency is an issue of great concern for health care policy decision makers and has important implications for the efficiency of the overall health care sector itself as well as for the cost containment efforts and the restructuring of the health care system.

The administrative cost efficiency of the United States health care system has received much attention during the last years, and has been under continuous criticism since it became widely known that the country's administrative costs are higher than those of any other country in the world.

As criticism on administrative inefficiency of the U.S. health care system has intensified, the need for detailed empirical studies has become imperative. To answer the question of administrative efficiency, this study undertakes an empirical investigation of the largest component of the health care sector; the hospital sector. The variety of proposed health care reform proposals that involve the reduction of administrative costs of hospitals

consider the application of Electronic Data Interchange as the potential mechanism towards streamlined administration, cost efficiency and cost containment.

Efficiency is the main concern of all economic sectors and a variety of models have been developed to examine every aspect of it. In this dissertation, the two leading approaches to efficiency measurement (Stochastic Frontier and Data Envelopment Analysis) are used and compared. To increase the reliability and comparability of estimates, a variety of models are estimated.

In addition, an integrated model that incorporates the characteristics of the Stochastic Frontier with Data Envelopment Analysis techniques is developed. The model provides a new approach for incorporating "Technologically Consistent" information into DEA in the form of weight restrictions.

In this integrated framework the extent of administrative efficiency of hospitals is evaluated. In a second stage analysis, the determinants of inefficient performance are assessed with special attention to the effect of Electronic Data Interchange.

The results support the common belief that hospital administration is inefficient. Hospital administration appears to be the most significant determinant of hospital inefficiency. Furthermore, the results indicate that Electronic Data Interchange could be used as a mechanism of reducing administrative inefficiency.

This Dissertation is Respectfully Dedicated to my Parents,

Νικολαος and Σταυρουλα

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Introduction

The administrative cost efficiency of the United States health care system has received much attention during the last years, and has been under continuous criticism since it became widely known that the country's administrative costs are higher than those of any other country in the world. The United States allocates a large proportion of its health care expenditures to administration. The share of the administrative outlays was estimated to be approximately 25 percent of total health care expenditures or $232,300 million in 1993 (Hellander et. al., 1994). Even if the validity of international comparisons (in terms of costs, access and quality of health care provided) is questionable, the U.S. administrative health care system seems to be the most expensive in the world. The United States, as reported by Poullier (1992), spends approximately $150 per capita for health care administration, while Germany and the Netherlands spend only 58 and 45 percent of the U.S. level, respectively.

As Evans (1990) pointed out: "No system can run itself; there must be some outlays for administration, management, and reimbursement." But is the cost of administering the current health care system justified by its benefits? Even if it is not possible to determine the optimal administrative share, the rising health care expenditures of the U.S. as a proportion of GDP and the deepening crisis in the health care system have intensified the debate over strategies to control any component of total costs.

Over the past 30 years, health care costs in the United States have grown at a higher rate than overall economic growth. Total health care spending as a percentage of GDP has increased from 5.6 percent in 1965 to 13.9 percent in 1994 and is projected to be 15.9 percent in the year 2000 and 18 percent by the year 2005 (Burner S. and D. Waldo, 1995). The most important factors contributing to the explosion of health care spending in the United States include: the general economy-wide price inflation (47%), excess medical inflation (22%), demographic factors such as the aging of the population and population growth (10%), advances in health care technology, intensity/utilization of services, and the cost of administration (Levit K. et al., 1991). There is evidence from the hospital sector that administrative expenditures grew faster (at a 90 percent rate of growth) than any other component of hospital costs between 1983-90 (Shulkin et al., 1993).

The investigation and measurement of administrative efficiency is an issue of great concern for health care policy decision makers and has important implications for the efficiency of the overall health care sector itself as well as for the cost containment efforts and the restructuring of the health care system.

Administrative costs are "expenses related to the management or supervision of the provision of health care coverage and services" as defined by the Office of Technology Assessment (U.S. OTA 1993). However, there is no widely accepted definition of what constitutes administrative cost for each sector of the health care system. Considerable debate exists about what administrative components to include in cost estimates, how costs should be measured, what quality of data should be used, and whether various efficiency proposals offer real savings. Existing studies rely on available data that is of limited quality and derive their estimates on the basis of broad assumptions. Often, in order to arrive at estimates, information is extrapolated from the state to the national level and from one time period to the next. However, comparison of reported estimates is difficult and in addition the validity of the existing estimates is questionable (U.S. OTA, 1993). The difficulty of comparisons stems from the fact that differences in estimates can be attributed to lack of uniform definition as well as to differences in prices, administrative functions and efficiency. Furthermore, empirical investigation of the factors that influence administrative efficiency has not been undertaken so far.

One of the most important attempts to define administrative costs and provide the framework for accurate measurement was made by Kenneth Thorpe in the 1992 workshop sponsored by the Robert Wood Johnson Foundation (Thorpe, 1992). Thorpe defined administrative costs of each health care sector as composed of four functions (transaction related, benefits management, selling and marketing, and regulatory/compliance) and he treated them as "inputs" in the production of health care services. He considered six sectors of the health care system (health insurance, hospitals, nursing homes, physicians, firms, and consumers), but his initial list is not comprehensive and can be expanded. Existing estimates of administrative costs for three sectors (hospitals, health insurance, and physicians) range between $73.6 billion in 1983 and $220.3 billion in 1993. Lewin-VHI (1993) provided a "synthesis" estimate of $126.1 billion for the three sectors combining a variety of empirical estimates into a summary form expressed in 1991 dollars. Health care policy analysts and researchers have long attributed the rising burden of administrative cost to the structure of the health care system. There is a variety of proposed health care reform strategies that involve the reduction of administrative costs of the health care system. Studies that evaluate the effects of the alternative proposals offer estimates of the magnitude of the administrative cost as well as possible savings from restructuring the system. Among the most important health care reform proposals are the

Single Payer, the Individual Vouchers or Tax Credits, the Pay-or-Play and the Managed Competition. At one end, the advocates of a single payer system favor an overall structural change in the way the health system is financed. The single payer, "Canadian Type," system could achieve cost containment and significant reduction in administrative costs through a government sponsored tax-financed system. At the other end, proposals offer reforms of the current system that promise cost control and elimination of administrative inefficiency. The estimates of administrative cost savings of the competing approaches to health care system reform range from $2.8 to $113 billions for a single year (U.S. OTA, 1993). However, the cost saving estimates of all proposals involving administrative cost reductions are based to a large extent on the application of Electronic Data Interchange (EDI) technology. Analysts consider Electronic Data Interchange as the potential mechanism towards streamlined administration, cost efficiency, and cost containment.

Electronic Data Interchange (EDI) is an integrated computerized-communication system of information transferring directly between two electronic entities (computers). The application of an electronic communication network in health care, based on common formats and standards, could significantly reduce administrative costs associated with the diverse nature of the U.S. health care system, where there are many independent providers of health services dealing with many independent consumers whose bills are paid by a multitude of independent payers.

In response to mounting criticism of the administrative inefficiency of the U.S. health care system, the Secretary of the U.S. Department of Health and Human Services, Dr. Louis Sullivan, in November 1991, formed three "workgroups" to examine the problem and propose solutions: The Workgroup for Electronic Data Interchange, the Taskforce on Patient Information, and the Workgroup on Administrative Costs and Benefits (Marder, 1993).

The Workgroup on Electronic Data Interchange (WEDI) was established to investigate how to reduce the administrative costs of the health care system through widespread adoption of electronic communications technology (WEDI, 1992). WEDI has been working with the American National Standards Institute (ANSI) to link the health care system using common standards. Standardization of data elements and electronic transmission rules will facilitate exchange of information and communication among the many separate entities in the health care system (Sedor, 1989). The development of a national electronic communication network in health care could create significant administrative savings. Currently the health care system uses more than 400 formats for electronic transactions. Implementation of ANSI standard formats would condense the hundred of formats to less than six and eliminate paperwork while establishing a uniform format for efficient data transmission (Bergman, 1993).

Electronic Data Interchange extends the organizational boundaries of the firm's information system and enables interconnectedness and the rapid exchange of information with the information systems of its trading partners. The Electronic Data Interchange technology has been applied in many industries worldwide for years and its strategic importance as a tool of promoting efficiency and delivering competitive advantages has been documented (Krcmar, H. et al., 1993).

In 1992, WEDI estimated possible annual administrative savings through automation of claims submission, claims inquiry, enrollment, eligibility and payment remittance transactions to range between $4 and $10 billion (WEDI, 1992). In 1993, WEDI engaged the services of the Tiber Group, Inc. to carry out research designed to provide more accurate and detailed estimates of administrative cost savings due to the application of Electronic Data Interchange. The new estimates expanded to include six more transactions. The combined estimates of potential savings ranged from $12.9 to $26 billion (WEDI, 1993).

Electronic Data Interchange implementation involves not only savings but also costs. WEDI estimated the one-time implementation cost for providers to range between $3.8 and $11.2 billion in 1993 (WEDI, 1993). In 1992, another study (HCFA) reported that Electronic Data Interchange could save providers $152.5 billion over 8 years at an investment cost of $38.6 billion and net savings of $113.9 billion (Lewin-VHI, 1993). The health care industry that recently accounts for 14 percent of GDP devotes a large portion of its expenditures to health care information systems. One study reports that approximately 1.5 to 2 percent of GDP is spent on health information systems (Sheffler, 1986).

The impact of information technology on other industries, implemented for many years to improve performance, has been surrounded by controversy as the reported studies are contradictory or inconclusive (Mukhopadhyay et al, 1995). While businesses invest heavily in information technology, the expected rate of return has not been realized. The debate in the literature is concentrated around the so called "Robert Solow's Paradox": '*You can see the computer age everywhere but in the productivity statistics*,' which has puzzled decision makers (Oliver and Sichel, 1994).

The low contribution of information technology may be attributed to several factors: Mismanagement of information technology and misallocation of its resources (X-inefficiency, allocative inefficiency); Difficulty of accurately measuring the information technology's stock as an input as well as the output produced in this process; The rapid depreciation of computer information systems capital stock; The fact that computers actually were not everywhere, as their estimated share accounted for only 2% of the private capital stock; The direct comparison of costs and benefits is misleading as the pay-offs to information technology investment are not immediate [Oliver and Sichel, 1994; Brynjolfsson, 1991].

As criticism of administrative inefficiency of the U.S. health care system has intensified, the need for detailed empirical studies has become imperative. Efficiency is a main concern of all economic sectors and a variety of models have been developed to examine every aspect of it.

To answer the question of efficiency this study undertakes an empirical investigation of the largest component of the health care sector; the hospital sector. The hospital sector accounts for approximately 40 percent of the total health care expenditures.

To assess hospital efficiency and hospital administrative efficiency, the two leading methodologies of measuring the efficiency of a set of productive units are employed: The parametric Stochastic Frontier and the non-parametric Data Envelopment Analysis. The following section explains the unique advantages and limitations of the two approaches. Inefficiency imposes a substantial burden on producers and it pays to investigate its main determinants and propose solutions. In order to assess the degree of efficient performance and its main influences a two-stage methodology is applied. The first stage models the performance of the decision-making unit (hospital, administrative hospital sector), and the second stage investigates the factors that influence this performance. Special attention will be paid to the impact of information technology, and in particular the effect of Electronic Data Interchange application on hospital administratiion.

In addition, this study attempts a direct comparison of the main tools of efficiency measurement. Estimates of inefficiency are very sensitive to method (approach) used and within a given approach to model specification or assumptions made. The inefficiency index obtained from the same sample with the two alternative approaches may be very different (Button et al., 1992). The differences may be due to the different assumptions employed by the two techniques. Estimates of the stochastic frontier depend on the specification of the functional form of the model and the assumption about the distribution of the one-sided error term, while estimates of DEA, which have no statistical properties, are subject to flexibility of the value-free model assigned multipliers and to data inaccuracies.

A comparative analysis will be undertaken and the similarities or differences will be investigated. The stochastic frontier model will be compared to alternative DEA formulations and extensions. Since the technology under consideration is a multiple-output and multiple-input technology, only a parametric cost function can be estimated. A cost function accommodates multiple-outputs and multiple-inputs and yields technical and allocative efficiency. The DEA technique that also accommodates multiple-outputs and multiple-inputs models a production function and yields only technical efficiency.

The differences in estimates between the two approaches reported so far may be due to the different modeling behavior of the two models as well.

Recent developments of DEA methodology (as the Cone Ratio/Assurance Region and the cost-minimizing DEA) extended its boundaries towards an overall cost-minimizing goal. The first technique, the Cone Ratio/Assurance Region, in the absence of input prices, incorporates information through a set of multiplier restrictions and enriches the estimated technical efficiency with elements of allocative efficiency [Thompson et al., 1990; Charnes et al., 1990]. In addition, this technique limits the flexibility of multipliers that can lead to erroneous results. Studies have found that often the DEA-assigned weights (multipliers) do not reflect the actual importance of the factors of production [Thompson et al., 1990; Dyson and Thanassoulis, 1988; Wong and Beasley, 1990]. The estimated frontier and the resulted measure of efficiency may be unrealistic if the assigned weights are unreasonable. The extended DEA model, the "Cone-Ratio/ Assurance Region," introduces constraints on multipliers that reflect "experts' opinions" about the actual importance of respective inputs or outputs [Charnes et al., 1990; Thompson et a., 1990].

This paper proposes a new approach for incorporating price information into estimation and at the same time restricting the DEA weight flexibility. This method provides a link between the two approaches (stochastic and DEA) and attempts to bring the estimated inefficiencies closer. Specifically, the mathematical programming - DEA model is used in conjunction with the econometric - stochastic frontier model. The stochastic approach model is estimated and the estimated production characteristics are used to constrain the weights of the DEA model. The set of regression based constraints form the *Technologically Consistent-Assurance Region* (TC-AR) that guides the DEA multipliers to objective estimating grounds in terms of both weight flexibility and overall cost efficiency.

The second technique incorporates into estimation, in addition to output and input vectors, a vector of input prices and yields overall cost efficiency, allocative and technical (Färe et al., 1994). The cost-minimizing DEA is the mathematical programming analog to the stochastic cost frontier model.

In addition to the weight-restricted DEA, the cost minimizing-DEA model will be estimated. As the cost-minimizing DEA model accounts for both technical and allocative inefficiency, its estimated inefficiency is expected to be closer to inefficiency obtained from the stochastic frontier model. Finally, comparison and combination of the desirable features of the two approaches will improve the accuracy and reliability of the results.

1.1 The Plan of the Thesis

The overall purpose of this paper is:

(1) to examine the extent of administrative hospital inefficiency, an issue of great concern among health care reformers and policy makers;

(2) to identify potential sources of administrative inefficiency focusing mainly on the effect of electronic data interchange technology;

(3) to critically evaluate the alternative approaches to efficiency measurement (stochastic frontier and DEA) and to propose and develop links that might bring estimated inefficiencies closer and might increase their accuracy for policy analysis.

For the first time, to my knowledge, the efficiency of the health care related administration is econometrically evaluated, as well as the impact of EDI technology on efficiency in the health care sector in general. Estimates of efficiency are obtained parametrically and non-parametrically. In addition, the TC-AR model provides a new methodology of specifying boundary conditions in a DEA/Cone-Ratio framework that links the two leading efficiency models (stochastic and DEA) and increases the reliability of estimation.

The analysis proceeds in two steps. In the first step a frontier model (stochastic and DEA) is estimated, and a firm specific index of inefficiency is constructed. The second step evaluates the determinants of inefficiency focusing on administrative technology (EDI). Special attention will be paid to econometric specification of an inefficiency regression model.

The second section of this study, that follows this introduction, describes the methodology of the two approaches to efficiency measurement; the stochastic frontier approach and the mathematical programming approach (DEA). The third section illustrates the specification and estimation of the hospital cost frontier function and related econometric issues. The specification and estimation of the administrative hospital cost frontier function is contained in the fourth section. The fifth section investigates the efficiency of the above functions using alternative DEA models, included the weight restricted and the cost-minimizing DEA. The sixth section discusses the modeling of inefficiency and the contribution of EDI to administrative inefficiency. An evaluation of findings, concluding observations, and policy implications are included in the seventh section.

2

Measuring Efficiency: The Stochastic Frontier and the Data Envelopment Analysis Approaches

2.1 Introduction

Over the past two decades a number of econometric and mathematical programming techniques have been developed for the estimation of frontiers (production and cost) and the measurement of economic efficiency (allocative and/or technical efficiency). The economic concept of frontier defines the optimum behavior. In economics the optimizing behavior of the firm is taken as given and economic models examine the performance of the firm assuming efficiency. However, firms may fail to optimize their performance, particularly in the short run and produce below the maximum possible production frontier or above the minimum possible cost frontier. Deviations from the frontier (production or cost) which provides the benchmark indicate inefficient performance.

A production function relates the maximum output obtainable from a given set of inputs and a given level of technology. Since the production function defines the maximum performance (optimal), deviations from the frontier are interior points, take only negative values and are considered as less efficient combination of inputs.

A cost function specifies the minimum possible total cost of operation given the levels of outputs, input prices and the level of technological knowledge. Since the cost frontier defines the minimum cost of operation, deviations from the cost frontier are positive and indicate inefficiency. Inefficiency reflects the firm's inability to meet its objectives.

The objective of measuring efficiency is the identification of best performers as well as the identification of worst performers. Then, the determinants of their performance can be analyzed. The information derived from the analysis could be helpful to the industry as well as to the government for policy analysis.

2.2 Efficiency Measurement Methods

Farrell (1957) provided the basic framework of measuring inefficiency. He introduced the formulation and estimation of frontiers as a generalization of the Pareto efficiency concept. Farrell termed inefficiency the deviations of actual performance from an optimal frontier and used Linear Programming techniques to estimate it. Farrell's work motivated the development of a number of theoretical techniques and empirical applications.

Followers extended the mathematical programming approach but also they developed an alternative econometric approach. All the developments in frontier estimation can be generally classified according to the estimation technique used as mathematical programming (Data Envelopment Analysis, DEA) and econometric techniques or according to the statistical properties of estimators as deterministic (non-parametric) and stochastic (parametric) approaches. Førsund et al. (1980), Bauer (1990), and Seiford, and Thrall (1990) provide an excellent classification and review of the studies and techniques of frontier estimation.

In general, inefficiency can be classified as technical inefficiency or allocative inefficiency. Technical inefficiency is defined as performance above the minimum possible cost or below the maximum possible output obtainable from a given set of inputs. Technical inefficient performance is the result of excessive use of inputs. Allocative inefficiency, which reflects the optimal choice of inputs, is defined as performance deviated from the least cost expansion path (Førsund et al., 1980). In the literature the notion technical inefficiency is used interchangeably with the term X-inefficiency. However, there are some differences between the two definitions. The term X-inefficiency introduced by Leibenstein (1966) to define the existence of non-allocative and not strictly technical inefficiency. Leibenstein's X-inefficiency is not subject to neoclassical optimization framework and includes additional organizational aspects of human behavior not controllable by the decision maker as motivation, effort, and work ethic [Leibenstein, 1977; Leibenstein and Maical, 1992].

A production function frontier that theoretically includes only input levels as its arguments yields only technical inefficiency estimates. The cost function that includes input prices as well as output levels provides overall inefficiency (technical and allocative).

While the traditional estimation method of ordinary least squares (OLS) measures the average economic behavior allowing deviations from the average to sum to zero, the stochastic frontier specifies the "optimum" and not the "average" behavior, so deviations from the optimum are one-sided and non-zero. The observed actual production can not exceed the maximum possible (optimal) production defined by the production frontier and the actual cost of operation can not fall below the minimum possible cost that determines the cost frontier (Lovell, C.A.K., 1995). The estimated frontier can provide quantitative information on firm specific performance and is superior to the traditional optimizing model (OLS) since the later becomes a testable hypothesis (Schmidt and Lovell, 1979).

The stochastic frontier, proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977), specifies a composite error regression model that integrates a two-sided random component and a one-sided component representing inefficiency. Specifically this model distinguishes between random shocks and firm specific effects. This model is based on the assumption that the frontier is stochastic rather than fixed. Each firm shares the same functional form but each firm is subject to a unique frontier, which is stochastic and can vary randomly as the firm's productive or cost possibilities. The stochastic econometric approach provides total residual inefficiency for each productive unit, but it can not break this measure down by input/output components and identify their efficient level of operation.

Data Envelopment Analysis (DEA) is a non-parametric technique, which was developed by Charnes, Cooper, and Rhodes (1978) following Farrell's objectives. The deterministic approach to inefficiency measurement, constructs a piecewise linear surface, "the empirical frontier," and converts the basic elements of production (inputs and outputs) into an efficiency index which reflects the firm's relative performance. DEA evaluates each productive unit and provides specific detailed information about its performance, which the alternative parametric approach can not provide. Specifically, not only is the total inefficiency measured but also the deviations of all inputs (excess consumption) and outputs (slacks) from benchmark efficient levels. Having information on the efficiency level of each productive unit as well as efficiency by input/output component, the decision-makers can apply the appropriate policy to improve the performance of inefficient productive units.

The estimation of deterministic frontiers by mathematical programming does not rely on a specific functional form, so, it is not subject to functional misspesification. Also, no restrictive assumptions are imposed or implied other than the convexity of the data set. In addition, the Data Envelopment Analysis can accommodate multiple input/multiple output production functions with flexibility. Even environmental factors not strictly defined inputs and outputs can be included in the estimation process (Seiford and Thrall, 1990). However, the obtained DEA estimates have no statistical properties. So, tests of significance, statistical inferences and goodness of fit measures can not be carried out. Another disadvantage of the deterministic frontier is the significant influence exercised on estimates by sampling outliers, data errors and variable selection. Summing up all the uncontrollable influences with inefficiency can seriously bias the estimates upward or downward as statistical noise appears as inefficiency.

The stochastic frontier is not sensitive to inaccurate observations and allows the separation of random effects or statistical noise from the firm-specific (controllable) effects. However, this technique is subject to a selected (explicit) functional form and possible misspecification. Also, the validity of certain assumptions regarding the statistical properties of the composite term is questionable.

The omission of critical variables and the number of variables (inputs and outputs) included affects the estimates of both approaches (Seiford and Thrall, 1990). The stochastic approach is subject to limitations of independent observations (degrees of freedom) left for estimation, as the frequently used flexible functional form specification requires multi-interaction terms and a large numbers of estimated coefficients. DEA estimates, also, depend on the relation between the dimensions of the s + m matrix (s-outputs and m-inputs) and the number of observations (Decision-Making Units). So, as the number of variables increases the number of efficient found DMUs increases (Seiford and Thrall, 1990). The efficiency rating of a given DMU will not decrease with an additional variable and it will not increase if a variable is omitted (Epstein and Henderson, 1989).

The stochastic cost frontier, which includes arguments of both outputs and input prices, allows the estimation of both technical and allocative inefficiencies or total inefficiency. The mathematical programming technique, which relates inputs and outputs, measures technical efficiency. Alternative DEA models have been developed in addition to the basic model. A cost-minimizing DEA model that incorporates input prices yields overall cost efficiency (technical and allocative). An extended DEA formulation, the Assurance Region/Cone Ratio, which incorporates external information in the form of weight restrictions into estimation, may provide estimates of efficiency closer to the overall level.

2.3. *Review of the Literature*

The excessive growth of expenditures of the health care sector has initiated substantial research to identify the causes and propose solutions. The health care sector is dominated by not-for-profit "firms" and organizations with unique characteristics that are not subject to market optimization criteria of other sectors of the economy. The approaches of profit-maximization and utility-maximization as well as a mixed approach have been investigated extensively in the literature of hospital behavior. However, both are subject to criticism.

The profit-maximizing behavior has been criticized as inappropriate for the health sector and the utility-maximizing model as unnecessarily complex (Estaugh, 1992).

An alternative approach, proposed by Cowing, Holtman and Powers, (1983), involves the optimization of a cost minimizing behavior, a general assumption consistent with the character and mission of the health care sector (hospitals, physicians, e.t.c.).

However, theoretical and empirical economic models exist suggesting that the hypothesis of cost minimizing behavior may not occur in the hospital sector and in the health care sector in general (Sloan and Steinwald, 1980).

Newhouse (1970) questioned the economic behavior of nonprofit organizations to produce at the minimum cost level. Cost inefficiency results either from a preference to (more expensive) quality or existence of barriers to entry in the nonprofit hospital market. Newhouse argues that philanthropy and third party reimbursement promotes inefficiency (gives some latitude for inefficiency) and prevents entry for profit makers. All these conditions can weaken the least cost behavior.

Lee (1971) developed the utility maximizing theory of hospital behavior to explain the departure from cost minimization and optimal behavior. The deviations from the minimum cost operation are attributed to a utility maximizing hospital (as opposed to profit or sales maximizing) which is motivated to increase the stock of inputs without any adequate increase in outputs, stimulating waste and inefficiency.

The hospital firms are subject to uncertain demand for their services that may distort their optimizing behavior. Hospitals in order to fulfill their special mission prefer to maintain an excess capacity and may fail to reach the efficient “frontier” level of operation. The uncertain environment in which hospitals operate distorts the structure of their cost function. Gaynor and Anderson (1995), and Friedman and Pauly (1981) estimated a cost function that included uncertain demand as an argument to examine how the uncertainty of demand affects the hospital cost structure and efficiency. They found that uncertain demand is a significant factor of hospital cost behavior.

Empirical studies focused on regulated industries found evidence of distortions of optimal input ratios and significant allocative inefficiency in government regulated firms (Färe et al., 1985). Regulation of the hospital sector drew attention and the possible effects on cost structure and inefficiency were extensively studied (Sloan and Steinwald, 1980). Market conditions in the health care industry as restrictions, interventions and heavy regulations, the reimbursement system (third-party payments), and the dominance of the non-for-profit organizations can distort the optimal combination of choices (inputs, outputs, and technology) and consequently the marginal behavior of the firm. However, under these conditions the traditional optimizing model is not appropriate and produces biased coefficients.

Empirical hospital cost studies that relaxed the assumptions of cost minimizing behavior reported significant departures from the optimal behavior. Goldman and Grossman (1983) examined the allocative inefficiency of Community Health Centers and found evidence of inefficient mix of inputs. A firm specific index of inefficiency was constructed which was modeled to identify the possible sources of inefficiency as well as the cost savings associated with efficient performance.

Eakin and Kniesner (1988) questioned the cost minimizing behavior of hospitals and developed an economic model to estimate the extent of hospital (allocative) inefficiency in the United States. They estimated an average inefficiency between 4 and 5 percent ($2.2

billion in 1976) using a data set of 331 U.S. hospitals for the period 1975-76. Eakin (1991) investigated the determinants of hospitals' allocative inefficiency of this study. Zuckerman et al, (1994) applied the stochastic cost frontier to a sample of U.S. hospitals and found significant inefficiency. Hospital inefficiency was as high as 18.8 percent. Controlling for output and patient characteristics as well as output quality the overall (technical and allocative) inefficiency was reduced to 13.4 percent.

Data Envelopment Analysis has been applied to a variety of health care settings: Sherman (1984), Grosskorf and Valdmanis (1987), and Byrnes and Valdmanis (1989; 1995) modeled the efficiency of the hospital sector; Chilingerian (1995) evaluated the efficiency of physicians in hospitals; Banker and Morey (1986b) and Capettini et al., (1985) examined the efficiency of pharmacies; Nunamaker (1983), Rosko et al., (1995) and Kooreman (1994) investigated the efficiency of the nursing home sector as well as its determinants.

Banker, Conrad and Strauss (1986) compared the stochastic and DEA approaches using a sample of North Carolina hospitals. The two models exhibited similarities and differences in terms of estimated marginal rates of output transformation and returns to scale.

A comparative analysis of DEA and translog regression was conducted by Banker, Charnes, Cooper and Maindirata, (1988). They found that the DEA estimates approximated better a "true production function" (obtained by simulation) than the translog model that allows for inefficiency. Wagstaff, (1989), estimated hospital efficiency and compared deterministic and stochastic techniques and concluded that the stochastic model performs better. So, the literature provides inconclusive or contradictory comparative evaluations of the two approaches.

However, the Stochastic Frontier and the Data Envelopment Analysis could be considered "complementary" techniques to efficiency evaluation. Both share unique advantages and limitations or weaknesses (Sherman, 1984). Consequently, the application and coordination of the two techniques can improve the quality of estimates and can advance the understanding of inefficient behavior and its determinants. This study intends the application and coordination of the two methods.

2.4 The Stochastic Frontier Model

The stochastic econometric cost frontier model may be written as:

$$C=f(Y,W;X)e^{v+u} \quad \text{or} \quad lnC_i=lnC(Y,W;X)+v_i+u_i \tag{2.4-1}$$

where C is total cost, Y is a vector of outputs, W is a vector of input prices, and X represents other output characteristics and cost determinants.

The composite one-sided disturbance term ($\varepsilon_i = v_i + u_i$) is defined as the sum of the errors v_i and u_i. The v_i component of ε_i follows a symmetric distribution and reflects the random effects of exogenous socks and measurement errors. In the stochastic frontier environment, by assumption, v_i is normally distributed with mean 0 and constant variance ($v_i \sim N(0, \sigma_v^2)$). The distribution of v_i is:

$$f(v)=\frac{1}{\sqrt{2\pi}\sigma_v}\exp\left[-\frac{1}{2}\left(\frac{v}{\sigma_v}\right)^2\right] \tag{2.4-2}$$

The u_i component of ε_i is one-sided and captures the firm-specific deviations from the stochastic frontier. The assumption of how the second component of the composite error is distributed is critically important. In the literature four distributional assumptions are employed for the inefficiency term u_i: the half-normal distribution with mean zero ($u_i \sim N|(0, \sigma_v^2)|$), the truncated normal with nonzero mean ($u_i \sim N|(\mu, \sigma_v^2)|$), the exponential, and the gamma distribution.

One of the most widely used distributions is the half normal ($u_i \sim |N(0,\sigma_u^2)|$), (Cowing, Reifschneider and Stevenson, 1983).

The half-normal distribution of u_i is:

$$f(u / \sigma_u^2) = \left(\frac{1}{\sqrt{2\pi}\,\sigma_u} \right) \exp\left[-\frac{1}{2} \left(\frac{u}{\sigma_u} \right)^2 \right] \qquad u_i > 0$$

(2.4)-3

$$= 0 \qquad u_i \leq 0$$

The joint density function of the composite error $\varepsilon_i = v_i + u_i$ under this assumption, following Stevenson, (1980), is:

$$f(\varepsilon / \sigma^2, \lambda) = \frac{2}{\sigma} \phi \left(\frac{\varepsilon}{\sigma} \right) \left[1 - \Phi \left(-\frac{\varepsilon \lambda}{\sigma} \right) \right] \qquad -\infty < \varepsilon < +\infty \qquad (2.4)\text{-}4$$

where $\sigma^2 = \sigma_v^2 + \sigma_u^2$; $\lambda = \sigma_u/\sigma_v$; ϕ is the standard normal density function and Φ is the standard cumulative distribution function.

The parameter $\lambda = \sigma_u/\sigma_v$ indicates the degree of asymmetry of the composite error ε or the level of inefficiency. The greater the distance of actual firm performance from the frontier, the larger the parameter λ, and the larger the degree of inefficiency. Performance on the frontier (optimal performance) implies that λ equals zero and $\varepsilon_i = v_i$ and the stochastic frontier model reduces to OLS.

The log-likelihood function of the model (under a half-normal distribution of u_i), following Bauer (1990), is:

(2.4)-5

$$\ln L(\ln C / \beta, \lambda, \sigma^2) = \frac{n}{2}\ln\frac{2}{\pi} - n\ln\sigma - \left(\frac{1}{2\sigma^2}\right)\sum_i^n \varepsilon^2 + \sum_i^n \ln\left[1 - \Phi\left(-\frac{\varepsilon\lambda}{\sigma}\right)\right]$$

The model is estimated by maximum likelihood with OLS estimates as started values. Inefficiency is calculated from the residuals of the model. The residual of the model is the composite term ε, ***($\varepsilon = lnC-\beta'x$).*** Average inefficiency (mean of u) equals average ε (residuals of the model) since the mean of v by assumption is zero: $E(u)=E(\varepsilon)=(2/\pi)^{1/2}\sigma_u$. The predicted value is calculated as $\beta'x - E[u]$.

The firm specific inefficiency (or observation specific inefficiency) can be obtained as the expected value of the inefficiency term u conditional on the composite error ε as proposed by Jodrow et al. (1982):

$$E(u / \varepsilon) = \left(\frac{\sigma_u^2 \sigma_v^2}{\sigma^2}\right)\left[\frac{\phi\left(\frac{\varepsilon\lambda}{\sigma}\right)}{1 - \Phi\left(-\frac{\varepsilon\lambda}{\sigma}\right)} + \frac{\varepsilon\lambda}{\sigma}\right] \qquad (2.4)\text{-}6$$

However, as Greene, (1993), pointed out the expected value of the inefficiency term is an unbiased estimator of u but it is inconsistent. The variance of the estimator does not approach zero as the sample size increases indefinitely. The index of inefficient obtained above from the single equation cost function incorporates both Farrell's technical inefficiency and allocative inefficiency. However, the separation of the two components and the share of allocative in a stochastic environment has not been definitely answered. A variety of approaches have been proposed but they are based on specification restrictions and assumptions that are subject to criticism. The decomposition of total inefficiency into its components might generate conceptual benefits but involves restrictive assumptions and methods that depart from the objectives of this study. The stochastic frontier model is criticized for its distributional assumption of the error term. This assumption is considered very restrictive particularly when a cross sectional model is used. For a cost function the residuals are positively skewed when inefficiency is present.

2.5 The Data Envelopment Analysis (DEA) Model

Charnes, Cooper, and Rhodes (1978) operationalized the conceptual framework of Farrell (1957) introducing a mathematical programming model to efficiency measurement. The linear programming approach after that was generalized and was extended in a series of papers [Seiford and Thrall, 1990; Ali and Seiford, 1993].

Let's consider a set of *n* multiple input, multiple output productive units or Decision-Making-Units (DMU). Each DMU_k in the process of producing the vector of outputs $\boldsymbol{Y_k}$ consumes the vector of inputs $\boldsymbol{X_k}$.

The efficiency problem involves the maximization of the ratio of the sum of the weighted outputs to the sum of the weighted inputs for each DMU subject to the constraint that the efficiency of each unit is lower or equal to 1.

$$\max_{\mu,\nu} \vartheta_0 = \frac{\sum_{r=1}^{s} \mu_r y_{r0}}{\sum_{i=1}^{m} \nu_i x_{i0}} \qquad \text{subject to:} \quad \frac{\sum_{r=1}^{s} \mu_r y_{rk}}{\sum_{i=1}^{m} \nu_i x_{ik}} \le 1$$

$$\text{and} \quad \mu_r,\ \nu_i \ge 0 \tag{2.5)-1}$$

where y_{rk} = the rth output of DMU k for $k = 1,\dots,n$

x_{ik} = the ith input of DMU k $r = 1,\dots,s$

μ_r = weight (coefficient) of rth output $i = 1,\dots,m$

ν_i = weight (coefficient) of ith input

Charnes, Cooper, and Rhodes (1978) used the fractional programming theory of Charnes and Cooper (1962) to transform the above nonlinear system to a linear programming problem, where the numerator of the ratio is maximized and the denominator is set equal to 1 (model 2.5-2). The mathematical programming formulation has a dual representation. It can be stated as an envelopment problem (also called Primal), or a multiplier problem (also called Dual). One of the two equivalent formulations needs to be solved and then the duality of linear programming yields solutions for the second.

	The multiplier form:		The envelopment form:	
	$\max_{\mu,\nu}\ \vartheta_0 = \mu Y_k,$		$\min_{\theta\lambda}\ \theta,$	
Subject to:	$\nu X_k = 1,$	Subject to:	$\mathbf{Y}\lambda \geq Y_k,$	(2.5)-2
	$\mu\mathbf{Y} - \nu\mathbf{X} \leq 0,$		$\theta X_k - \mathbf{X}\lambda \geq 0,$	
	$\mu \geq 0, \quad \nu \geq 0,$		$\lambda \geq \mathbf{0},$	

The parameter θ is a scalar that satisfies the condition $\theta \leq 1$ meaning that the DMU is efficient if $\theta = 1$ and inefficient if θ is lower than 1.

The following formulation (2.5)-3 and (2.5)-4, (the additive model, developed by Charnes, Cooper, Golany, Seiford and Stutz (1985)), provides an illustrative introduction to DEA analysis.

The Y_k, X_k are the vectors of s outputs and m inputs for DMU_k, and **Y**, and **X** are the s x **n** and **m** x **n** matrices of outputs and inputs, respectively. The optimal solution of the multiplier problem yields the **n** sets of multipliers or coefficients (μ, ν), while μ^k, and ν^k indicate the vectors of their lower bounds.

The parameter λ^k (n-vector) identifies the efficient peer group for each DMU and defines a projected point on the envelopment surface, $(\tilde{Y}_t, \tilde{X}_t)$, for each actual point (Y_k, X_k). The projected point can be expressed as $(\tilde{Y}_t, \tilde{X}_t) = (Y_k + s^k, X_k - e^k)$. For efficient DMU the projected point equal to the actual point (since $s^k = 0$, and $e^k = 0$). The peer group or the convex combination of dominating DMUs of each inefficient DMU constructs the frontier.

The optimal solution of the envelopment problem (for each DMU_k) yields the output slacks s^k (output s-vector), and the excess inputs e^k (input m-vector).

The CRS model (CCR): The Constant Returns to Scale Model

	The multiplier form:		The envelopment form:	
	$\max_{\mu,\nu} \quad \mu Y_k - \nu X_k$		$\min_{\lambda,s,e} \quad -(\mu^k s + \nu^k e)$	
subject to:	$\mu \mathbf{Y} - \nu \mathbf{X} \leq \mathbf{0}$,	subject to:	$\mathbf{Y}\lambda - s = Y_k$	(2.5)-3
	$\mu \geq \mu^k, \quad \nu \geq \nu^k$		$-\mathbf{X}\lambda - e = -X_k$,	
			$\lambda \geq \mathbf{0}, \; s \geq \mathbf{0}, \; e \geq \mathbf{0}$	

The VRS model (BCC): Variable Returns to Scale Model

	The multiplier form:		The envelopment form:	
	$\max_{\mu,\nu,\omega} \quad \mu Y_k - \nu X_k + \omega$		$\min_{\lambda,s,e} \quad -(\mu^k s + \nu^k e)$	
subject to	$\mu \mathbf{Y} - \nu \mathbf{X} + \omega \mathbf{1} \leq \mathbf{0}$,	subject to	$\mathbf{Y}\lambda - s = Y_k$	
	$\mu \geq \mu^k, \quad \nu \geq \nu^k$		$-\mathbf{X}\lambda - e = -X_k$,	(2.5)-4
			$\mathbf{1}\lambda = 1$	
			$\lambda \geq \mathbf{0}, \; s \geq \mathbf{0}, \; e \geq \mathbf{0}$	

The model is solved n times for each DMU. The optimal solution reflects the efficiency of the DMU_k being evaluated. The empirical production frontier (envelopment surface) is determined and the relative efficiency of each unit is estimated. An efficient DMU is located on the envelopment surface ($\mu_k Y - \nu_k X = 0$), while an inefficient one falls below the envelopment surface.

The relative efficiency is equivalent to Pareto efficiency. A DMU is defined as Pareto efficient if there is no other DMU or a linear combination of DMUs that can improve one of its input/output levels without at the same time deteriorating at least one of its remaining input output levels.

The above formulation (model 2.5-3) termed CCR after Charnes, Cooper, and Rhodes (1978). The CCR model assumes constant returns to scale (CRS) forcing the hyperplane (envelopment surface) to pass through the origin. The efficiency score derived under CRS measures overall technical efficiency. Banker, Charnes and Cooper (1984) provided a variable returns to scale formulation (VRS), termed BCC model. The additional constraint introduced in the envelopment form, $\mathbf{1}\lambda = 1$, (equivalent to $\sum_{i=1}^{n} \lambda_i = 1$), is related to the additional variable ω in the multiplier form. Both λ and ω allow for Variable Returns to Scale (VRS).

In the multiplier form of the VRS formulation, maximization of the objective function yields the virtual multiplier vectors (also called coefficients or prices) for each DMU: the μ^k (output s-vector), and v^k (input m-vector), and in addition, the variable ω^k. The DMU k, in this case, is efficient if it lies on the empirical frontier defined by the $\mu^k\mathbf{Y} - v^k\mathbf{X} + \omega^k = 0$ condition. In CRS the supporting hyperplane of the envelopment surface passes through the origin.

In the VRS formulation the sign of the variable ω for an efficient observation may indicate the type of returns to scale; decreasing for $\omega < 0$, increasing for $\omega > 0$, or constant returns for $\omega = 0$ (Banker, Charnes and Cooper, 1984). But the type of returns to scale of inefficient DMUs can not be determined with this method (Olesen, 1995). The estimation of returns to scale generalized and extended from a single measure (ω) to an interval estimate by Banker and Thrall (1992).

For DMUs that are technically efficient DMUs under the VRS formulation, the range of ω values defined by a lower and an upper bound identifies the type of returns to scale. A positive range indicates increasing returns to scale and a negative range decreasing returns to scale. However if the range includes zero the returns to scale are constant [Banker and Thrall, (1992); Banker, Bardhan and Cooper, (1996)].

The VRS formulation yields "pure" technical efficiency. In many empirical studies the overall technical efficiency obtained under the CRS formulation is decomposed into its two components, scale and pure technical efficiency.

Employing the same data, equality of the efficiency score obtained under CRS with the one obtained under VRS indicates the absence of scale inefficiency. The difference between the two scores implies that the DMU is scale inefficient.

Färe et al., (1994) developed a method to infer returns to scale for both efficient and inefficient DMUs. The ratio of CRS to VRS determines the scale efficient DMUs. For inefficient DMUs, a different linear formulation is solved, the non-increasing returns to scale (NIRS). The ratio of the CRS to NIRS indicates increasing (equals to 1) or decreasing (less than 1) returns to scale. The Färe et al., (1994) approach is used in this study and it is illustrated in appendix 2.1.

The coefficients μ_r, v_i, also, may provide estimates of production technology characteristics such as marginal productivities. In addition, their ratios may express marginal rates of transformation of outputs (μ_r/μ_j) and marginal rates of input substitution (v_i/v_h) (Banker and Maindirata, 1986).

There is a variety of DEA models in the literature that provide extensions of the basic CCR and BCC models. The variety of data envelopment models for efficiency measurement can be classified:

(1) according to the form of envelopment surface; constant returns to scale (CRS) or variable returns to scale (VRS);

(2) according to orientation; input-oriented, output-oriented or non-oriented; and

(3) according to multiplier lower bounds (pricing mechanism: equal bounds or DMU specific (Ali, Lerme and Seiford, 1995).

Extensions of the model include (for both CRS and VRS surfaces, and both input and output orientation):

i) the multiplicative model that defines a piecewise log-linear (Cobb-Douglas) surface (Charnes, Cooper, Seiford and Stutz, 1982, 1983);

ii) the use of categorical variables in estimation (Banker and Morey, 1986b);

iii) the use of non-discretionary characterization of inputs or outputs that accommodate variables not controlled by the DMU and excludes them from the evaluation of the unit (Banker and Morey, 1986a);

iv) Weight restrictions [Dyson and Thanassoulis, (1988); Thompson et al., (1990)].

v) The Cost-DEA analysis (Färe et al., 1994).

The following discussion illustrates the extensions that will be used in the analysis. Specifically the two-staged input orientated model, the weight restricted model and the cost-DEA model.

The mathematical programming technique evaluates the n DMUs in the data set and constructs the envelopment surface as well as the projection of each actual point (Y_k, X_k)

on this surface. The radial distance δ^k of actual performance from its projection reflects the relative efficiency of the unit. This distance is a function of weighted output slacks and excess inputs: $\delta^k = -(\mu^k s^k + v^k e^k)$.

Oriented models, input-oriented or output-oriented, maximize a proportional reduction in inputs (π) or a proportional increase in outputs (η) respectively, necessary to reach the projected point. The objective function can be stated as: **min** $\theta = 1 - \pi$ for the input-orientation and **max** $\phi = 1 + \eta$ for the output-orientation.

Oriented models can be estimated with two alternative methods, in one or two stages. One method employs an infinitesimal constant, (non-Archimedian constant, ($\in$), satisfying the conditions $0 < \in < 1/N$, $N>0$), to obtain the projected point in one stage solution. The non-Archimedean constant is a very small number (as 10^{-6}) ensuring that inputs are non-zero and that the inputs/outputs are assigned a positive (even small) weight (Wong et al., 1990). The one stage, non-Archimedean, dual linear programming formulation for the input-oriented model for the CRS and VRS surfaces is presented below: equation (2.5)-5 and (2.5)-6 (Ali et al, 1995).

However, the one stage non-Archimedean model can yield inaccurate results. The optimal radial movement (θ or ϕ) is accurately measured but this movement is an intermediate point and not always sufficient to reach the frontier (Ali and Seiford, 1993). The radial movement may result in non-zero output slacks and excess inputs for efficient DMUs.

The two-stage formulation guarantees that the projected point lies on the frontier (total projection) and the output slacks or input excess for efficient DMUs are zero . The estimation involves two steps: the first step determines the maximum input reduction π

(optimal θ) or the maximum output augmentation η (optimal ϕ), while the second step identifies the projection point.

The input-oriented formulation (envelopment form) is given below: equations (2.5)-7 and (2.5)-8 (Ali and Seiford, 1993). The input-oriented model in the first stage determines the optimal input reduction or the parameter θ that defines an intermediate point (Y_k, $\theta^k X_k$). The second stage yields the projection point on the frontier[1], (Y_k + s , $\theta^k X_k$ - e).

Comparing oriented with standard formulations, the oriented models applied to the same set of DMUs may yield different efficient scores or projected points, but the envelopment surface and the set of efficient/inefficient DMUs remains the same (Ali et al., 1993).

Coelli (1997) developed an alternative multi-stage methodology for orientated models. This approach reaches the projected point through a sequence of radial movements.

Another aspect of DEA estimation is the sensitivity of the constructed frontier to units that inputs and outputs are measured. A change in the units of measurement has no effect on the relative efficiency of DMUs but affects significantly the envelopment surface as well as the efficient scores. This dependence is associated with the lower bounds on multipliers. The basic DEA model assumes the value of 1 as the lower bound for multipliers of the objective function (1s + 1e). This assumption implies an equal marginal evaluation across non-zero output slack and non-zero excess inputs. For example, the marginal worth of a unit of hospital output slack (admission) is equivalent to the marginal worth of a unit of excess hospital input (hour or clerical FTE). In this case, a units-invariant model that allows flexibility in the selection of lower bounds can be estimated.

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[1] The Second stage yields the parameter L which indicates efficiency without output slacks or excess inputs.

One Stage Approach (Input-Oriented)

	Multiplier Form		Envelopment Form	
CRS				(2.5)-5
	$\max_{\mu,v} \quad \mu Y_k$		$\min_{\lambda,s,e} \quad \theta - \epsilon(\mu^k s + v^k e)$	
Subject to:	$vX_k = 1$	Subject to:	$\mathbf{Y}\lambda - s = Y_k$	
	$\mu\mathbf{Y} - v\mathbf{X} \leq 0$		$\theta X_k - \mathbf{X}\lambda - e = 0$	
	$\mu \geq \epsilon\mu^k, \quad v \geq \epsilon v^k$		$\lambda \geq 0, \ s \geq 0, \ e \geq 0$	
VRS				(2.5)-6
	$\max_{\mu,v,\omega} \quad \mu Y_k + \omega$		$\min_{\lambda,s,e} \quad \theta - \epsilon(\mu^k s + v^k e)$	
Subject to:	$vX_k = 1$	Subject to:	$\mathbf{Y}\lambda - s = Y_k$	
	$\mu\mathbf{Y} - v\mathbf{X} + \omega\mathbf{1} \leq 0$		$\theta X_k - \mathbf{X}\lambda - e = 0$	
	$\mu \geq \epsilon\mu^k \quad v \geq \epsilon v^k$		$\mathbf{1}\lambda = 1$	
			$\lambda \geq 0, \ s \geq 0, \ e \geq 0$	

Two Stage Approach (Input-Oriented, Envelopment Form)

CRS	First Stage		Second Stage	(2.5)-7
	$\min_{\theta,\lambda,s,e} \ \theta$		$\min_{\lambda,s,e} \quad -(\mu^k s + v^k e)$	
Subject to:	$\mathbf{Y}\lambda - s = Y_k$	Subject to:	$\mathbf{Y}\lambda - s = Y_k$	
	$\theta X_k - \mathbf{X}\lambda - e = 0$		$\theta^k X_k - \mathbf{X}\lambda - e = 0$	
	$\lambda \geq 0, \ s \geq 0, \ e \geq 0$		$\lambda \geq 0, \ s \geq 0, \ e \geq 0$	
VRS	First Stage		Second Stage	(2.5)-8
	$\min_{\theta,\lambda,s,e} \ \theta$		$\min_{\lambda,s,e} \quad -(\mu^k s + v^k e)$	
Subject to:	$\mathbf{Y}\lambda - s = Y_k$	Subject to:	$\mathbf{Y}\lambda - s = Y_k$	
	$\theta X_k - \mathbf{X}\lambda - e = 0$		$\theta^k X_k - \mathbf{X}\lambda - e = 0$	
	$\mathbf{1}\lambda = 1$		$\mathbf{1}\lambda = 1$	
	$\lambda \geq 0, \ s \geq 0, \ e \geq 0$		$\lambda \geq 0, \ s \geq 0, \ e \geq 0$	

The unit-invariant model sets DMU specific bounds as

$$\mu^k \geq 1/y_{rk} \qquad r = 1,\ldots, s$$

$$v^k \geq 1/x_{ik} \qquad i = 1, .., m$$

and allows the distinction of marginal worth across inputs and outputs of a DMU as well as the distinction of marginal worth of outputs or inputs across DMUs.

Since in the unit-invariant formulation the marginal evaluation across inputs and outputs differs, the projection and the efficiency scores are invariant to units of measurement. Nevertheless, the classification of efficient DMUs that the two variations yield is the same (Ali et al., 1993).

2.5.1 Weight Restrictions and DEA

DEA evaluates the relative efficiency of each DMU in order to build the envelopment surface "empirical frontier." In this attempt, the set of weights (multipliers) μ, and ν of outputs and inputs, respectively, are freely determined by DEA, but remain strictly positive (non-zero). This positivity constraint is the only restriction imposed on the model. However, the flexibility of multipliers is "a strength and a weakness" in DEA estimation (Thomson et al., 1990). The complete flexibility of weights is the strength of this method. A DMU is rendered relatively inefficient with its own favorably selected set of weights. Sometimes the constructed empirical frontier badly depicts the actual performance. This may be due to misspesification of inputs or/and outputs or an insufficient available data set.

Dyson and Thanassoulis (1988) argued that there is excess flexibility in input /output multipliers in DEA. The multipliers are assigned to assess the relative efficiency of each DMU. But in many cases the relative "overall" performance is not reflected in the evaluation of a DMU as a result of this multiplier flexibility. Specifically, in DEA analysis, sometimes a DMU is evaluated efficient because it outperforms in a single input/output of minor importance while other factors are ignored. In this case, the flexibility of multipliers tends to benefit performance of minor factors and overlooks the performance of more important factors. In general, the evaluation process may assign extreme values to multipliers. In this case, controlling the flexibility of virtual multipliers may improve the estimated frontier.

A variety of methods of restricting the flexibility of DEA multipliers have been proposed [Thomson et al., (1990), Dyson and Thanassoulis, (1988) and Wong and Beasley, (1990), Cook et al., (1995), Charnes et al., (1990)]. The restrictions involve bounds on individual multipliers or ratios of multipliers. However, assigning weights to multipliers is a difficult task. In general, the interpretation of multipliers is not clear. So, the determination of constraints lacks a theoretical basis. If information about the relative importance of factors in production is available then weight restrictions may be effectively assigned.

The polyhedral "Cone-Ratio" DEA model provides an extension to the "DEA value-free" model and restricts the multipliers to fall in specific cones (Charnes et al., 1990). The polyhedral Cone-Ratio DEA model introduces additional information into the classical DEA model in a form of constrained virtual multipliers, termed Assurance Regions.

The setting of weight restrictions eliminates excess flexibility and inappropriate multiplier values and in addition allows further discrimination among relatively efficient DMUs (Boussofiane et al., 1991). The efficiency rating of the restricted model will be lower than the unrestricted model, if the restrictions are binding.

Consider a finite number of both inputs and outputs of a productive process as well as a finite number of productive units (DMUs). Let's select one of the inputs and outputs to be the numeraire. The marginal substitution ratio of a multiplier with respect to selected numeraire falls in the range of :

$$0 \le \mu_r/\mu_1 \le \infty \quad \text{and} \quad 0 \le v_i/v_1 \le \infty$$

Setting specific nonnegative multiplier bounds, the set of restrictions can be written as:

$$a_r \le \mu_r/\mu_1 \le b_r \quad \text{or} \qquad a_r\mu_1 \le \mu_r \le b_r\mu_1$$

$$c_i \le v_i/v_1 \le d_i \qquad\qquad c_iv_1 \le v_i \le d_iv_1$$

which imply that μ_r ranges from $a_r\mu_1$ to $b_i\mu_1$ and v_i ranges from c_iv_1 to d_iv_1.

The above relationships are equivalent to:

$$\mu_r - b_r\mu_1 \leq 0 \text{ and } \quad v_i - d_iv_1 \leq 0 \quad \text{with} \quad b_r \geq a_r \geq 0 \quad r = 2, \ldots, s$$

$$-\mu_r + a_r\mu_1 \leq 0 \quad -v_i + c_iv_1 \leq 0 \quad d_i \geq c_i \geq 0 \quad i = 2, \ldots, m$$

The set of boundary conditions define the matrix of restricted output multipliers P_{11}, and the matrix of restricted input multipliers R_{22} which in turn define the corresponding cones. The intersection matrix of multiplier bounds termed Assurance Region (Thompson et al., 1990) can be written as:

$$Q = \begin{bmatrix} P_{11} & 0_{12} \\ 0_{21} & R_{22} \end{bmatrix} \quad \text{and the vector of multipliers as:} \quad M = \begin{bmatrix} \mu \\ v \end{bmatrix}$$

Where P_{11} represents the output cone (2s-2 by s matrix) and R_{22} the input cone (2m-2 by m matrix). The 0_{12} and 0_{21} are null matrices. The corresponding cones are:

$$P_{11}\mu \leq 0, \quad \mu \geq 0 \quad \text{(defines the output cone U)}$$

$$\text{and} \quad R_{22}v \leq 0, \quad v \geq 0 \quad \text{(defines the input cone V)}$$

In Matrix notation, the set of multiplier restrictions can be written as

$$\begin{bmatrix} P_{11} & 0_{12} \\ 0_{21} & R_{22} \end{bmatrix} \begin{bmatrix} \mu \\ v \end{bmatrix} \leq 0$$

The sum form representation of input/output cones reduces the Cone-Ratio model to a DEA standard model with transformed data and simplifies its estimation (Charnes, Cooper, Huang, and Sun 1990). A modified DEA model (Input-Oriented, Envelopment Form, VRS surface) is given below, model 2.5-9 (Thompson et al., 1995).

Input-Oriented, Envelopment Form (AR/cone Ratio), VRS

	First Stage		Second Stage
(AR)	$\min_{\theta,\lambda,s,e}\ \theta$	(AR)	$\min_{\lambda,s,e}\ -(\mu^k s + v^k e)$ (2.5)-9
Subject to:	$Y\lambda - s = Y_k$	Subject to:	$Y\lambda - s = Y_k$
	$\theta X_k - X\lambda - e = 0$		$\theta^k X_k - X\lambda - e = 0$
	$P_{11}\mu \le 0$		$P_{11}\mu \le 0$
	$R_{22}v \le 0$		$R_{22}v \le 0$
	$1\lambda = 1$		$1\lambda = 1$
	$\lambda \ge 0,\ s \ge 0,\ e \ge 0$		$\lambda \ge 0,\ s \ge 0,\ e \ge 0$

Empirical studies have assigned arbitrary constraints on multipliers based on assumed relative importance of variables or on "expert opinions" and "environmental factors" (Thomson et al., 1990). In a different method, Dyson and Thanassoulis (1988) proposed weight restrictions on individual multipliers obtained from the coefficients of a regression model in the case of a single input only. In this limited case of a multiple output and single input production process, the restrictions reflect the allocation of the input to the production of each output.

Wong and Beasley, (1990), proposed a method of restricting weight flexibility based on the importance of each input/output in the production process. The importance of each input and output is reflected by their relative proportions. The proportion of total output (S_k) for DMU k associated with output 1, reflects the importance of output 1 in the production process, and can be restricted to fall in the range of $[a_i, b_i]$. The specified proportion constraints, $a_r \le (\mu_1 Y_{1k}/S_k) \le b_r$, which are based on "value judgment," prevent some outputs from being ignored in the evaluation process. The same approach is applicable to inputs.

The imposition of bounds on multipliers to reduce their flexibility results in a different efficiency evaluation of DMUs (worse or improved). Cook et al., (1995), specified boundary conditions based not only on managerial judgment of relative input/output importance in production, but also on quality and reliability of available data.

A review and evaluation of the applied methods of restricting weight flexibility is provided by Allen and et al., (1997).

This paper introduces multiplier restrictions based on technologically consistent characteristics of the production process derived from a multiple input multiple output stochastic frontier model (or regression analysis in general). The "Technologically Consistent - Assurance Region" (TC-AR) provides an extension of the "Assurance Region"/Cone-Ratio DEA model [Thompson et al., (1990); Thompson et al., (1995); Charnes et al., (1990)]. The TC-AR set of multiplier restrictions, obtained from the coefficients of a theoretically consistent papametric model applied to the same body of data, outperforms any subjectively defined AR based on "expert opinions" or other environmental variables. The boundary conditions obey the productive characteristics assessed by a parametric model estimated in an earlier stage.

The Stochastic cost frontier analysis yields valuable information about economic characteristics, which is more accurate (objective) than any managerial value judgment. The regression based boundary conditions form a "Technologically Consistent - Assurance Region" (TC-AR), that restricts the flexibility of multipliers towards overall efficiency. In addition, the differences of the two methods can be assessed and their weaknesses or strengths can be identified.

Charnes et al., (1978) and Banker, Charnes and Cooper (1984) developed a connecting link between the classical production function and the DEA formulation via axiomatic statements and Shephard's distance function. Banker, Conrad and Strauss, (1986) shown that the ratio of multipliers (in a DEA formulation) may provide estimates of:

marginal rates of transformation of output i for j (μ_i/μ_j) - which indicates by how many units of output j can be produced for each unit reduction of output i;

marginal rate of substitution (ν_i / ν_j); and

marginal product of input i for output r (μ_r / ν_i).

But economic ratios obtained from DEA solutions can not be reliably defined. As multipliers can be assigned values close to zero (larger than the non-Archimedean ε), their ratios become meaningless. In addition, the great flexibility of multipliers limits their ability for economic interpretation.

The imposition of weight bounds, based on marginal rates of substitution obtained from a parametric regression model run through the same body of data, is expected to guide DEA estimation closer to the true production frontier and enrich the efficiency scores with elements of allocative efficiency. The imposition of this type of restrictions (termed Assurance Ratio I in the literature) yields equivalent solutions and relative efficiency scores regardless of input or output orientation (Allen et al., 1997).

Another important aspect of the weight restrictions in DEA analysis is the increased ability of the restricted model to discriminate among DMUs. As described in 2.2 the number of efficient DMUs increases with the dimensions of the (m + s) input/output matrix holding the sample size constant. However, the incorporation of restrictions provides DEA additional flexibility in the process of identifying the relative efficient DMUs.

2.5.2 DEA and Overall Cost Efficiency

Overall cost efficiency is defined as the sum of technical efficiency and allocative efficiency. Let's consider the simple case of using two inputs (x_1, x_2) to produce one output (Y) as illustrated in figure 1.

The isoquant (YY') and the isocost line CC' determine the cost minimizing level of production (point A), given the vector of inputs (x1, x2), the vector of input prices (w_1, w_2), and output level Y.

A firm operating at point (B) produces inefficiently above the minimum possible cost.

The overall efficiency (total economic efficiency) of operation at point B is defined as:

$$OE(y, x, w)=(OK/OB)$$

The overall efficiency can be decomposed into its technical and allocative components.

The technical component of efficiency, which indicates the departure from the isoquant, is:

$$TE(y, x)=(OP/OB)$$

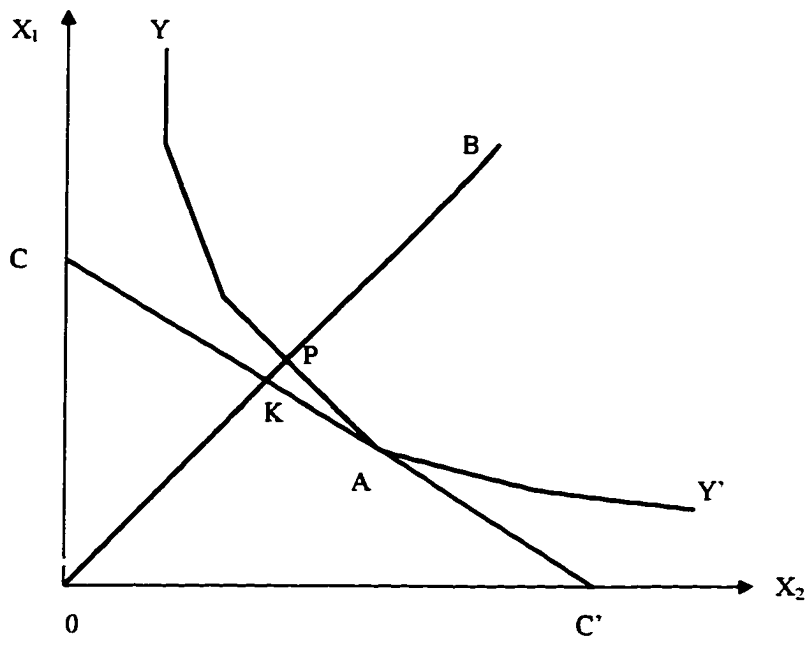

Figure 2.1: The Measurement of Efficiency

The technical component of efficiency indicates that the firm can produce the same output at point P with a lower amount of inputs.

The allocative component of efficiency, which reflects the departure from the optimal combination of inputs is:

$$AE(y,x,w)=(OK/OP)$$

The allocative efficiency implies that the firm can produce the same output at point A with a different combination of inputs and a lower cost.

So, the overall efficiency is the product of its two components

$$OE(y, x, w) = TE(y,x).AE(y,x,w) \text{ or } OK/OB=(OP/OB).(OK/OP)$$

[Färe et al., 1994, Førsund et al, 1980; Byrnes and Valdmanis, 1995]. The above decomposition of total efficiency into its allocative and technical components illustrates the basic framework proposed by Farrell (1957).

In a DEA input-oriented framework, the overall cost efficiency can be modeled as the ratio of the minimum possible cost to the observed cost.

$$OE(y, x, w) = MinCost(y, x, w)/ObservedCost(x, w)$$

The minimum cost can be obtained from a cost minimizing linear programming problem.

$$\mathrm{Min}_{x,\lambda}\ \ \mathbf{x}^{*}\mathbf{w}$$

$$\text{s.t. } \mathbf{y}\boldsymbol{\lambda} - \mathrm{y} \geq 0$$

$$-\mathbf{x}\boldsymbol{\lambda} + \mathbf{x}^{*} \geq 0$$

Where $\mathbf{x}^{*}$ is the obtained set of cost minimizing input quantities given the input prices and the output levels. Moreover, the overall efficiency can be decomposed into its technical and allocative components.

The technical efficiency TE(y, x) is provided by the solution of the CRS model. Given the TE(y,x) and the OE(y, x, w), the ratio of the overall cost to technical efficiency provides the allocative efficiency AE(y, x, w) = OE(y, x, w) /TE(y,x).

In addition, the technical efficiency can be further decomposed into its pure technical VRS(y, x), and scale efficiency components.

The VRS(y, x) is the input-oriented DEA model that allows for variable returns to scale, while the scale is the ratio of constant to variable efficiency score CRS(y, x)/VRS(y, x). The technical efficiency gives the proportion that inputs can be reduced and still produce the given levels (observed) of outputs. Scale inefficient DMUs produce beyond the most productive scale size (decreasing returns to scale) or produce below the most productive scale size. The appendix 2.1 illustrates the computation of scale efficiencies using DEA.

Appendix 2.1 Returns to Scale and DEA

There are different approaches that attempt to determine the scale efficiency at the observed point of production of every DMU as highlighted in section 2.5.

The approach of Banker (1984) and Banker and Thrall (1992) uses the intensity variable λ obtained from the solution of the CRS formulation to determine returns to scale. The approach of Banker, Charnes and Cooper, (1984), uses the sign of the single variable ω obtained from the VRS formulation to determine returns to scale of efficient DMUs. Banker and Thrall, (1992), extended this approach from the single variable ω to an interval estimate as previously discussed.

This study applies a method developed by Färe et al., (1994), which identifies the type of returns to scale for both efficient and inefficient DMUs. The technique is based on a DEA formulation that accounts for non-increasing returns to scale (NIRS). Specifically, the following additional DEA problem is solved:

$$\begin{array}{ll} \text{NIRS} & \min_{\theta,\lambda,s,e} \ \theta \\ \text{Subject to:} & \mathbf{Y}\lambda - s = Y_k \\ & \theta X_k - \mathbf{X}\lambda - e = 0 \\ & \mathbf{1}\lambda \leq 1 \\ & \lambda \geq 0, \ s \geq 0, \ e \geq 0 \end{array}$$

This model is the VRS formulation with the constraint $1\lambda \leq 1$ imposed.

The returns to scale are determined by the outcome of two ratios. The first ratio of technical efficiency score to pure technical score S(y, x) = CRS(y, x)/VRS(y, x) identifies the scale efficient DMUs. For scale efficient DMUs, S(y, x)=1 and also the efficiency scores obtained under CRS and VRS formulations are equal (CRS(y, x)=VRS(y, x)=1). For the scale inefficient DMUs where S(y, x) ≤ 1 the NIRS solution is used. Specifically, the second ratio is calculated:

$$S(y, x) = CRS(y, x)/NIRS(y, x)$$

If the ratio of CRS to NIRS equals 1 then increasing returns to scale prevail. If the ratio is lower than 1 then the returns to scale are decreasing.

3

The Hospital Cost Frontier Function

3.1 Introduction

One of the most extensive debates in the literature on the empirical investigation of hospital behavior is the specification of the functional form of hospital cost functions. Basically, studies on the specification and estimation of hospital cost functions in the literature can be classified as following three approaches; an "ad hoc" approach, the neoclassical approach, and an "eclectic" approach [Breyer, 1987; Vita, 1990; Grannemann et al., 1986, Cowing, Holtmann and Powers, 1983; Rosko and Broyles, 1988].

The "ad-hoc" approach employs an additive-linear functional form to explain variations in unit costs (average costs per patient or per patient day) as a function of a set of possible hospital determinants. The ad hoc structure of hospital cost function is motivated by the "organizational anomaly" of the hospital sector which weakens the competitive profit maximizing economic behavior and modeling (Pauly and Redisch, 1973). The ad hoc character of these models also called "behavioral" has been criticized for ignoring the theoretical justification of production technology. Criticism focused on the absence of input prices from the set of the cost determinants which implies zero input substitutability, the inability to control for the multiple-output nature of the hospital behavior and the examination of economies of scale or scope using cross-sectional data [Cowing et al. 1983; Rosko and Broyles, 1988].

The second approach is based on the neoclassical theory of the firm and makes use of the duality between the cost and the production function. In these models, termed neoclassical or technological cost functions, the total cost is a function of input prices and output levels in a flexible functional form specification. This approach takes into account many disadvantages of the ad-hoc specification. First, it is theoretically consistent and it is not based on a priori restrictions (at least the restrictions can be tested before their imposition) and second economies of scale or scope and input substitution elasticities are easily estimable from the cost structure [Cowing et al., 1983; Vita, 1990].

However, there is a number of studies that employ an "eclectic" approach which combines the above approaches. The third approach that combines 'ad-hoc' and neoclassical features (also called quasi-technological), expressed in a flexible functional form specification, has superior advantages. The cost function follows the theoretically consistent multiple input-output representation and includes additional variables to control for important behavioral features of hospitals such as teaching, ownership, the role of physician, market conditions, etc [Rosko and Broyles, 1988; Vita, 1990].

In early 1980's economists introduced 'flexible functional forms' in the estimation of hospital cost functions and facilitated the analysis of multi-product technologies (Christensen et al., 1976). One member of the family of flexible functional forms, the translog may be viewed as a second-order Taylor series expansion of an arbitrary differentiable function around a specified point. The cost function can be written as:

$$\ln C = f(\ln Q, \ln W; \ln X) \qquad (2.1)\text{-}1$$

The flexible functional form represents arbitrary technologies in the neighborhood of the approximation point, which is usually the sample mean (Vita, 1990). The estimated function provides a reasonable representation of cost behavior when it is evaluated at points that are in the neighborhood of the sample means. However, Vita, (1990) noted that flexible functional forms perform poorly when evaluated away from their approximation point.

The translog cost function does not impose apriori restrictions on the structure of production (homotheticity restriction) or on the elasticities of substitution (homogeneity restriction). However, the restrictions can be statistically tested before their imposition. Unfortunately, the ability of a flexible functional form specification is constrained by the limited data sets of the hospital sector in both sample sizes and missing observations, given the large number of parameters to be estimated [Breyer (1987); Newhouse, (1994)]. In addition, multicollinearity, heteroscedasticity, and endogeneity, although treatable statistical departures from the classical regression model, always tend to limit the quality of estimates. So, because a complete specification is very difficult to be achieved, a trade off between a multi-input multi-output representation and a flexible functional form is necessary. There is evidence that the translog functional form is sensitive to the combination of inputs and does not perform as a well-behaved function for all combinations of inputs (Caves and Barton, 1990).

There is a plethora of empirical studies on hospital cost estimation that reflect the sequence of methodological developments, policy concerns and objectives. Economies of scale and scope, the marginal cost of outputs, the substitutability of inputs in the production as well as the effect of market conditions and the effectiveness of regulation to control cost remain the most important issues in the literature. The flexible functional forms have replaced the ad-hoc specification and the restrictive structural assumptions of neoclassical models.

Conrad and Strauss (1983), Cowing and Holtman (1983), Grannemann, Brown and Pauly (1986), Vita (1990), and Breyer (1987) are a few representative studies that provide a multiple-output analysis of hospitals and the latest developments in estimation of cost functions using flexible functional forms.

The flexible specification has become the standard approach to modeling the hospital cost behavior and it is used in this study.

3.2 Econometric "Issues"

The model is estimated in a translog specification as discussed previously. To test the flexibility of the functional form-against more restrictive types-the F test is used. The joint significance of all the higher order terms is tested.

An estimation problem that the flexible functional form models face is the problem of multicollinearity among the explanatory variables, which limits its advantages. Multicollinearity as a sample specific phenomenon can not be avoided in general and results in imprecise and insignificant estimates, but it has no effect on the unbiasedness statistical property of the estimators.

Heteroscedasticity, a standard estimation problem in cross-sectional models, also may cause estimation problems and reduce the reliability of hospital cost function estimates. Under heterodcedasticity the estimators of an OLS model are unbiased but not efficient. Caudill et al., (1995) pointed out that heteroscedasticity, in a stochastic frontier formulation, can seriously affect the estimated firm specific inefficiency. The firm specific inefficiency measure, as developed in section 2.4, is based on the residuals of the estimated function and so it is subject to specification errors caused by heteroscedasticity. Since the firm specific frontier is defined according to the variation of the residuals, the presence of heteroscedasticity can seriously affect the estimation of frontier functions. Higher dispersion due to heteroscedasticity can be labeled inefficiency. Caudill et al., 1995, found that heteroscedasticity overestimates the coefficients of the cost function and it also affects the efficiency ranking of firms by overstating the inefficiency of small firms and understating the inefficiency of large firms

In this study, the residuals from the OLS regression are used as weights in the stochastic frontier estimation. Estimates obtained from the weighted stochastic frontier model are compared with a variety of estimated frontier and non-frontier estimates to assess their sensitivity.

The single equation model also suffers from specification errors related to endogeneity of outputs and input prices in a total cost function. The assumption of exogeneity of hospital output and price of inputs is a common practice in the literature [Carey and Stefos, 1992; Conrad and Strauss, 1983; Grannemann et al., 1986; Vita, 1990]. Recent studies employ instrumental variables in a first stage estimation and the fitted values are used in a second stage cost estimation. Zuckerman et al., (1994), used instrumental variables for endogenous tested inputs and outputs. Gaynor and Anderson (1995), also, found evidence of endogeneity and replaced outputs with instruments.

3.3 Variables and Data

One of the problems in hospital cost specification is the multi-product nature of the hospital and how to control it in a regression analysis. The flexibility of the functional form contrasts with the multiple hospital output as the sample size allows only representation in aggregated inputs and outputs or case mix variables. Hospitals provide simple and complex heterogeneous services or procedures. To account for the heterogeneity (diversity) of hospital outputs and at the same time to limit their number, three categories of outputs are used in this study: inpatient admissions, patient days and outpatient (net of admissions) visits.

All hospitals in the sample exhibit non-zero levels for the three categories of outputs as required by the translog specification employed. The three outputs employed in this study can not completely control for the complexity, severity and case mix of every hospital. Empirical studies control for case mix according to the data available, using admissions or days by diagnostic category, [Vita, 1990; Grannemann et al., 1986], or using the Medicare's (HCFA) case mix index (Zuckerman et al., 1994). Although the Medicare case mix involves a proportion of the total hospital cases, it has been used as substitute for an unavailable overall measure. In this study, the 1993 Medicare case mix is used in a second specification to adjust admissions and inpatient days.

Hospitals can adjust most of factors of production in the short run, but potentially there are some fixed factors that cannot be adjusted during this period. As suggested by Breyer (1987), the number of maintained beds (set up and staffed) can be included in the model representing another type of output (size related output). However, the number of beds is included in many studies to reflect a proxy for capital inputs (fixed factor) and a measure of the hospital's size. The inclusion of beds as a fixed input leads to a short-run cost functional relationship (Vita, 1990). The inclusion of both admissions and patient days renders the variable of (hospital size) beds meaningless. In addition the high collinearity between beds and patient days creates estimation problems. For that reason, the number of beds is not included in the specified model.

Admitting physicians are usually not employed by the hospital and draw no salaries from it. However, they provide a significant portion of the labor necessary to produce hospital care. The omission of admitting physicians from the cost function may cause a specification error [Bays, 1979; Rosko and Broyles, 1988]. Physicians participate in management, administrative and medical/clinical activities. The Hospitals-Actual data set, employed in this study, includes physician-related data. So, a measure of physician-staff size is included to control for the physician input. This measure is calculated as the total annual physician hours and enters as an exogenous factor in estimation that does not affect the marginal costs.

The available data set permits the calculation of a variety of hospital input prices as the wage of labor input and the prices of capital, supplies, and contract services. Two kinds of labor are used.

The price (wage) of health care delivery FTE personnel (RNS) and the price of administrative FTE personnel (CLR) are calculated as annual cost divided by the annual number of hours.

The price of capital is the price level depreciation allowance (PLDA) in excess of historical costs of owned or capitalized lease equipment, as calculated by the New Jersey Department of Health. A price level depreciation factor - a price index that takes into account indexes as the Hospital Equipment Cost Index (HECI), the bureau of labor statistics (BLS) and the Producer Price Index (PPI) - is calculated each year by the Department of Health (New Jersey). This factor is multiplied by the amounts of actual depreciation reported each year to yield their replacement values. The sum of the differences between depreciation and its replacement value over the past 20 years is the price level depreciation allowance for each hospital.

The price of supplies (PSUP), and contract services (PCSER) are calculated as the annual cost per category divided by the sum of inpatient admissions and outpatient visits. These measures reflect the average amounts spent per patient served.

In order to control for the multidimensional character of hospital outputs a third set of variables is included. The vector of environmental factors includes variables that influence the level of hospital cost but have no effect on marginal costs or on the substitutability of inputs. The number of medical residents in each hospital can be included to control for two unmeasured hospital outputs teaching and research activity (Hadley and Swartz, 1989). Empirical studies of hospital cost behavior indicate that Medicaid patients are relatively more expensive to hospitals. In general, Medicaid patients stay longer than other patients on average, so they have higher cost per admission.

Also, outpatient visits and departmental services differ widely by category. To control for output characteristics, Medicare or Medicaid admissions and/or patient days, outpatient same day surgery visits, and MSA beds as a percentage of totals are included in regression.

The small sample size and the requirements, in terms of coefficients, of the employed functional form limit the ability to include a variety of control variables. In addition, one of the objectives of this study is the comparison of the parametric and the non-parametric techniques, which require a comparable set of inputs and outputs.

The data used in this study, the 1993 New Jersey Acute Hospital Actuals, provides a detailed and definitionally uniform data set of 83 acute care hospitals that is subject to the State regulatory guidelines. One hospital has been deleted from the data set because its data included an extensive Long-Term Care Facility.

The vast majority of hospitals are non-governmental not-for-profit organizations and a few are church operated or under governmental control. The sample does not include for-profit hospitals. However, the uniformity of the data does not insure the applicability of findings at the national level. The purpose of using data from a single state in this study is to take advantage of a unique survey conducted by Response Analysis Corporation (RAC) for the state of New Jersey and involves the degree of implementation of electronic data interchange technology in the state. The hospital (New Jersey Actuals) data set is combined in a second stage estimation with the survey data.

Table 3.1 lists the means, standard deviations, minimum and maximum values of the variables in 1993.

Table 3-1
Descriptive Statistics: The Hospital Stochastic Cost Frontier Function

Variable	Mean	Std. Dev.	Minimum	Maximum	Description
TCOST	97941.6	60665.6	16623.0	327279.0	Total Hospital Cost ($000)
ADTOT	13786.4	7628.8	2028.0	39206.0	Admissions Total
PDTOT	95543.7	47782.9	17109.0	228331.0	Patient Days Total
VNATOT	145741.0	119484.1	10896.0	769918.0	Visits Net of Adm. Total
MBEDTOT	355.8	161.5	86.0	799.0	Maintained Beds Total
HPHYS	88441.1	153027.7	0.0	0762984.0	Physician Hours (Salaries)
HPHYF	49666.5	81185.7	0.0	0540163.0	Physician Hours (Fee)
PHOURS	138107.7	171950.5	3007.0	794508.0	Phys. Hours (Salaries+Fee)
CPHYS	3067.8	5631.8	0.0	40997.0	Cost ($000) Salaries Physic.
CPHYF	1954.4	2348.4	0.0	13015.0	Cost ($000) Fee Physician
HEMP	2724233.9	1467216.4	482146.0	6455889.0	Hours NonPhysician Employees
CEMP	46251.9	27752.8	7712.0	149261.0	Cost ($000) Salaries Employee
CSUPP	15482.2	10438.7	1852.0	49508.0	Cost ($000) Supplies
CDFI	7286.3	4443.2	373.0	18662.0	Cost ($000) Deprec & Interest
CCSER	5843.0	4130.2	933.0	24817.0	Cost ($000) Contract Services
RNS	0.0231	0.0065	0.0168	0.0769	Wage/Hour RNS ($000)
CLR	0.0122	0.0054	0.0074	0.0423	Wage/Hour CLR ($000)
SUP	0.1148	0.0858	0.0301	0.7696	Price of Supplies ($000)
CSER	0.0457	0.0270	0.0049	0.1581	Price of Contract Serv.($000)
PLDA	239.7	162.4	8.0	769.0	Price Level Depreciation
ADMCARE	4618.4	2403.3	886.0	12940.0	Admissions Medicare
PDMCARE	48727.0	23346.0	10795.0	132662.0	Patient Days Medicare
ADMCAID	1729.3	1747.5	75.0	9454.0	Admissions Medicaid
PDMCAID	10159.0	11679.0	543.0	60185.0	Patient Days Medicaid
PADMD	0.1244	0.0999	0.0116	0.5083	Medicaid Admissions (%)
MSABED	0.6982	0.1226	0.1256	0.9560	MSA Beds (%)
VSDS	0.0278	0.0185	0.0000	0.0976	Same Day Surgery Visits (%)
PLANTSF	443810.7	256592.3	56323.0	1169984.0	Plant Square Feet (B5)
RESID	31.7	52.7	0.0	254.0	Residents Total Number

3.4 The Model

The hospital cost function has the following structure:

$$C=f(Y,W;X)e^{v+u} \tag{3.4-1}$$

and its general translong specification becomes:

$$lnC_i=lnC(Y,W;X)+v_i+u_i \tag{3.4-2}$$

The estimated model is:

$$\ln C(Y,W;X)=\alpha_0+\sum_{i=1}^{m}\alpha_i\ln Y_i+\sum_{j=1}^{n}\beta_j\ln W_j+\frac{1}{2}\sum_{i=1}^{m}\sum_{h=1}^{m}\gamma_{ih}\ln Y_i\ln Y_h$$

(3.4)-3

$$+\frac{1}{2}\sum_{j=1}^{n}\sum_{r=1}^{n}\delta_{jr}\ln W_jW_r+\sum_{i=1}^{m}\sum_{j=1}^{n}\phi_{ij}\ln Y_i\ln W_j+\theta_0\ln B+\frac{1}{2}\theta(\ln B)^2$$

$$+\sum_{i=1}^{m}\pi_i\ln Y_i\ln B+\sum_{j=1}^{n}\vartheta_j\ln W_j\ln B+\sum_{h=1}^{k}\rho_hX_h+v_i+u_i$$

where

$\ln C$ = the natural logarithm of total cost;

$\ln Y$ = the natural logarithm of a vector of hospital outputs;

$\ln W$ = the natural logarithm of a vector of input prices;

$\ln B$=the natural logarithm of a vector of fixed factors;

X = the natural logarithm of a vector of all other environmental factors that influence hospital costs.

The appropriate sets of parametric restrictions[1] are imposed on the above cost function:

[1] Appendix 3.1 provides the sets of parametric restrictions imposed.

Symmetry of the translog cost function requires: $\gamma_{ih}=\gamma_{hi}$ for all i and h, $\delta_{ir}=\delta_{jr}$ for all j and r, according to Young's theorem.

Linear homogeneity in the input prices is imposed by the following restrictions:

$$\sum_{j=1}^{n}\beta_j = 1; \quad \sum_{j=1}^{n}\delta_{jr} = 0 \text{ for all } r; \quad \sum_{j=1}^{n}\phi_{ij} = 0 \text{ for all } i; \quad \sum_{j=1}^{n}\vartheta_j = 0;$$

The cost function defines the minimum cost of producing a certain vector of outputs given the input prices. Duality theory (Shephard, 1953 and 1970) defines the link (under certain regularity assumptions) between the production and the cost functions of a firm. Application of Duality theory with its underlying conditions of an optimizing behavior precludes (eliminates) any kind of inefficiency (Färe, Grosskorpf, and Lovell 1985). However, relaxation of the more strict assumptions makes possible the coexistence of Duality and inefficiency. The estimation of the cost function is preferable to the estimation of the production function given the multi-output nature of hospitals. The estimation of the cost function makes possible, based on the duality principle, the recovery of the characteristics of the production function. Färe and Primont, (1995), have shown that the cost of using duality, in terms of lost information from the conversion, is minimal for both deterministic and stochastic frontiers. The empirical results of four cost specifications follow. Specifically, OLS estimates corrected for heteroscedasticity and OLS estimates with weighted variables are presented in tables 3-2 and 3-3 respectively. Table 3-4 presents estimates pertaining to stochastic frontier. An additional stochastic cost frontier model with case-mix adjusted admissions and patient days is included (table 3-5). Discussion of empirical findings follows (section 3.6).

3.5 Empirical Results

Table 3-2:

OLS: CORRECTED FOR HETEROSCEDASTICITY

Dependent variable is the Log of Total Cost
Model size: Observations = 83,
Parameters = 41, Deg.Fr. = 42
R-squared =0.98020, Adjusted R-squared = 0.96135
Model test: F[40, 42] = 51.99, Prob value = 0.00000
Breusch - Pagan chi-squared = 32.7097, with 40 degrees of freedom

Variable Description		Coefficient	Standard Error	t-ratio	P[|T|>t]
Constant	α_0	0.23739	0.84567E-01	2.807	0.00755
Admissions	Y1	0.32709	0.82596E-01	3.960	0.00028
Pat.Days	Y2	0.24457	0.70027E-01	3.493	0.00114
Visits	Y3	0.19339	0.62824E-01	3.078	0.00366
PhysHours	PH	0.59889E-01	0.12690E-01	4.719	0.00003
RNS	X1	0.47585	0.75755E-01	6.281	0.00000
RNS*RNS	X11	-0.74937	0.48264	-1.553	0.12801
CLR	X2	0.15820	0.74955E-01	2.111	0.04081
CLR*CLR	X22	-0.20021	0.20472	-0.978	0.33369
Supplies	X3	0.15259	0.51074E-01	2.988	0.00468
Supp*Supp	X33	-0.47286	0.21130	-2.238	0.03059
Contract	X4	0.63349E-01	0.28688E-01	2.208	0.03274
Contr*Contr	X44	0.37367E-01	0.59145E-01	0.632	0.53095
Adm*Adm	Y11	-0.55747	0.39814	-1.400	0.16880
PDays*Pdays	Y22	-0.65483	0.32837	-1.994	0.05265
Vis*Vis	Y33	-0.79222	0.22185	-3.571	0.00091
PHours*PHours	PH2	0.22000E-01	0.12329E-01	1.784	0.08159
Adm*PDays	Y12	0.48160	0.33203	1.450	0.15435
Adm*Vis	Y13	0.46594	0.18711	2.490	0.01681
PDays*Vis	Y23	0.15800E-02	0.26528	0.006	0.99528
Adm*RNS	Y1X1	-0.58003	0.36621	-1.584	0.12073
Adm*CLR	Y1X2	0.62829	0.44002	1.428	0.16072
Adm*Supp	Y1X3	0.33013	0.17418	1.895	0.06494
Adm*Contr	Y1X4	0.35301E-01	0.10465	0.337	0.73754
PDays*RNS	Y2X1	-0.38761E-01	0.48244	-0.080	0.93635
PDays*CLR	Y2X2	-0.46881	0.56777	-0.826	0.41364
PDays*Supp	Y2X3	0.12960	0.23991	0.540	0.59190
PDays*Contr	Y2X4	0.98417E-01	0.87515E-01	1.125	0.26715
Vis*RNS	Y3X1	0.73322	0.32453	2.259	0.02911
Vis*CLR	Y3X2	0.26382E-01	0.31327	0.084	0.93329
Vis*Supp	Y3X3	-0.79407	0.19298	-4.115	0.00018
Vis*Contr	Y3X4	-0.14295	0.97323E-01	-1.469	0.14933
RNS*CLR	X12	0.15020	0.32007	0.469	0.64130
RNS*Supp	X13	0.63535	0.26987	2.354	0.02331
RNS*Contr	X14	0.59879E-01	0.12554	0.477	0.63587
CLR*Supp	X23	-0.25171E-01	0.20512	-0.123	0.90292
CLR*Contr	X24	0.21090	0.12496	1.688	0.09887
Supp*Contr	X34	-0.30741	0.10585	-2.904	0.00585
% Mcaid Adm	PADMD	0.55787	0.11806	4.725	0.00003
% Bed MSA	MSABED	-0.25213	0.10204	-2.471	0.01762
% SDS Visits	VSDS	-1.1206	0.68253	-1.642	0.10811

Table 3-3:

OLS: WEIGHTED REGRESSION

Dependent variable is the Log of Total Cost
Model size: Observations = 83,
Parameters = 41, Deg.Fr. = 42
R-squared = 0.99627, Adjusted R-squared = 0.99273
Model test: F[40, 42] = 280.76, Prob value = 0.00000

Variable Description		Coefficient	Standard Error	z=b/s.e.	P[|Z|>z]
Constant	α_0	0.25275	0.84183E-01	3.002	0.00268
Admissions	Y1	0.30131	0.85105E-01	3.541	0.00040
Pat.Days	Y2	0.28683	0.79270E-01	3.618	0.00030
Visits	Y3	0.19848	0.61979E-01	3.202	0.00136
PhysHours	PH	0.53109E-01	0.13322E-01	3.986	0.00007
RNS	X1	0.48219	0.74764E-01	6.450	0.00000
RNS*RNS	X11	-0.72257	0.41400	-1.745	0.08093
CLR	X2	0.13393	0.70774E-01	1.892	0.05844
CLR*CLR	X22	-0.12872	0.18600	-0.692	0.48892
Supplies	X3	0.16453	0.53929E-01	3.051	0.00228
Supp*Supp	X33	-0.41562	0.20139	-2.064	0.03904
Contract	X4	0.68390E-01	0.29380E-01	2.328	0.01992
Contr*Contr	X44	0.45541E-01	0.58767E-01	0.775	0.43837
Adm*Adm	Y11	-0.30905	0.37852	-0.816	0.41424
PDays*Pdays	Y22	-0.49379	0.32078	-1.539	0.12372
Vis*Vis	Y33	-0.83695	0.22071	-3.792	0.00015
PHours*PHours	PH2	0.19217E-01	0.11172E-01	1.720	0.08543
Adm*PDays	Y12	0.20382	0.29064	0.701	0.48313
Adm*Vis	Y13	0.47459	0.20470	2.319	0.02042
PDays*Vis	Y23	0.64678E-01	0.27840	0.232	0.81629
Adm*RNS	Y1X1	-0.35683	0.34045	-1.048	0.29459
Adm*CLR	Y1X2	0.43589	0.39627	1.100	0.27134
Adm*Supp	Y1X3	0.29922	0.17866	1.675	0.09397
Adm*Contr	Y1X4	0.35577E-01	0.10902	0.326	0.74417
PDays*RNS	Y2X1	-0.45720	0.42692	-1.071	0.28421
PDays*CLR	Y2X2	-0.15859	0.50291	-0.315	0.75251
PDays*Supp	Y2X3	0.17756	0.24918	0.713	0.47611
PDays*Contr	Y2X4	0.11505	0.89448E-01	1.286	0.19835
Vis*RNS	Y3X1	0.84126	0.27369	3.074	0.00211
Vis*CLR	Y3X2	-0.67339E-01	0.26668	-0.253	0.80065
Vis*Supp	Y3X3	-0.78938	0.19385	-4.072	0.00005
Vis*Contr	Y3X4	-0.15731	0.10308	-1.526	0.12700
RNS*CLR	X12	0.99143E-01	0.27114	0.366	0.71462
RNS*Supp	X13	0.64939	0.22984	2.825	0.00472
RNS*Contr	X14	0.34095E-01	0.11532	0.296	0.76748
CLR*Supp	X23	-0.61484E-01	0.19220	-0.320	0.74905
CLR*Contr	X24	0.24598	0.11474	2.144	0.03206
Supp*Contr	X34	-0.33144	0.10427	-3.179	0.00148
% Mcaid Adm	PADMD	0.51848	0.12615	4.110	0.00004
% Bed MSA	MSABED	-0.28087	0.10213	-2.750	0.00596
% SDS Visits	VSDS	-1.0686	0.65146	-1.640	0.10095

Table 3-4:

STOCHASTIC FRONTIER HOSPITAL COST FUNCTION ESTIMATES

Dependent variable	Log of Total Cost	N=83
Log likelihood function	193.7419	
Variance components:	$\sigma^2(v)$= 0.00014	
	$\sigma^2(u)$= 0.00131	

Variable Description		Coefficient	Standard Error	z=b/s.e.	P[|Z|>z]
Constant	α_0	0.17640	0.71887E-01	2.454	0.01414
Admissions	Y1	0.30108	0.66681E-01	4.515	0.00001
Pat.Days	Y2	0.25868	0.65333E-01	3.959	0.00008
Visits	Y3	0.20312	0.56559E-01	3.591	0.00033
PhysHours	PH	0.61041E-01	0.12396E-01	4.924	0.00000
RNS	X1	0.52048	0.70961E-01	7.335	0.00000
RNS*RNS	X11	-0.75473	0.52520	-1.437	0.15071
CLR	X2	0.90284E-01	0.59985E-01	1.505	0.13229
CLR*CLR	X22	-0.48105E-01	0.26102	-0.184	0.85378
Supplies	X3	0.17614	0.51440E-01	3.424	0.00062
Supp*Supp	X33	-0.35868	0.21802	-1.645	0.09994
Contract	X4	0.64857E-01	0.19408E-01	3.342	0.00083
Contr*Contr	X44	0.46930E-01	0.39087E-01	1.201	0.22989
Adm*Adm	Y11	-0.28244	0.45246	-0.624	0.53247
PDays*Pdays	Y22	-0.39837	0.36365	-1.095	0.27331
Vis*Vis	Y33	-0.89016	0.23416	-3.801	0.00014
PHours*PHours	PH2	0.26035E-01	0.13404E-01	1.942	0.05210
Adm*PDays	Y12	0.11551	0.34604	0.334	0.73852
Adm*Vis	Y13	0.47329	0.22929	2.064	0.03900
PDays*Vis	Y23	0.15671	0.26338	0.595	0.55185
Adm*RNS	Y1X1	-0.57519	0.37415	-1.537	0.12422
Adm*CLR	Y1X2	0.57526	0.34888	1.649	0.09917
Adm*Supp	Y1X3	0.25532	0.23414	1.090	0.27550
Adm*Contr	Y1X4	0.59798E-01	0.78330E-01	0.763	0.44522
PDays*RNS	Y2X1	-0.19102	0.53289	-0.358	0.71999
PDays*CLR	Y2X2	-0.38897	0.51885	-0.750	0.45345
PDays*Supp	Y2X3	0.30378	0.23973	1.267	0.20510
PDays*Contr	Y2X4	0.66537E-01	0.83222E-01	0.800	0.42399
Vis*RNS	Y3X1	0.89054	0.26825	3.320	0.00090
Vis*CLR	Y3X2	-0.52919E-01	0.23345	-0.227	0.82067
Vis*Supp	Y3X3	-0.78224	0.19562	-3.999	0.00006
Vis*Contr	Y3X4	-0.15214	0.70681E-01	-2.152	0.03136
RNS*CLR	X12	0.70091E-01	0.32542	0.215	0.82947
RNS*Supp	X13	0.66200	0.24982	2.650	0.00805
RNS*Contr	X14	0.65127E-01	0.90189E-01	0.722	0.47022
CLR*Supp	X23	-0.47297E-01	0.25396	-0.186	0.85226
CLR*Contr	X24	0.18502	0.94282E-01	1.962	0.04971
Supp*Contr	X34	-0.31696	0.83259E-01	-3.807	0.00014
% Mcaid Adm	PADMD	0.56585	0.11670	4.849	0.00000
% Bed MSA	MSABED	-0.24402	0.90954E-01	-2.683	0.00730
% SDS Visits	VSDS	-0.74804	0.49548	-1.510	0.13111
λ (lamda)	σ_u/σ_v	3.1037	1.3479	2.303	0.02130
σ	$\sqrt{(\sigma^2_u+\sigma^2_v)}$	0.38030E-01	0.47614E-02	7.987	0.00000

Table 3-5:

STOCHASTIC FRONTIER HOPSITAL COST FUNCTION ESTIMATES
(CASE-MIX[2] ADJUSTED MODEL)

Dependent variable	Log of Total Cost	N=83
Iterations completed	54	
Log likelihood function	174.7303	
Variance components:	$\sigma^2(v)$= 0.00045	
	$\sigma^2(u)$= 0.00121	

Variable Description		Coefficient	Standard Error	z=b/s.e.	P[|Z|>z]
Constant	α_0	0.12021	0.75246E-01	1.598	0.11015
Admissions	Y1	0.34391	0.74093E-01	4.642	0.00000
Pat.Days	Y2	0.17888	0.82609E-01	2.165	0.03036
Visits	Y3	0.15264	0.68795E-01	2.219	0.02650
PhysHours	PH	0.71686E-01	0.11664E-01	6.146	0.00000
RNS	X1	0.49978	0.73774E-01	6.774	0.00000
RNS*RNS	X11	-0.89748	0.40723	-2.204	0.02753
CLR	X2	0.31656	0.61144E-01	5.177	0.00000
CLR*CLR	X22	-0.63247E-01	0.17805	-0.355	0.72242
Supplies	X3	0.16710E-01	0.58371E-01	0.286	0.77467
Supp*Supp	X33	-0.98315	0.19791	-4.968	0.00000
Contract	X4	0.41732E-01	0.30717E-01	1.359	0.17427
Contr*Contr	X44	0.43441E-01	0.52690E-01	0.824	0.40968
Adm*Adm	Y11	0.13802	0.48015	0.287	0.77377
PDays*Pdays	Y22	-0.54141	0.34351	-1.576	0.11500
Vis*Vis	Y33	-1.0915	0.24019	-4.544	0.00001
PHours*PHours	PH2	0.16863E-01	0.11394E-01	1.480	0.13888
Adm*PDays	Y12	-0.11841	0.36604	-0.323	0.74632
Adm*Vis	Y13	0.44069	0.23873	1.846	0.06489
PDays*Vis	Y23	0.14323	0.30574	0.468	0.63945
Adm*RNS	Y1X1	-0.96703	0.38631	-2.503	0.01231
Adm*CLR	Y1X2	1.1281	0.33875	3.330	0.00087
Adm*Supp	Y1X3	0.36144	0.26015	1.389	0.16473
Adm*Contr	Y1X4	0.12111	0.98870E-01	1.225	0.22059
PDays*RNS	Y2X1	0.41931	0.44349	0.945	0.34441
PDays*CLR	Y2X2	-1.5974	0.36465	-4.381	0.00001
PDays*Supp	Y2X3	0.28691	0.29852	0.961	0.33650
PDays*Contr	Y2X4	0.11142	0.10330	1.079	0.28077
Vis*RNS	Y3X1	0.56821	0.28556	1.990	0.04662
Vis*CLR	Y3X2	0.58314	0.23569	2.474	0.01335
Vis*Supp	Y3X3	-1.0907	0.19359	-5.634	0.00000
Vis*Contr	Y3X4	-0.25336	0.10880	-2.329	0.01988
RNS*CLR	X12	-0.94325E-01	0.26763	-0.352	0.72451
RNS*Supp	X13	0.78708	0.21759	3.617	0.00030
RNS*Contr	X14	0.10453	0.11484	0.910	0.36267
CLR*Supp	X23	0.36072	0.20589	1.752	0.07977
CLR*Contr	X24	0.11809	0.11322	1.043	0.29695
Supp*Contr	X34	-0.32744	0.97609E-01	-3.355	0.00079
% Mcaid Adm	PADMD	0.54461	0.11524	4.726	0.00000
% Bed MSA	MSABED	-0.18585	0.98249E-01	-1.892	0.05854
% SDS Visits	VSDS	0.87740	0.55818	1.572	0.11598
λ (lamda)	σ_u/σ_v	1.6357	0.34825	4.697	0.00000
σ	$\sqrt{(\sigma^2_u+\sigma^2_v)}$	0.40760E-01	0.51905E-02	7.853	0.00000

[2] Appendix 3.2 briefly evaluates this model.

3.6 Cost Function Diagnostics

The economic behavior of the firm has a "dual" representation of its optimum properties, as the two functions, (production and cost), contain the same information. Duality theory ensures that under certain regularity conditions the cost function can be used to derive a description of the characteristics of the production function. The development of duality theory that links the production with the cost function advanced significantly the estimating techniques of the two functions. Assuming cost minimizing behavior and certain regularity conditions (positivity, homogeneity, monotonicity, and concavity), a well-behaved cost function can be estimated empirically and the structure of production can be recovered (Färe and Primont, 1995). The production function limits the empirical analysis to a single output or an aggregated output index and so it is subject to possible misspecification problems. However, the cost function can be used in the estimation of multiple output as well as multiple input productive units.

The cost and its "dual" production characteristics are derived in this section. The OLS characteristics are almost similar to the stochastic frontier characteristics.

Multicollinearity as expected exists in this single equation model. The VIF indicators have values above 10 for the outputs and inputs. Particularly the squared and the interaction variables are highly correlated. Despite the high degree of collinearity, the majority of coefficients are statistically significant (OLS model). The explanatory power of all equations estimated is very good - a characteristic of the translog specification -and the model overall is highly significant. The functional form was tested against the simpler Cobb-Douglas. The null hypothesis that all the higher order terms jointly equal zero is rejected.

Testing the specification for omitted variables, the Ramsey RESET-test fails to reject the hypothesis that the model has no omitted variables. The probability value for this test (F-test) is 96 percent. The Ramsey-test uses powers of the fitted values of the original model, which will be zero under the assumption of no specification error.

Also, a specification test, the link test, based on Tukey (1949) and Pregibon (1980) for the specification of the dependent variable can be used for the correct specification of the independent variables. The dependent variable is regressed on its prediction and its prediction squared. The significance of the two coefficients in this regression provides evidence of incorrect specification. The link test, also, supports the correct specification hypothesis of the model.

The presence of heteroscedasticity is not significant (OLS model) as the Breusch-Pagan test indicates (Table 3-2). A second test, the Coo-Weisberg for heteroscedasticity, that models the variance as a function of the fitted values of the dependent variable indicates homescedastic errors. However, the presence of a lower degree of heteroscedasticity can bias the inefficiency index, so a weighted model is estimated based on the residuals of the OLS regression.

From the analysis that follows, the model exhibits all the expected properties of a well-behaved cost function. The cost function evaluated at the point of means is an increasing function of outputs and input prices.

The cost elasticities for the three output measures (Admissions, Inpatient Days and Outpatient Visits) are obtained by differentiating the cost function with respect to each output.

(3.6)-1

$$\frac{\partial \ln C}{\partial \ln Y_i} = \left(\frac{Y_i}{C}\right)\left(\frac{\partial C}{\partial Y_i}\right) = \left(\frac{MC_{Y_i}}{AC_{Y_i}}\right) = \alpha_i + \sum_{h}^{m} \gamma_{ih} \ln Y_h + \sum_{j}^{n} \phi_{ij} \ln W_j + \pi_i \ln B \qquad \text{(i=1......... m)}$$

Because of the normalization of variables around their means the cost elasticities equal to the first order output coefficients (the higher order terms equal zero).

To derive the marginal cost estimates, the cost elasticity of each output is multiplied by the fitted cost and divided by the actual output.

$$MC_{Y_i} = \alpha_i \left(\frac{\hat{C}}{Y_i}\right) \qquad \text{(3.6)-2}$$

The output elasticities and marginal costs are consistent with the findings reported in the literature. The marginal cost of admitting one more patient is $1,888.5. The marginal cost of an additional patient day is $263.3 while the extra visit costs the hospital $80.1, all evaluated at their means.

Table 3-6: Output Cost Elasticities and Marginal Costs

	Elasticities OLS[a]	Elasticities Frontier[b]	Marginal Cost OLS[a]	Marginal Cost Frontier[b]
Admissions	0.32709	0.30108	$2.076.2	$1888.5
	(3.960)	(4.515)	(3.960)	(4.515)
Patient Days	0.24457	0.25868	$226.1	$236.3
	(3.493)	(3.959)	(3.493)	(3.959)
Outpatient Visits	0.19339	0.20312	$77.2	$80.1
	(3.078)	(3.591)	(3.078)	(3.591)

a: t-statistics in parentheses
b: asymptotic z-statistics in parentheses

The overall economies of scale for a multi-product translog cost function are determined according to the following formula (Cowing and Holtman, 1983), which is the extension of the single-output function:

(3.6)-3

$$SCE = 1 - \sum_{i}^{m} \frac{\partial \ln C}{\partial \ln Y_i} = 1 - \left(\sum_{i}^{m} \alpha_i + \sum_{i}^{m} \sum_{h}^{m} \gamma_{ih} \ln Y_h + \sum_{i}^{m} \sum_{j}^{n} \phi_{ij} \ln W_j + \sum_{i}^{m} \pi_i \ln B \right)$$

Since the variables are mean-scaled all the second order terms equal to zero. Therefore, the SCE reduces to: $SCE = 1 - \sum_{i}^{m} \alpha_i$

Table 3-7: Economies of scale

OLS	Frontier
0.23495	0.23712
(4.570)	(5.383)

Asymptotic z-statistics in parentheses

Positive SCE value indicates scale economies and negative SCE value indicates scale diseconomies.

SCE reflects the percentage change in total cost resulted from a simultaneous percentage change in all three outputs. Which means that a 10% proportional increase of all outputs (holding physician hours constant) would increase total cost by 2.4% (less than 10%).

The Allen-Uzawa partial elasticities of substitution for the translog cost function, are calculated as :

(3.6)-5

$$\sigma_{ih} = \left(\frac{\delta_{ih} + S_i S_h}{S_i S_h} \right) = \left(\frac{\delta_{ih} + \beta_i \beta_h}{\beta_i \beta_h} \right) \quad \text{and} \quad \sigma_{ii} = \left(\frac{\delta_{ii} + S_i^2 - S_i}{S_i^2} \right) = \left(\frac{\delta_{ii} + \beta_i^2 - \beta_i}{\beta_i^2} \right)$$

Because of normalization of the sample the first order coefficients are cost elasticities and fitted shares of inputs. The factor demand for inputs elasticities, own and cross, can be obtained using the above elasticities of substitution:

$$\varepsilon_{ih} = \sigma_{ih} S_h \quad \text{and} \quad \varepsilon_{ii} = \sigma_{ii} S_i \tag{3.6)-6}$$

Table 3-8: Allen-Uzawa Factor Demand Elasticities (Own-Cross) -Frontier

	RNS	CLR	PSUP	PCSER	PCAP
X1=RNS	-1.9296	1.2968	4.2789	1.5246	0.23389
	(-2.226)	(0.344)	(1.971)	(0.987)	(0.261)
X2=CLR	0.22495	-1.4425	-0.17824	2.9431	-0.98706
	(0.368)	(-0.516)	(-0.119)	(1.895)	(-1.260)
X3=PSUP	1.4481	-0.34774	-2.8603	-4.7108	0.58718
	(4.011)	(-0.114)	(-1.719)	(-2.140)	(0.645)
X4=PCSER	0.18999	2.1142	-1.7346	-0.21156	0.19893
	(1.153)	(1.187)	(-2.162)	(-0.384)	(0.701)
X5=PCAP	0.06662	-1.6207	0.49420	0.45471	-0.03294
	(0.273)	(-1.044)	(0.552)	(0.604)	(-0.043)

Asymptotic z-statistics in parentheses

The expected negative sign of own price elasticities is obtained for all inputs indicating negatively sloped demand for inputs and a well-behaved cost function. Supplies is the most elastic input to price changes. The own price elasticities of RN and Supplies are statistically significant at the 2.6 and 8.6 levels of significance, respectively. The elasticities of CLR, Contract Services and Capital are statistically insignificant.

The cross-price elasticities of demand are the indicators of net substitution in production. The positive cross-price elasticities of demand indicate substitute factors and the negative complementary factors. The negative elasticity of substitution reflects the absence of competition between the two factors but also reflects the lack of opportunities to gain in efficiency by substituting a cost inflated input (Estaugh, 1992). The cross-price elasticity reveals high and significant substitutability between RN Services and Supplies, and complementarity between supplies and contract services.

Table 3-9: Allen-Uzawa Factor Elasticities of substitution

	RNS	CLR	PSUP	PCSER
CLR	2.4916			
	(0.351)			
PSUP	8.2212	-1.9742		
	(2.381)	(-0.113)		
PCSER	2.9293	32.598	-26.745	
	(1.009)	(1.159)	(-1.737)	
PCAP	0.44938	-10.933	3.3337	3.0672
	(0.263)	(-1.035)	(0.594)	(0.635)

Asymptotic z-statistics in parentheses

The elasticities of substitution that measure the change in relative input shares caused by the change in their relative prices, indicate the large substitution possibilities between RN Services and Supplies, RN Services and Contract Services. The elasticities of substitution are different from unity and support the translog specification against the Cobb-Douglas.

3.7 Stochastic Frontier Estimated Inefficiency

Table 3-10

Descriptive Statistics: Hospital Stochastic Frontier Cost Inefficiency

Variable	Mean	Std. Dev.	Minimum	Maximum	1st Quart	Median	3rd Quart
INEFFICIENCY	0.0404	0.0417	0.0027	0.1528	0.0403	0.0777	0.1153
COST INEF/NCY	$4,292	$7,132	$127	$50,016	$12,599	$25,071	$37,544

Note: Cost inefficiency is in thousand of dollars.

The results indicate that the average inefficiency is 4.04 percent of total costs. The exponential specification yielded comparable results. The coefficient of correlation between the normal and exponential specification equals 0.9443. The hospital specific inefficiency ranges between 0.27 and 15.28 percent. Eleven hospitals have an inefficient index that exceeds 10 percent.

This estimate can be translated into a dollar value. Inefficiency causes each hospital on average $4,292.67 thousand additional spending. The excess cost of inefficient hospitals ranges between $127.2 and $50,015.71 thousand.

Appendix 3.3 illustrates the distribution of the hospital stochastic cost frontier function. Since the determinants of hospital performance are of considerable interest, the estimated hospital specific inefficiency (index) of the stochastic frontier is modeled in section 6. The stochastic inefficiency scores will be compared with inefficiency estimates obtained using alternative DEA formulations.

Appendix 3.1

Parametric Restrictions of the Hospital Cost Function

Economic theory requires that the cost function be linearly homogeneous in all input prices:

$$\sum_{j=1}^{n}\beta_j = 1; \quad \sum_{j=1}^{n}\delta_{jr} = 0 \ \text{ for all } r; \quad \sum_{j=1}^{n}\phi_{ij} = 0 \ \text{ for all } i; \quad \sum_{j=1}^{n}\vartheta_j = 0;$$

$\Sigma\beta_j = 1$	$\beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 = 1$	$\beta_5 = 1 - (\beta_1 + \beta_2 + \beta_3 + \beta_4)$
$\Sigma\delta_{jr} = 0$ for all r	$\delta_{11} + \delta_{12} + \delta_{13} + \delta_{14} + \delta_{15} = 0$	$\delta_{15} = -(\delta_{11} + \delta_{12} + \delta_{13} + \delta_{14})$
	$\delta_{12} + \delta_{22} + \delta_{23} + \delta_{24} + \delta_{25} = 0$	$\delta_{25} = -(\delta_{12} + \delta_{22} + \delta_{23} + \delta_{24})$
	$\delta_{13} + \delta_{23} + \delta_{33} + \delta_{34} + \delta_{35} = 0$	$\delta_{35} = -(\delta_{13} + \delta_{23} + \delta_{33} + \delta_{34})$
	$\delta_{14} + \delta_{24} + \delta_{34} + \delta_{44} + \delta_{45} = 0$	$\delta_{45} = -(\delta_{14} + \delta_{24} + \delta_{34} + \delta_{44})$
	$\delta_{15} + \delta_{25} + \delta_{35} + \delta_{45} + \delta_{55} = 0$	$\delta_{55} = -(\delta_{15} + \delta_{25} + \delta_{35} + \delta_{45})$
$\Sigma\phi_{ij} = 0$ for all j	$\phi_{Y1X1} + \phi_{Y1X2} + \phi_{Y1X3} + \phi_{Y1X4} + \phi_{Y1X5} = 0$	$\phi_{Y1X5} = -(\phi_{Y1X1} + \phi_{Y1X2} + \phi_{Y1X3} + \phi_{Y1X4})$
	$\phi_{Y2X1} + \phi_{Y2X2} + \phi_{Y2X3} + \phi_{Y2X4} + \phi_{Y2X5} = 0$	$\phi_{Y2X5} = -(\phi_{Y2X1} + \phi_{Y2X2} + \phi_{Y2X3} + \phi_{Y2X4})$
	$\phi_{Y3X1} + \phi_{Y3X2} + \phi_{Y3X3} + \phi_{Y3X4} + \phi_{Y3X5} = 0$	$\phi_{Y3X5} = -(\phi_{Y3X1} + \phi_{Y3X2} + \phi_{Y3X3} + \phi_{Y3X4})$
	$\phi_{BEDX1} + \phi_{BEDX2} + \phi_{BEDX3} + \phi_{BEDX4} + \phi_{BEDX5} = 0$	$\phi_{BEDX5} = -(\phi_{BEDX1} + \phi_{BEDX2} + \phi_{BEDX3} + \phi_{BEDX4})$

Appendix 3.2

Descriptive Statistics of the Case Mix Adjusted Stochastic Frontier Model

The marginal costs of outputs for the case mix adjusted model are:

Variable	Marginal Cost	Standard Error	z=b/s.e.	P[|Z|>z]
Admissions	$1934.9	416.8	4.642	0.00000
Inpatient Days	$ 146.5	67.7	2.165	0.03036
Outpatient Visits	$ 53.9	24.3	2.219	0.02650

The inefficiency index obtained from the case mix adjusted model averages 3.39 percent. It ranges between 0.33 and 14.44 percent. The marginal cost of the case mix adjusted model is higher for the admissions and lower for the patient days and outpatient visits than the marginal costs obtained from the unadjusted model.

Appendix 3.3

The Distribution of the Stochastic Frontier Hospital Cost Inefficiency

The distribution of the hospital cost inefficiency is illustrated below.

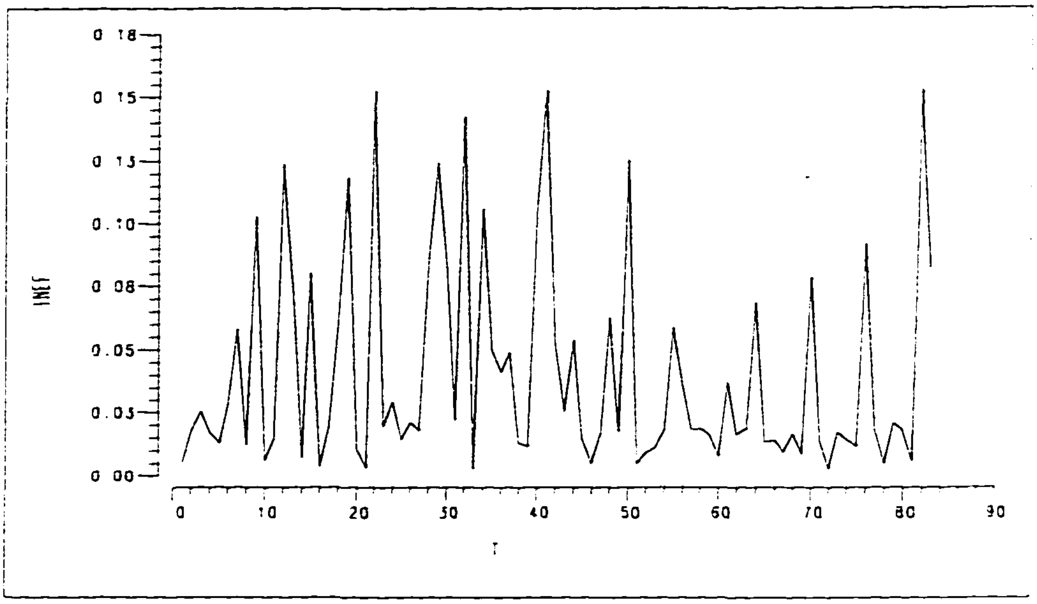

Figure 3.1: Hospital Specific Inefficiency

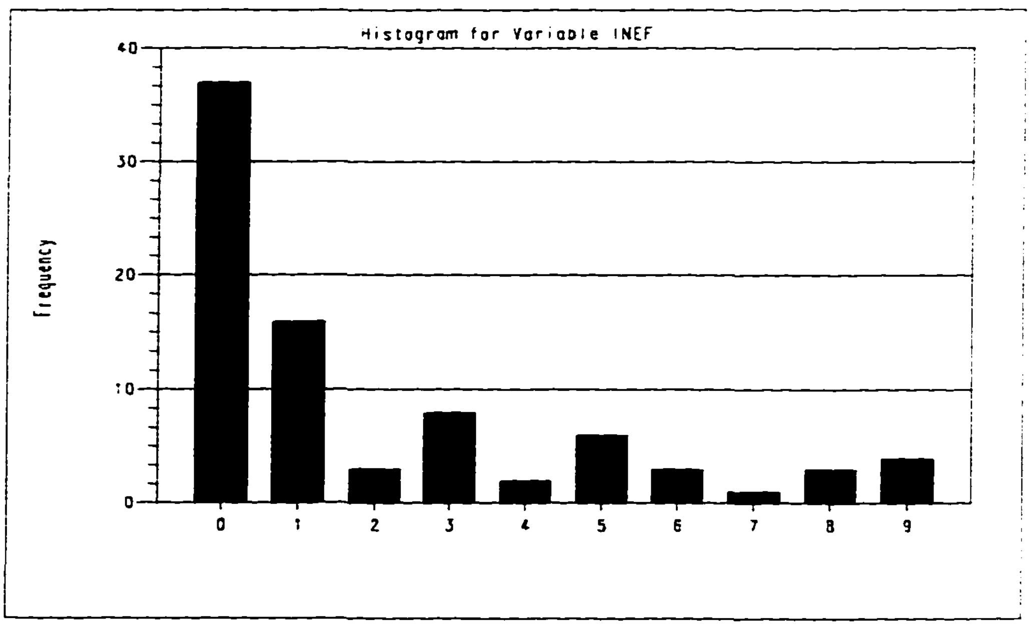

Figure 3.2: The Distribution of Hospital Cost Inefficiency

4

The Administrative Hospital Cost Frontier Function

4.1 Introduction

The administrative cost debate motivated by the work of Himmelstein and Woolhandler (1986) and Woolhandler and Himmelstein (1991). The two studies advocate a single-payer health care system for the United States and evaluate the administrative cost savings that could be achieved under such a system. A number of studies continued the debate presenting estimates of the costs of administering health care as part of a proposed overall reform of the health care system [Himmelstein et al. (1986); Hellander et al. (1994); Poullier (1992); Sheils et al. (1992); Woolhandler et al. (1991)] as well as providing or criticizing definitional and theoretical issues [Thorpe (1992); Gauthier et al. (1992); Danzon (1992)]. The lack of a common conceptual definition on administrative costs and the lack of adequate and consistent information from which to make calculations resulted in estimates that vary widely and in most cases can not be compared. The character of the research environment within which the search for "accurate estimates" of administrative costs is taking place actually describes the complexity of the health care system itself.

At least one researcher has concluded that administrative costs account for almost one fourth of all health care expenditures (Hellander et al., 1994). This alone focuses attention on the question of efficiency in administration.

Several definitions of administrative costs have been used by researchers pursuing the problems of measuring such costs. The National Health Account's (NHA) definition is widely used as the basis for estimating insurers' administrative costs. However, this definition excludes the administrative costs incurred by providers, employers and consumers and understates the level of administrative cost of the health care system (Evans, 1990).

Thorpe (1992) provided the basis for the conceptual framework for accurate measurement of administrative costs. He developed four functions (transaction related activities, benefits management, selling and marketing, and regulation/compliance) for each of six sectors (insurers, hospitals, physicians, nursing homes, employers, consumers) of the health care system. Thorpe pointed out the difficulty of identifying administrative costs. He described the components of each function, but existing studies illustrate how difficult the operationalization of the concept is rather than a conceptual definition as such. Studies published after Thorpe's conceptual framework continue to speculate and accumulate information from different sources to form estimates. One of the most important impediments is the lack of reliable accounting-type data.

4.2. Hospital Administration and its Structure

The difficulty of measuring administrative costs of hospitals is attributed to multi-product nature of hospital services, diversity of services, and to the variety of inputs used. Hospitals are organizations consisting of many departments that perform different functions but each department supports the hospital's main objective; the provision (production) of health care (AHA, 1986). In addition to medical care, hospitals produce clinical research and medical education programs.

The administrative department provides a variety of complex functions. The first step in deriving an estimate of the total cost of administration is the provision of a descriptive list of these functions and services.

The following table illustrates Thorpe's listing of administrative cost functions in hospitals. The hospital is guided to its objectives by the policy-making administrative staff that manages all hospital's operations. The policy-making administrative staff includes the CEO (chief executive officer), presidents, vice-presidents, and heads of the departments. The complexity of hospital's administration depends mainly on its type (f.e. HMO), the size of the hospital, as well as on government initiatives, reimbursement policies, market and social forces, physician and medical staff integration, and medical technology.

The admitting office performs a variety of tasks such as providing information and communication services, appointing, scheduling, reservation, reception, registration, orientation, census management, coordination of initial tests, and discharge notification. The admitting office often performs all these functions for inpatient, outpatient and emergency patients. The degree of automation (i.e. manual level -typewriters-, automated or computerized) of this administrative function may affect admitting office's costs and efficiency significantly. Computerized admitting offices allow patient registration/scheduling etc to be centralized, eliminating duplication, reducing paperwork and permitting intra-hospital flow of information.

The fiscal department performs the business functioning of the hospital firm dealing with patient accounts and payroll services as well as accounting services, budgeting, monitoring, and auditing. The billing function, one of the most complex functions of the fiscal department, consists of patient eligibility verification, claims submission and claims processing, coordination of benefits, collection of payments and remittance advice. The complexity of this function is heavily influenced by the multiple-payer character of the American health system as well as by the technological level of the function.

Table 4-1.

Administrative Cost Functions in Hospitals			
Function	**Output**	**Costs**	**Factors Influencing Costs**
Transaction Related	Patient Care, Sales, Revenue	Admitting, Billing, Account Receivable, Collections	Type of MIS, Uniformity of reimbursement system
Benefits Management	as above	Quality assurance, Medical records, Data processing	% of bills elect/ly filed, Scope and mixed of services
Sales and Management	Clinical Outcomes, Research, Education	Strategic planning, Finance control, Public relation, Advertising	Market Competition, Regulation, Ownership (public, for-profit, etc)
Regulation/Compliance	as above	Peer Review Organizations	State and Federal Laws

Source: Thorpe, K., 1992.

Computerization of this function is very important to administrative efficiency. Intra-hospital information networks that facilitate the flow of information among departments and inter-computer networks that link the hospital with its trading partners (payers, employers, physicians, patients) can provide organizational advantages streamlining administrative costs. Under the supervision of the chief financial administrator or another administrator, the data processing department (Hospital Information System), one of the most dynamic hospital departments, coordinates the flow of information within the hospital and with other parties located outside through computerized technology.

The medical record department, an important element of administration, is responsible for maintaining patient records. Medical records involve the functions of record filing, indexing, storing, sand retrieving patient's medical and administrative information. Like a health information bank for patients, medical records, provide information to practitioners and facilitate the flow of information for reimbursement policies, quality assurance and utilization review. The department's costs depend on the system used: paper or electronic. The computerized patient record recommended by the Institute of Medicine provides the state of the art technology for this department and a promise for significant cost savings.

Hospitals use a variety of Information Systems (AHA, 1986):

1. Shared-systems where the hospital shares a computerized information system with other hospitals,
2. "Turnkey-systems" where the venture installs and maintains the information system,
3. Customized-systems installed, developed and maintained by own technical resources,
4. Contracted facilities management services, where the hospital contracts on-site management, technical and data processing services.

The information system services are available for administrative as well as medical and patient care needs.

EDI is a relatively new technology, which is gaining popularity in the health care industry. However, EDI systems have a different mission from the traditional intra-hospital information systems. EDI technology links the hospital with its outside partners by crossing its organizational boundaries.

4.3 Review of the literature

The literature provides a variety of administrative cost estimates of the U.S. health care system. Most estimates were created for comparisons of the current system with other systems (mainly the single payer Canadian health care system) and for reform proposals. Based on different definitions of what constitutes administrative cost and on incomplete data, the administrative cost estimates can not be compared. However, reported estimates indicate the existence and the magnitude of the administrative problem and the need for reform. Almost all studies include the three sectors of hospitals, payers and physicians in their estimates, which provide a base for comparisons.

Himmelstein and Woolhandler (1986) estimates initiated the administrative debate labeling the administrative cost, "waste," and emphasizing the need for reform of the system overall. They estimated the cost of administration to be $73.6 billion (in 1983 dollars) for the three sectors consuming almost one fifth of the total amount spent on health care. In a revised estimate for 1987, Woolhandler and Himmelstein (1991) shown that the administrative cost for the three sectors ranged between $90.4 and $114.0 billion. The 37 percent increase of administration between 1983 and 1987 alarmed policy makers and initiated the debate. The estimate of $118.4 billion for 1991, reported by GAO, (1991), was not consistent with the rate of growth of previous studies but confirmed the existence of the problem. Lewin-VHI, (1993), estimated an $125,6 billion administrative cost for 1991, based on the US CBO, (1991), study, while Sheils et al, (1992) reported an estimate of $175 billion for the same year.

Lewin-VHI, (1993) synthesized the above studies in a single estimate expressed in 1991 dollars. The synthesis provides an average estimate that links the differences of estimated methods. This estimate equals to $126.1 billion for the three sectors of the United States system. One of the latest studies by Hellander, Himmelstein, Woolhandler and Wolfe, (1994), following the sequence of Himmelstein et al, (1986) and Woolhandler et al, (1991) reported that administration consumed about 25 percent of the total health care expenditures ($220.3 billion) in 1993.

Table 4-2.

Estimates of Administrative Cost[a]: A review of the Literature[b]

Year	Hospitals	Health Insurance	Physicians	Total	Hospital administration % of Total Hospital Exp.
1983[1]	$26.9	$15.6	$31.1	$73.6	18.3%
1987[2]	$39.3	$25.3	$25.8-49.4	$90.4-114.0	20.2%
1991[3]	$43.7	$42.8	$31.9	$118.4	15.4%
1991[4]	$93.9	$38.2	$43.3	$175.4	33.4%
1991[5]	$41.0	$38.6	$45.9	$125.6	
1993[6]	$81.7	$54.3	$84.3	$220.3	24.8%
1991[7]	$44.7	$38.1	$43.3	$126.1	
1990[8]	$63.5				24.8%
1994[9]					26.0%

(a) In billions of dollars.
(b) Tsaprounis and Kirchhoff (1994)
(1) Himmelstein and Woolhandler (1986)
(2) Woolhandler and Himmelstein (1991)
(3) GAO (June 1991, April 1992)
(4) Sheils et al., (1992)
(5) CBO estimates calculated by Lewin-VHI (1993) and based on US CBO Dec., 1991.
(6) Hellander et al., (1994)
(7) Lewin-VHI (1993): A synthesis estimate that combines (2), (3), (4) and (5) in 1991 dollars.
(8) Woolhandler et al., (1993)
(9) Woolhandler et al., (1997)

Hospital administration on the above studies ranges between 15.4 and 33.4 percent of total hospital costs, Table 4-2. The above studies used different definitions of administration and different data sources. The definitions used by Himmelstein et al., (1986), Woolhandler et al., (1991), Hellander et al., (1994), and GAO, (1991) share a common definitional base including items such as general accounting, medical records, data processing, patient accounting and admitting. However, their data sources and estimated assumptions are very different. The first two studies use data on hospital administration from a single state (California), the third uses Medicare cost reports, and finally, GAO estimates are based on American Medical Association's Monitrend data. Sheils et al., (1992), define as administrative all functions but patient care, and include cafeteria and hospital net revenue in their estimate inflating administration to 33.4% of total.

Woolhandler and Himmelstein, (1997) continued the sequence of health care administrative cost studies and found that in 1994 the administrative share of hospitals reached 26 percent on average. The share of administration ranged between 22.9 percent for public hospitals to 34 percent for for-profit hospitals.

They concluded that competition and market forces tend to influence the size of administration.

The administrative cost is influenced heavily by the state's regulatory/competitive environment. In 1980's eight states adopted mandatory rate-setting programs and four states, including New Jersey and New York, implemented an all-payer regulatory approach. Studies found that hospitals that operate in a regulatory state environment (New York) incur lower administrative costs than hospitals that operate under more competitive systems (California's selective contracting competitive environment). Specifically, the percentage of administrative to total operating cost was estimated to be 14.14% in New York and 22.47% in California (Marder,1993).

Himmelstein et al., (1996) analyzed employment data (US Bureau of the Census March Current Population Survey) for the period 1968-1993. During this period the administrative employment of the health care sector increased from 0.719 to 2.792 million FTEs. The share of the health care employment to total employment increased from 18.1 percent to 27.1 percent. They found that a large proportion (27 percent) of health care employees produce mostly paperwork. This study will test the hypothesis posed by the authors: "Does more administration increase efficiency or waste time and trees?"

In addition, the effects of competition, and other hospital specific and hospital area characteristics will be investigated.

4.4 The Cost of Administration

The data used in this study, the 1993 New Jersey Actuals, provide a detailed and definitionally uniform data set (for 83 acute care hospitals) subject to the state regulatory guidelines. However, the uniformity of the state data does not insure applicability of findings at a national level.

Table 4-3.

Administrative Cost Structure			
	Total Cost ($000) Mean	**% of Total Cost TCOST**	**% of Administrative Cost ADMC**
TCOST	97941.57	100.00	------
ADMC	14323.78	15.14	100.00
A&G	6879.96	7.09	46.61
FIS	4112.05	4.55	30.04
MRD	957.10	1.05	7.03
PCC	952.25	1.03	6.84
OGS	866.59	0.84	5.72
PHY	195.27	0.20	1.23
DEPR	360.56	0.38	2.53

The total administrative cost is the sum of the following functions:

- A & G: Administrative and General (Outside Collection Costs etc),
- FIS: Fiscal (Inpatient Admitting/Billing/Accounts Receivable, Outpatient Registration/Billing/Accounts Receivable, Payroll),
- MRD: Medical Records,
- PCC: Patient Care Coordination (includes Utilization Review),
- OGS Other General Services Costs (includes only the items: Plant Related Security/other, and Clinically Related-Tumor Registry/Medical Library/Photo),

- PHY: Physician Coverage (includes the items: Medical Administration-Non Graduate Medical Education Programs).
- DEPR Deprecation and interest attributed to administration.

Costs related to Education and Research were excluded from the analysis. The following table provides a summary of the administrative functions:

4.5 Variables and Data

The total administrative cost is the dependent variable and is derived by summing up the costs of all non-patient functions devoted to administration.

The vector of output includes the number of inpatient admissions and outpatient visits as a proxy of the administrative production. The administrative hospital cost function, as the total hospital cost function, is a multi-product function in nature, but its outputs can be approximated by the total number of patients served (admitted inpatients and outpatients). A natural measure of administrative output, and a common base of administrative cost savings studies, is the number of claims. However, the definition of a "claim" is not common or widely accepted. A HCFA study (Lewin-VHI, 1993) and WEDI (WEDI, 1992, 1993) consider any line item on a billing statement (visit, test, procedure performed) as a separate claim.

Lewin-VHI defines a claim as the entire medical bill and not as a line item. A medical bill on average includes four line items "claims" (Lewin-VHI, 1993). Every inpatient admission and outpatient visit includes an unspecified number of "claims" as defined above. In this study a definition similar to that of Lewin-VHI is considered.

The vector of input prices includes:

(1) the hourly wage of the administrative personnel (total cost of clerical personnel divided by total hours),

(2) the price of administrative supplies and other expenditures is calculated as expenditures on administrative supplies and other expenditures divided by the number of beds,

(3) the price of contract services and lease services is calculated as expenditures divided by the sum of admissions and visits.

(4) the price of capital calculated as depreciation and interest of administrative equipment plus the proportion of fixed plant depreciation devoted to administration (total fixed plant depreciation multiplied by the share of administrative area) divided by the percentage of administrative area to total hospital.

(5) the wage of physicians on administrative tasks is calculated as cost per hour.

Other administrative cost determinants include hospital beds that reflect the size of the hospital.

The data set used in this study, the 1993 New Jersey Actuals, described in previous section.

The level of administrative costs depends on state and federal regulations and policies. Regulations at the state or national level affect the administrative functions as well as the total operating cost. Possibly the effect is different and cost control policies may reduce hospital's cost growth but at the same time impose additional regulatory burden on the administrative function. The proportion of administration to total hospital cost does not necessarily mean inefficiency, so California spends on hospitals per capita less than New

York (Thorpe et al. 1992). The share of administration to total cost for the state of New Jersey is 15.14 % almost equal to that provided by Thorpe above for the state of New York. Descriptive statistics of the variables used in estimation are presented in the following table (4-4).

Table 4-4
Descriptive Statistics: The Administrative Stochastic Cost Frontier Function

Variable	Mean	Std. Dev.	Minimum	Maximum	Description
TCOST	97941.57	60665.64	16623.00	327279.00	Total Hospital Cost ($000)
AMC	14323.78	9062.08	2594.16	63051.35	Administrative Cost ($000)
ADTOT	13786.45	7628.88	2028.00	39206.00	Admissions
VNATOT	145741.00	119484.08	10896.00	769918.00	Outpatient Visits
MBEDTOT	355.86	161.52	86.00	799.00	Number of Beds
HPHYS	4175.72	11000.68	0.00	63374.00	Hours of Physicians on Adm.
CPHYS	202.55	457.73	0.00	2781.00	Cost of Physicians ($000)
EH	460571.88	225567.85	94624.00	1151835.00	Employee Hours
EC	7207.55	4280.71	1315.00	29281.00	Employee Cost ($000)
HCLRE	95309.67	69802.16	9259.00	372882.00	Hours of Clerical Personnel
CCLRE	1187.20	988.26	98.00	4956.00	Cost of Clerical Per ($000)
WSUP	3995.23	3169.33	693.00	17306.00	Cost of Suppl & Other ($000)
WCON	2674.71	2445.43	324.00	15746.00	Cost of Contr & Lease ($000)
WCAP	760.40	480.45	14.14	2019.38	Cost of Capital ($000)
PLANTSF	438757.33	253911.77	56323.00	1169984.00	Plant Size (Hospital)
ADMPLT	63810.52	39377.29	5325.00	171025.00	Plant Size (Administration)
FTEEH	221.43	108.45	45.49	553.77	FTE Employees
FTEHPHYS	2.01	5.29	0.00	30.47	FTE Physicians
FTEHCLRE	45.82	33.56	4.45	179.2702	FTE Clerical
FTEEC	31.78	5.25	21.44	69.0664	FTE Employee Cost
FTECPHYS	107.51	107.78	0.00	938.1405	FTE Physician Cost
FTECCLRE	25.47	11.25	15.42	88.0540	FTE Clerical Cost
H1	0.0122	0.0054	0.0074	0.0423	Wage/Hour-Clerical ($000)
X2	10.6255	4.8027	4.1911	29.8379	Price of Supplies ($000)
X3	0.0199	0.0121	0.0031	0.0638	Price of Contract ($000)
X4	57.1974	43.4479	1.4962	249.2130	Price of Capital ($000)
WPHY	0.0518	0.0517	0.0010	0.4510	Wage/Hour-Physician ($000)
AGPLT	0.1115	0.0637	0.0086	0.3160	AG&G Plant Size (%)
FISPLT	0.0240	0.0158	0.0000	0.0693	FIS Plant Size (%)
MRDPLT	0.0125	0.0062	0.0000	0.0325	MRD Plant Size (%)
PCCPLT	0.0047	0.0032	0.0000	0.0164	PCC Plant Size (%)
PLT	0.1527	0.0669	0.0216	0.3502	% ADM/Total plant size

4.6 The Model: Hospital Administrative Cost Function

The administrative cost function follows the translog functional form:

$$\ln ADC = f(\ln Y, \ln P; \ln X) + \varepsilon$$

The translog as a second order approximation to an arbitrary administrative cost function allows first and second order effects to be investigated and the possibility of functional restrictions to be statistically tested before their imposition.

where

$\ln ADC$ = the natural logarithm of total administrative cost;

$\ln Y$ = the natural logarithm of a vector of hospital administrative outputs;

$\ln P$ = the natural logarithm of a vector of administrative input prices;

A = the natural logarithm of a vector of a fixed factor;

X= other environmental factors that affect the administrative function;

ε is the composite error (v + u)

The translog approximation of the administrative cost function can be written as:

$$\ln ADC(Q,P,X) = \alpha_0 + \sum_{i=1}^{m} \alpha_i \ln Q_i + \sum_{j=1}^{n} \beta_j \ln P_j + \frac{1}{2} \sum_{i=1}^{m} \sum_{h=1}^{m} \gamma_{ih} \ln Q_i \ln Q_h$$

$$+ \frac{1}{2} \sum_{j=1}^{n} \sum_{r=1}^{n} \delta_{jr} \ln P_j P_r + \sum_{i=1}^{m} \sum_{j=1}^{n} \phi_{ij} \ln Q_i \ln P_j + \theta_0 \ln A + \frac{1}{2} \theta (\ln A)^2$$

$$+ \sum_{i=1}^{m} \pi_i \ln Q_i \ln A + \sum_{j=1}^{n} \vartheta_j \ln P_j \ln A + \sum_{h=1}^{k} \rho_h X_h + v_i + u_i$$

The appropriate sets of parametric restrictions are imposed on the above function:

Symmetry of the translog cost function requires: $\gamma_{ih} = \gamma_{hi}$ for all i and h, $\delta_{ir} = \delta_{jr}$ for all j and r, according to Young's theorem.

Linear homogeneity in the input prices is imposed by the following restrictions:

$$\sum_{j=1}^{n}\beta_j = 1; \quad \sum_{j=1}^{n}\delta_{jr} = 0 \text{ for all } r; \quad \sum_{j=1}^{n}\phi_{ij} = 0 \text{ for all } i; \quad \sum_{j=1}^{n}\vartheta_j = 0;$$

Since a number of hospitals do not employ physicians in administrative functions and so their prices equal zero, a small value was assigned to these hospitals before taking logs. The dependent variable (total administrative cost) and the input prices are normalized. The price of capital is the normalization factor. The characteristics of the production function are recovered from the cost function. The application of Duality theory discussed in the previous section.

The empirical results of a variety of cost functions, OLS and stochastic frontier that allow for comparisons, follow. First, OLS estimated functions are presented; two OLS corrected for heteroscedasticity models (tables 4-5 and 4-6). Second, the system of equations, of the cost function and the factor cost share equations, is estimated using maximum likelihood estimation of constrained linear systems, (SURE). The results are presented in table 4-7. Finally, the stochastic cost frontier estimated model is presented (table 4-8).

4.7 Empirical Results:

Table 4-5

OLS: Corrected For Heteroskedasticity

Dependent variable is the Log of Total Administrative Cost
Model size: Observations = 83,
Parameters = 36, Deg.Fr. = 47
R-squared = 0.98483, Adjusted R-squared = 0.97354
Model test: F[35, 47] = 87.19, Prob value = 0.00000
Breusch - Pagan chi-squared = 31.3420, with 35 degrees of freedom

Variable Description		Coefficient	Standard Error	t-ratio	P[|T|>t]
Constant		0.10775	0.19739E-01	5.459	0.00000
Admissions	Y1	0.26585	0.77814E-01	3.416	0.00132
Visits	Y2	0.30630	0.42395E-01	7.225	0.00000
Adm*Adm	Y11	-0.36169E-01	0.49824	-0.073	0.94244
Vis*Vis	Y22	0.21724	0.15051	1.443	0.15554
Beds	BED	0.32155	0.85942E-01	3.742	0.00050
Beds*Beds	BED2	-0.73919E-01	0.48151	-0.154	0.87865
Adm*Vis	Y1Y2	-0.27433E-01	0.11824	-0.232	0.81754
Adm*Beds	Y1BED	-0.70993E-01	0.45183	-0.157	0.87582
Vis*Beds	Y2BED	0.32769E-01	0.22551	0.145	0.88509
CLR	H1	0.33192	0.55526E-01	5.978	0.00000
CLR*CLR	H11	-0.61259	0.10700	-5.725	0.00000
Supplies	X2	0.31740	0.27762E-01	11.433	0.00000
Supp*Supp	X22	-0.12957	0.97344E-01	-1.331	0.18958
Contr/Lease	X3	0.29253	0.24516E-01	11.932	0.00000
Contr*Contr	X33	0.89627E-01	0.55862E-01	1.604	0.11532
Phys Wage	WP	0.25137E-01	0.17663E-01	1.423	0.16129
PhysW*PhysW	WP2	0.15277E-01	0.87801E-02	1.740	0.08841
Adm*CLR	Y1H1	-0.11949	0.32375	-0.369	0.71374
Adm*Supp	Y1X2	0.70493E-02	0.19678	0.036	0.97158
Adm*Contr	Y1X3	-0.41885E-01	0.11593	-0.361	0.71950
Adm*PhysW	Y1WP	0.53081E-01	0.43412E-01	1.223	0.22753
Vis*CLR	Y2H1	0.17951	0.12928	1.389	0.17153
Vis*Supp	Y2X2	-0.20537	0.98571E-01	-2.083	0.04268
Vis*Contr	Y2X3	0.17959	0.57475E-01	3.125	0.00305
Vis*PhysW	Y2WP	0.93901E-02	0.21023E-01	0.447	0.65717
CLR*Supp	H1X2	0.32655	0.90355E-01	3.614	0.00073
CLR*Contr	H1X3	0.19050	0.58249E-01	3.270	0.00201
CLR*PhysW	H1WP	0.15904E-02	0.24533E-01	0.065	0.94858
Supp*Contr	X2X3	-0.20655	0.35310E-01	-5.850	0.00000
Supp*PhysW	X2WP	-0.18211E-01	0.21023E-01	-0.866	0.39074
Contr*PhysW	X3WP	0.12444E-01	0.17529E-01	0.710	0.48129
Beds*CLR	BEDH1	-0.20255	0.41895	-0.483	0.63101
Beds*Supp	BEDX2	0.18929	0.27396	0.691	0.49300
Beds*Contr	BEDX3	-0.80516E-02	0.13627	-0.059	0.95313
Beds*PhysW	BEDWP	-0.56438E-01	0.48645E-01	-1.160	0.25183

Table 4-6

OLS: Corrected for Heteroscedasticity(WHITE's Method)

Variable Description		Coefficient	Standard Error	z=b/s.e.	P[|Z|>z]
Constant		0.10775	0.22923E-01	4.701	0.00000
Admissions	Y1	0.26585	0.11003	2.416	0.01568
Visits	Y2	0.30630	0.57138E-01	5.361	0.00000
Adm*Adm	Y11	-0.36169E-01	0.62480	-0.058	0.95384
Vis*Vis	Y22	0.21724	0.20018	1.085	0.27781
Beds	BED	0.32155	0.13289	2.420	0.01553
Beds*Beds	BED2	-0.73919E-01	0.70642	-0.105	0.91666
Adm*Vis	Y1Y2	-0.27433E-01	0.17746	-0.155	0.87714
Adm*Beds	Y1BED	-0.70993E-01	0.62002	-0.115	0.90884
Vis*Beds	Y2BED	0.32769E-01	0.26980	0.121	0.90333
CLR	H1	0.33192	0.75656E-01	4.387	0.00001
CLR*CLR	H11	-0.61259	0.15399	-3.978	0.00007
Supplies	X2	0.31740	0.39434E-01	8.049	0.00000
Supp*Supp	X22	-0.12957	0.11660	-1.111	0.26645
Contr/Lease	X3	0.29253	0.35803E-01	8.171	0.00000
Contr*Contr	X33	0.89627E-01	0.86006E-01	1.042	0.29736
Phys Wage	WP	0.25137E-01	0.24989E-01	1.006	0.31444
PhysW*PhysW	WP2	0.15277E-01	0.13156E-01	1.161	0.24554
Adm*CLR	Y1H1	-0.11949	0.41884	-0.285	0.77543
Adm*Supp	Y1X2	0.70493E-02	0.25924	0.027	0.97831
Adm*Contr	Y1X3	-0.41885E-01	0.19821	-0.211	0.83264
Adm*PhysW	Y1WP	0.53081E-01	0.67087E-01	0.791	0.42881
Vis*CLR	Y2H1	0.17951	0.19007	0.944	0.34495
Vis*Supp	Y2X2	-0.20537	0.13238	-1.551	0.12081
Vis*Contr	Y2X3	0.17959	0.94816E-01	1.894	0.05822
Vis*PhysW	Y2WP	0.93901E-02	0.26948E-01	0.348	0.72750
CLR*Supp	H1X2	0.32655	0.12723	2.567	0.01027
CLR*Contr	H1X3	0.19050	0.89922E-01	2.118	0.03413
CLR*PhysW	H1WP	0.15904E-02	0.36437E-01	0.044	0.96518
Supp*Contr	X2X3	-0.20655	0.52947E-01	-3.901	0.00010
Supp*PhysW	X2WP	-0.18211E-01	0.33235E-01	-0.548	0.58372
Contr*PhysW	X3WP	0.12444E-01	0.20887E-01	0.596	0.55133
Beds*CLR	BEDH1	-0.20255	0.52451	-0.386	0.69937
Beds*Supp	BEDX2	0.18929	0.34591	0.547	0.58422
Beds*Contr	BEDX3	-0.80516E-02	0.23634	-0.034	0.97282
Beds*PhysW	BEDWP	-0.56438E-01	0.79410E-01	-0.711	0.47726

Table 4-7

Constrained MLE for Multivariate Regression Model(SURE)

Constrained MLE for Multivariate Regression Model
First iter: 0 F= 229.7493 log|ã|= -19.72551
Last iter: 4 F= 627.3829 log|ã|= -29.30705
Number of observations used in estimation = 83

Variable Description		Coefficient	Standard Error	z=b/s.e.	P[|Z|>z]
Constant	A	0.50385E-01	0.23851E-01	2.112	0.03465
Admissions	Y1	0.19862	0.93726E-01	2.119	0.03408
Visits	Y2	0.20137	0.38970E-01	5.167	0.00000
Adm*Adm	Y11	0.50279	0.59870	0.840	0.40102
Vis*Vis	Y22	0.24510E-01	0.13801	0.178	0.85904
Beds	BED	0.44579	0.11702	3.810	0.00014
Beds*Beds	BED2	-0.27064	0.83666	-0.323	0.74633
Adm*Vis	Y1Y2	-0.40023	0.18088	-2.213	0.02692
Adm*Beds	Y1BED	-0.12173	0.66199	-0.184	0.85410
Vis*Beds	Y2BED	0.39542	0.25571	1.546	0.12202
CLR	H1	0.50348	0.84464E-02	59.610	0.00000
CLR*CLR	H11	-0.25755E-01	0.29676E-01	-0.868	0.38545
Supplies	X2	0.27416	0.96308E-02	28.467	0.00000
Supp*Supp	X22	0.19282E-01	0.32127E-01	0.600	0.54838
Contr/Lease	X3	0.19188	0.94560E-02	20.292	0.00000
Contr*Contr	X33	-0.64353E-02	0.28365E-01	-0.227	0.82052
Phys Wage	WP	0.18062E-01	0.28552E-02	6.326	0.00000
PhysW*PhysW	WP2	0.19991E-01	0.65064E-02	3.073	0.00212
CLR*Supp	H1X2	-0.18675E-01	0.10246E-01	-1.823	0.06835
CLR*Contr	H1X3	0.53012E-01	0.17209E-01	3.080	0.00207
CLR*PhysW	H1WP	0.73530E-03	0.47386E-02	0.155	0.87669
Supp*Contr	X2X3	-0.25102E-01	0.14009E-01	-1.792	0.07315
Supp*PhysW	X2WP	-0.12251E-01	0.96358E-02	-1.271	0.20359
Contr*PhysW	X3WP	-0.23907E-01	0.82954E-02	-2.882	0.00395
Adm*CLR	Y1H1	0.31732E-01	0.36486E-01	0.870	0.38445
Adm*Supp	Y1X2	0.34861E-01	0.33631E-01	1.037	0.29994
Adm*Contr	Y1X3	-0.60857E-01	0.30177E-01	-2.017	0.04373
Adm*PhysW	Y1WP	-0.22144E-01	0.98696E-02	-2.244	0.02485
Vis*CLR	Y2H1	0.25798E-02	0.48559E-01	0.053	0.95763
Vis*Supp	Y2X2	-0.32826E-01	0.48117E-01	-0.682	0.49510
Vis*Contr	Y2X3	0.23026E-01	0.44767E-01	0.514	0.60700
Vis*PhysW	Y2WP	-0.41272E-01	0.14073E-01	-2.933	0.00336
Beds*CLR	BEDH1	-0.40584E-01	0.17767E-01	-2.284	0.02236
Beds*Supp	BEDX2	0.35414E-01	0.19704E-01	1.797	0.07229
Beds*Contr	BEDX3	0.34183E-01	0.19400E-01	1.762	0.07807
Beds*PhysW	BEDWP	0.27843E-01	0.86496E-02	3.219	0.00129

Table 4-8

Stochastic Frontier: Hospital Administrative Cost Function

Dependent variable Total Administrative Cost
Number of observations 83
Iterations completed 46
Log likelihood function 178.6454
Variance components: $\sigma^2(v)$= 0.00047
$\sigma^2(u)$= 0.00092

Variable Description		Coefficient	St. Error	z=b/s.e.	P[|Z|>z]
Constant	A	0.79655E-01	0.13635E-01	5.842	0.00000
Admissions	Y1	0.28767	0.60194E-01	4.779	0.00000
Visits	Y2	0.31466	0.31465E-01	10.000	0.00000
Adm*Adm	Y11	-0.82132E-01	0.26246	-0.313	0.75433
Vis*Vis	Y22	0.24597	0.97615E-01	2.520	0.01174
Beds	BED	0.29241	0.74449E-01	3.928	0.00009
Beds*Beds	BED2	0.13417	0.46840	0.286	0.77453
Adm*Vis	Y1Y2	0.28865E-01	0.11338	0.255	0.79904
Adm*Beds	Y1BED	-0.90907E-01	0.32358	-0.281	0.77875
Vis*Beds	Y2BED	-0.79144E-01	0.15913	-0.497	0.61893
CLR	H1	0.36033	0.32556E-01	11.068	0.00000
CLR*CLR	H11	-0.69362	0.11047	-6.279	0.00000
Supplies	X2	0.29754	0.20301E-01	14.656	0.00000
Supp*Supp	X22	-0.16280	0.52694E-01	-3.089	0.00201
Contr/Lease	X3	0.29408	0.17917E-01	16.413	0.00000
Contr*Contr	X33	0.86547E-01	0.49798E-01	1.738	0.08222
Phys Wage	WP	0.17684E-01	0.14276E-01	1.239	0.21547
PhysW*PhysW	WP2	0.12605E-01	0.65967E-02	1.911	0.05602
Adm*CLR	Y1H1	-0.18620	0.22094	-0.843	0.39935
Adm*Supp	Y1X2	0.35040E-01	0.12609	0.278	0.78109
Adm*Contr	Y1X3	-0.37890E-01	0.13833	-0.274	0.78415
Adm*PhysW	Y1WP	0.50527E-01	0.58021E-01	0.871	0.38384
Vis*CLR	Y2H1	0.12446	0.10245	1.215	0.22444
Vis*Supp	Y2X2	-0.16578	0.63475E-01	-2.612	0.00901
Vis*Contr	Y2X3	0.20421	0.62681E-01	3.258	0.00112
Vis*PhysW	Y2WP	0.14836E-01	0.22114E-01	0.671	0.50230
CLR*Supp	H1X2	0.40345	0.76269E-01	5.290	0.00000
CLR*Contr	H1X3	0.18206	0.54694E-01	3.329	0.00087
CLR*PhysW	H1WP	0.28806E-01	0.29052E-01	0.992	0.32143
Supp*Contr	X2X3	-0.21818	0.32318E-01	-6.751	0.00000
Supp*PhysW	X2WP	-0.34037E-01	0.17654E-01	-1.928	0.05386
Contr*PhysW	X3WP	0.16928E-01	0.13823E-01	1.225	0.22072
Beds*CLR	BEDH1	-0.62514E-01	0.25855	-0.242	0.80895
Beds*Supp	BEDX2	0.16140	0.15947	1.012	0.31147
Beds*Contr	BEDX3	-0.77117E-01	0.17496	-0.441	0.65938
Beds*PhysW	BEDWP	-0.37977E-01	0.53979E-01	-0.704	0.48171
λ	σ_u/σ_v	1.4003	0.32105	4.361	0.00001
σ	$\sqrt{(\sigma_v^2+\sigma_u^2)}$	0.37343E-01	0.44341E-02	8.422	0.00000

The results are subject to considerable degree of multicollinearity. However, the coefficients of outputs and input prices remain significant and have the expected sign. All higher order coefficients are jointly significant (at the 0.2 percent level), so the translog specification is supported against the Cobb-Douglas.

The RESET test provides no evidence for omitted variables in the specification (the hypothesis of no omitted variables can not be rejected at traditional levels of significance). Also, the link test [Tukey (1949); Pregibon (1980)], indicates that there is no specification error.

Heteroscedasticity is not a serious problem in this model. The Breusch-Pagan and the Cook-Weisberg tests for heteroscedasticity are not significant at the traditional levels.

The empirical results indicate a well-behaved cost function that exhibits all the desirable properties.

The cost elasticities and the marginal costs of administrative outputs are presented below:

Table 4 -9: Output Cost Elasticities and Marginal Costs

	Elasticities OLS	Elasticities Frontier	Marginal Cost OLS	Marginal Cost Frontier
Admissions	0.26585 (3.416)	0.28767 (4.779)	331.96 (3.416)	356.94 (4.779)
Visits	0.30630 (7.225)	0.31466 (10.000)	24.044 (7.225)	24.544 (10.000)

Asymptotic z-statistics in parentheses

The marginal administrative cost of an admission is $356.94. The marginal administrative cost of an additional outpatient visit is $24.544, both evaluated at their means.

The overall economies of scale for the administrative cost function are presented below:

Table 4-10: Economies of Scale

OLS	Frontier
0.43387	0.42889
(5.557)	(4.719)

Asymptotic z-statistics in parentheses

SCE reflects the percentage change in total cost resulted from a simultaneous percentage change in all outputs. Which means that a 10% proportional increase of all outputs would increase total administrative cost by 4.3% (less than 10%).

The Allen-Uzawa factor demand elasticities and partial elasticities of substitution for the administrative cost function follow:

Table 4 -11: Allen-Uzawa Factor Demand Elasticities (Own-Cross)

	X1	X2	X3	WP	X4
X1=CLR	-2.5646	1.7163	0.9794	1.9893	2.9720
	(-8.019)	(6.059)	(4.581)	(0.818)	(1.191)
X2=SUP	1.4172	-1.2496	-0.4443	-1.6272	0.6783
	(5.698)	(-6.876)	(-3.708)	(-0.897)	(0.435)
X3=CON	0.7993	-0.4392	-0.4116	1.2514	-1.9240
	(5.543)	(-3.397)	(-2.431)	(1.407)	(-0.957)
WP=PHY	0.0976	-0.0967	0.0753	-0.2695	-0.7826
	(1.262)	(-1.589)	(1.396)	(-0.616)	(-0.900)
X4=CAP	0.2505	0.0692	-0.1987	-1.3439	-0.9437
	(1.795)	(0.482)	(-1.679)	(-0.814)	(-0.555)

Asymptotic z-statistics in parentheses

The administrative cost function is a well-behaved cost function. The own-price elasticities of demand for inputs are all negative. The elasticity of administrative personnel, supplies, and contract services are statistically significant. However, the demand elasticities of physician and capital inputs are insignificant at the traditional levels.

Table 4 -12: Elasticities of Substitution

	H1	X2	X3	WP
H1-CLR				
X2-SUP	4.7631			
	(6.063)			
X3-CON	2.7181	-1.4934		
	(5.054)	(-3.312)		
WP-PHY	5.5208	-5.4689	4.2551	
	(0.834)	(-0.890)	(1.391)	
X4-CAP	8.2482	2.2798	-65425	-44.257
	(1.250)	(0.435)	(-0.971)	(-0.756)

Asymptotic z-statistics in parentheses

The following table highlights key statistics for the inefficiency index obtained from the administrative stochastic frontier cost model.

Table 4-13

Descriptive Statistics
Administrative Stochastic Frontier Cost Inefficiency

Variable	Mean	Std. Dev.	Minimum	Maximum	1st Quart	Median	3rd Quart
INEFFICIENCY	0.0334	0.0350	0.0027	0.1748	0.0457	0.0887	0.1318
COST INEF/NCY	$470.28	$581.88	$26.24	$3,535.12	$903.5	$1,780.7	$2,657.9
ADMIN. COST	$14,323.8	$9,062.1	$2,594.2	$63,051.3	$17,708	$32,823	$47,937

Note: Cost inefficiency is in thousand of dollars.

The mean inefficiency of the hospital administrative cost function is 3.34 percent and ranges between 0.27 and 17.48 percent. The cost inefficiency expressed in dollars averages $470.28 thousand and ranges between $26.24 and $3,535.12 thousand.

Appendix 4.1 illustrates the distribution of the inefficiency index obtained from the administrative cost function. The determinants of the administrative function are investigated in section 6.

Appendix 4.1

The Distribution of the Stochastic Frontier Administrative Cost Inefficiency

The distribution of administrative cost inefficiency is illustrated below.

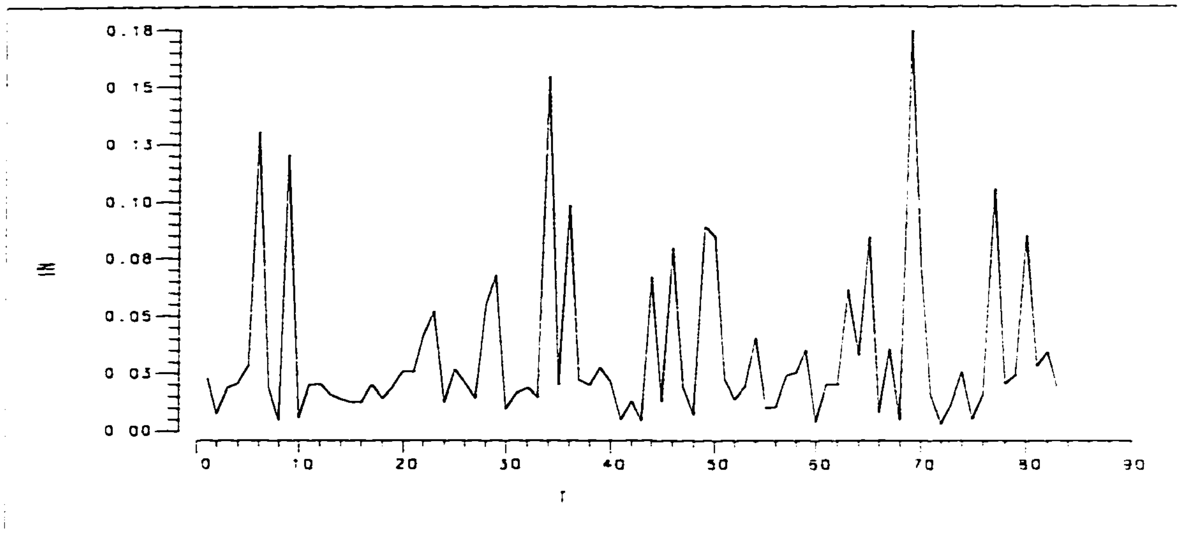

Figure 4.1: Administrative Hospital Specific Inefficiency

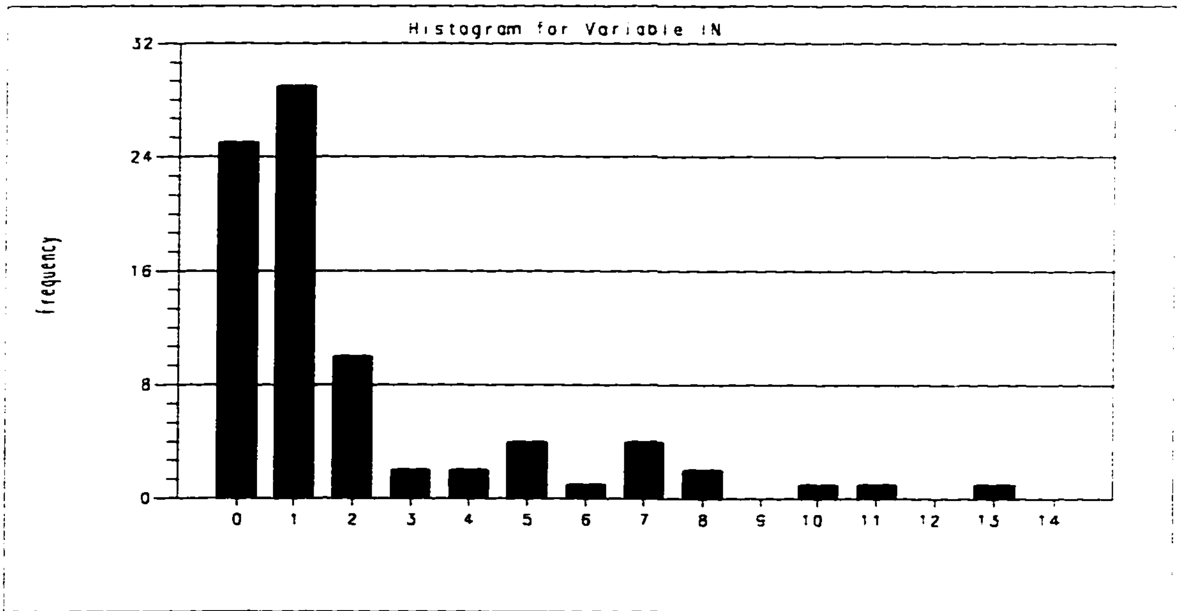

Figure 4.2: The Distribution of the Administrative Cost Inefficiency

5

The Data Envelopment Analysis Models

5.1 Introduction

Data Envelopment Analysis, the non-parametric technique, provides an attractive alternative to econometric technique for evaluating the performance of a productive unit relative to its peer group. Sherman (1984) suggested DEA as a "complement" to regression since it provides a flexible framework for modeling multiple-input multiple-output technologies. Indeed the mathematical programming technique is applicable to a multiple input and multiple output environment, as the regression technique, and in addition, provides insights into areas that the regression fails to focus on.

Data Envelopment Analysis can be used as a method of benchmarking relative firm performance in the industry, which can assign a numerical "grade" and a relative ranking. In addition, DEA provides the amounts of output slacks and the amounts of excess inputs that separate hospitals for an optimal (projected) level of performance. However, both techniques, regression and DEA, are superior to the traditional ratio analysis methods for assessing hospital performance.

This section applies the DEA estimating method to the same body of data employed in the previous two sections. Specifically, the hospital and the hospital administrative functions are estimated using the New Jersey 1993 Acute Care Hospital Actuals.

The DEA methodology has been accepted as the most appropriate method of analyzing the behavior of hospitals and not-for-profit organizations in general (Sherman, 1984). The majority of DEA models that assess hospital performance focus on technical efficiency and its components. The overall cost-minimizing performance can be evaluated and both allocative and technical efficiency levels can be measured, if the level of input prices is available (Färe et al., 1994).

As developed in the second section, the DEA technique builds, the "empirical frontier", a piecewise linear surface that envelops the data and evaluates the performance of its DMU relative to this structure. In this analysis, DEA, also, identifies the weak areas of performance in terms of input over-consumption and output under-production and provides their relative magnitudes.

In this section, hospital performance (total and administrative) is evaluated using both types of envelopment forms; Constant Returns to Scale and Variable Returns to Scale. All models estimated have an input orientation, which means, a proportional reduction of inputs is maximized (given the level of outputs) for each DMU.

First, a production function is estimated, which incorporates the output and input levels, allowing complete flexibility in the selection of weights. The full flexibility of assigned weights may result in weights that vary widely across DMUs. Also, their distribution tends to favor some factors (not always the most important factors in the production function) and ignore others. The Cone-Ratio and Assurance Region methods provide the latest developments of restricting the weights of DEA estimation technique and incorporating additional (price) information into estimation. Second a weight-restricted model is developed and estimated. The objective is to measure the firm specific performance exploring the advantages of alternative techniques. However, a cost-minimizing DEA model may be proved the non-parametric analog of the stochastic cost frontier since it incorporates directly output levels and input prices into estimation. Third, the components of overall cost efficiency will be obtained as described in section 2.5.2 using the cost-minimizing DEA model.

It is common in the empirical literature of DEA analysis to employ statistical tools (regression analysis) to explain the variability of the efficiency index (Grosskopf, 1996). The modeling of efficiency/inefficiency scores is the subject of the next section.

5.2 *Hospital Efficiency: Data, Variables, and Empirical Results*

In this section, hospital performance is evaluated using the DEA approach. The same inputs and outputs, used in estimation of the cost stochastic frontier, define the process of evaluating the cost efficiency of 83 hospitals (DMUs).

The three hospital outputs are: (i) the number of annual admissions (AD), (ii) the number of annual inpatient days (PD), and (iii) the number of annual outpatient visits (VIS).

The six inputs employed are the following: (i) the annual cost (hourly wage times labor hours) for RN services, (CRNS); (ii) the annual cost (hourly wage times labor hours) for clerical services, (CCLR); (iii) the annual cost of Supplies (CSUP); (iv) the annual cost of Contract Services (CCSER); (v) the cost of Capital defined as depreciation and interest (CDFI); and (vi) The number of Physician Hours, (PH).

The first five inputs are considered controllable (discretionary), while the number of physician hours is included as an non-discretionary input. The descriptive statistics are given below:

Table: 5 -1

Descriptive Statistics: The Hospital DEA Model (n=83)

	Variable		Mean	Std. Dev.	Minimum	Maximum
Admissions	AD	(y_1)	13786.45	7628.88	2028.00	39206.00
Patient Days	PD	(y_2)	95543.76	47782.99	17109.00	228331.00
Outpatient Visits	Vis	(y_3)	145741.00	119484.08	10896.00	769918.00
Cost of RN	CRNS	(x_1)	12114.98	7589.27	1712.00	35320.00
Cost of Clerical Emp.	CCLR	(x_2)	1187.20	988.26	98.00	4956.00
Cost of Supplies	CSUP	(x_3)	15482.16	10438.69	1852.00	49508.00
Cost of Contract Ser.	CCSER	(x_4)	5843.04	4130.18	933.00	24817.00
Cost of Capital	CDFI	(x_5)	7289.54	4470.07	373.00	18662.00
Physician Hours	PH	(x_6)	138107.71	171950.52	3007.00	794508.00

As noted by Ali, A. I., (1995) the wide range of values of variables in the data set as well as the large variability in the values of a single variable can create computational problems in DEA estimation. The values of multipliers, also, are sensitive to the values of the variables. In orienting models there is an inverse relationship between the values of variables and the assigned multipliers. The physician hours variable varies considerably among hospitals, but its non-discretionary characterization affects only the selection of the peer group and not the efficiency ranking.

The CRS model yields overall (technical plus scale) efficiency. The VRS model yields pure technical efficiency. Since the inputs are measured in terms of expenditures (price times quantity) they reflect also the choice of input prices and not only amounts. Efficient hospitals can achieve optimal performance by reducing the level of utilized productive resources by a percentage and still produce the same amounts of outputs. Therefore, one hospital's performance can be improved either by a reduction of inputs or by an augmentation outputs. The model estimated is input-oriented unit invariant presented in section 2.5, models (2.5)-7 and (2.5)-8 and optimizes the input reduction necessary to achieve the level of observed outputs. Table 5-2 summarizes the estimates of hospital DEA analysis.

Table:5 -2 Hospital DEA: Efficiency Estimates[1]

		All Hospitals			Inefficient Hospitals				Efficient Hospitals	
		Mean			Mean					
Model		Efficiency	Min	Max	Efficiency	Min	Max	Number	Number	(% of All)
CRS	(I)	0.8619	0.36	1.00	.7708	.36	.97	50	33	(39.76)
	(θ)	0.9042	0.41	1.00	.8410	.41	1.0	50		
VRS	(I)	0.9287	0.47	1.00	.8259	.47	.99	34	50	(60.24)
	(θ)	0.9427	0.51	1.00	.8601	.51	1.0	34		

[1] Note: θ (theta), the measure of radial efficiency, indicates the proportional reduction of inputs necessary to reach the frontier. I (Iota) measures total efficiency since takes into account relative prices and residual changes (entire "facet-defining plane") as obtained from the two-staged approach (equations 2.5-7 and 2.5-8).

The constant returns to scale envelopment form identifies 33 (39.76 percent of all) efficient hospitals and the variable returns to scale 50 (60.24 percent of all).

The mean efficiency of the CRS model which combines both technical and scale efficiencies is 0.8619. The pure technical efficiency is 0.9287 as measured by the VRS model. The VRS estimated efficiency is one component of overall efficiency, so its scores are lower than the CRS. The technical efficiency score indicates that hospitals could reduce inputs by as much as 14 percent and still support the same level of outputs.

Scale inefficiency is a major component of the technical inefficiency. The scale efficiency score is estimated using the Färe et al, (1994), approach described in the appendix 2.1.

The majority of hospitals experience decreasing returns to scale. Specifically, 48 hospitals operate under decreasing returns to scale (mean efficiency 0.78), 31 under constant returns to scale (mean efficiency 1) and 4 under increasing returns to scale (mean efficiency 0.81).

Table:5 -3 Hospital DEA: Returns to Scale

Type	Ave. Eff/cy	No of Hospitals	Admissions	Patient Days	No of BEDS	Cost per Admission	Cost per Pat. Day	Cost per Bed
IRS	0.81	4	5,483	40,681	158.5	$8,661	$1,129	$299,314
CRS	1.00	31	12,940	90,360	329.9	6,589	904	241,143
DRS	0.78	48	15,024	103,463	389.1	7,377	1,045	275,542

Note: In estimation of returns to scale all inputs, including physician hours, were considered discretionary.

Table 5-3 illustrates that DEA efficiency estimates support the traditional economic theory of a U-shaped average cost curve. Variables that are indicative of size of operation like the number of beds, admissions and patient days as well as the cost per unit of these variables reveal the relationship between hospital scale of operation and level of efficiency.

The average number of admissions of hospitals operating at increasing returns to scale is 5,483. The average number of admissions of efficient hospitals is 12,940 and increases to 15,024 for hospital operating under decreasing returns to scale. The number of patient days and the number of beds also follow the same pattern. The cost per admission, patient day and bed supports the traditional theory of the U-shaped average cost curve. The average cost is lower at the constant returns to scale portion of the average cost curve. Byrnes and Valdmanis, (1994), reported similar findings.

The DEA model provides information about the potential improvements in inputs and outputs by projecting the inefficient DMU on the empirically constructed frontier.

Table:5 -4 Hospital DEA: Average Output Slacks

Model	Hospitals		Admissions	Patient Days	Outpatient Visits
CRS	All	83	337.25	719.20	25,518.36
	Inefficient	50	559.83	1,193.87	42,360.48
VRS	All	83	84.77	689.71	13,197.03
	Inefficient	34	206.93	1,683.71	32,216.28

The output slack and the excess consumption of inputs analysis indicates potential improvements in efficiency by component. For example (under CRS) inefficient hospitals can increase admissions by 559.83, a 4.06 percent potential improvement and outpatient visits by 42,360.48, a 29.07 percent potential improvement (Table 5-4). Even if the DEA model as an input-orientated optimizes the input potential improvement, the output slacks signal hospitals that perform well below their possibilities.

Table 5-5 provides the input adjustments needed to make the average hospital efficient. The average hospital, for example, in order to optimize performance (under CRS) has to reduce the utilized level of RN services by $1,837.55 thousand, a 15.17 percent improvement. So, the efficient employment of the RN services could save sample hospitals $152,516.7 thousand. Similarly, spending for supplies and contract services could be lowered by an average $2,531 and $1,295 thousand respectively.

Table 5 -5 Hospital DEA: Average Excess Inputs

Model	Hospitals	RNS	CLR	CSUP	CSER	CDFI
CRS	All	1,837.55	288.43	2,531.03	1,295.20	1,564.01
	Ineff 50	3,050.33	478.79	4,201.51	2,150.03	2,596.25
VRS	All	1,055.70	113.00	1,451.42	965.06	688.80
	Ineff 34	2,577.14	275.85	3,543.18	2,355.89	1,681.49

The following table (5-6) summarizes the efficient levels of factors of production and the efficient allocation of inputs in more detail.

Table 5 -6. Hospital DEA: Efficiency Analysis (Means)

	Actual Value	Projected Efficient Value		Potential Improvement (Slacks)	
		CRS	VRS	CRS	VRS
Outputs					
Admissions	13,786.45	14,123.70	13,871.22	337.25	84.77
Patient Days	95,543.76	96,262.96	96,233.47	719.20	689.71
Visits	145,741.00	171,259.36	158,938.03	25,518.36	13,197.03
Inputs					
RNS	12,114.98	10,277.43	11,059.28	1,837.55	1,055.70
CLR	1,187.20	1,898.77	1,074.20	288.43	113.00
CSUP	15,482.16	12,951.13	14,030.74	2,531.03	1,451.42
CSER	5,843.04	4,547.84	4,877.98	1,295.20	965.06
CDFI	7,289.54	5,725.53	6,600.74	1,564.01	688.80

The reported slacks provide information about the relative contribution of inputs and outputs to inefficiency. The average potential improvement of inputs is $7,516.22

thousand (7.67%) evaluated under a CRS surface, which implies the level of overall inefficiency (technical and scale). For VRS surface, which is a measure of pure technical inefficiency, the average improvement is $4,273.98 thousand (4.36%). The potential improvement is the difference between actual and projected levels of inputs and outputs for the two surfaces (CRS, VRS).

5.2.1 The TC-AR Extension: Weight restricted DEA and Hospital Efficiency

DEA in the process of evaluating the efficiency of each DMU freely determines the value of input and output multipliers that maximize the relative performance. The following table (5-7) presents descriptive statistics of DEA input and output multipliers.

The obtained multiplier values can be characterized as the sets of coefficients that define the envelopment structure and reflect the marginal evaluation (price) of each input and output. The relative location of each DMU on the envelopment surface is given by the weighted average of inputs and outputs where the multipliers serve as weights.

$$\mu_1 AD + \mu_2 PD + \mu_3 VIS - \nu_1 RNS - \nu_2 CLR - \nu_3 CSUP - \nu_4 CSER - \nu_5 CDFI + \omega \leq 0$$

Efficient DMUs are located on the envelopment surface so the weighted average of outputs and inputs equals zero. The weighted average of inefficient DMUs is lower than zero and its location is compared against a projection on the surface. The projected point on the surface is a convex combination of efficient DMUs, the peer group or the comparison set. For an inefficient DMU, the differences between actual location and its projection determines the amounts of output slacks and excess inputs. The CRS envelopment surface goes through the origin and its constant term ω equals zero. For VRS surfaces ω can be positive, negative or zero indicating decreasing, increasing or constant returns to scale, respectively. But as noted in section 2.5, different values may exist for ω so its value and sign are not unique.

However, the flexibility of DEA multipliers was criticized as distorting the actual evaluations of inputs and outputs of some DMUs. Banker et al., (1988) reported that DEA misspecified DMUs as efficient in cases where the set of inputs or outputs included at least one variable with extreme values (very low or very large). This inability of DEA to handle boundary points of the production possibility set can possibly lead to differences in estimates comparing with the stochastic model. Table 5-7 summarizes the input and output multipliers obtained from the CRS and VRS models. The values of multipliers for a number of DMUs are very close to zero.

Table 5 –7 Hospital DEA: Input and Output multipliers

	CRS			VRS		
Variable	Mean	Min	Max	Mean	Min	Max
AD	0.0027	0.00004	0.04437	0.0103	0.00003	0.24013
PD	0.0018	0.00000	0.11691	0.0024	0.00001	0.13768
VIS	0.0002	0.00000	0.01442	0.0000	0.00000	0.00051
RNS	0.0085	0.00003	0.54802	0.0049	0.00003	0.08034
CLR	0.0038	0.00020	0.08303	0.0502	0.00020	2.60230
CSUP	0.0038	0.00002	0.10028	0.0128	0.00002	0.63343
CSER	0.0098	0.00004	0.61252	0.0027	0.00004	0.08087
CDFI	0.0176	0.00005	1.31687	0.0159	0.00006	1.00238

The variability of DEA multipliers is more indicative in a ratio form. In the following table the matrices indicate the range of a number of multiplier bounds that DEA freely determined. The range is given in the form of ratios of multipliers. The multiplier of admissions is μ_1, the multiplier of patient days is μ_2 and the multiplier of Visits μ_3. Inputs, CRNS/CCLR/CSUP/CSER/CDFI are numbered v_1 to v_5, respectively. The matrix P_{11} indicates that the multiplier ratio of admissions to patient days (μ_1 / μ_2) ranges between 0.1567 and 1,694.67, which means that the multiplier of patient days (μ_2) ranges between $0.1567\mu_1$ and $1,694.67\mu_1$. Also, the matrix R_{22} indicates that the CCLR multiplier ranges between $0.0096v_1$ to $7.7917v_1$ (relative to the multiplier of CRNS). The great flexibility of the marginal evaluations allowed by DEA may result in extreme evaluations for some inputs/outputs. This flexibility eventually diminishes the validity of the estimated performance.

The wide variation of weights for the same factor is considered "inappropriate" in the recent literature of DEA (Roll and Golany, 1993). To avoid unrealistic weighting of inputs and outputs specific bounds are developed and imposed on them. This study incorporates empirically evaluated standards into DEA estimation and attempts to restrict the DEA multipliers in a range of values that reflect the actual importance of each factor of production. The restrictions are derived from the parametrically evaluated productive characteristics of the hospital cost function and form a Theoretically Consistent Assurance Region (TCAR).

Table 5 -8

Hospital DEA: The obtained range of DEA multipliers, the CRS model

The matrix of input ratios:

$$
\begin{array}{c}
\begin{array}{ccccc} \quad v_1 & \quad v_2 & v_3 & v_4 & v_5 \end{array} \\
R_{22} = \begin{bmatrix}
-0.0096 & 1 & 0 & 0 & 0 \\
7.7917 & -1 & 0 & 0 & 0 \\
-0.0228 & 0 & 1 & 0 & 0 \\
72.5249 & 0 & -1 & 0 & 0 \\
-0.0033 & 0 & 0 & 1 & 0 \\
20.8051 & 0 & 0 & -1 & 0 \\
-0.0395 & 0 & 0 & 0 & 1 \\
17.0408 & 0 & 0 & 0 & -1
\end{bmatrix}
\end{array}
$$

The matrix of output ratios:

$$
\begin{array}{c}
\begin{array}{ccc} \quad \mu_1 & \quad \mu_2 & \mu_3 \end{array} \\
P_{11} = \begin{bmatrix}
-0.1567 & 1 & 0 \\
1694.6648 & -1 & 0 \\
-0.8497 & 0 & 1 \\
1333.8608 & 0 & -1
\end{bmatrix}
\end{array}
$$

Note: The two matrices (P_{11}, R_{22}) form the Q matrix with dimensions 2(s+m-2) x (s+m).
The coefficients : v_1 =crns, v_2 =cclr, v_3 =csup, v_4 =cser, v_5 =cdfi,
μ_1 =admissions, μ_2 =patient days, μ_3 =outpatient visits

The absence of clear interpretation and theoretical basis for the DEA multipliers renders the task of assigning multiplier bounds very difficult. Existing studies assign constraints on multipliers based on assumed relative importance, existed "price/cost" information, expert opinions, or environmental factors [Thomson et al., 1990; Thompson et al., 1996]. This study is the first attempt in the economic literature to link the two alternative evaluations of productive performance. The restrictions for output and input weights are not based on "environmental" factors but are derived from the parametrically evaluated productive characteristics of the hospital cost function. The incorporation of weight restrictions in DEA based on the empirical results obtained from the stochastic frontier parametric model seems more appropriate.

The output weight matrix is derived from the marginal rate of output transformation. The input weight matrix is derived from the marginal rate of input substitution. Specifically, ratios based on the marginal costs of hospital outputs and input prices provide the bounds of output weights and reflect the relative importance of each output in the production process. The multiplier bounds are defined by the minimum and maximum values of the respective marginal cost ratios. The following table (5-9) provides the matrices of imposed restrictions. The imposed range for the multiplier μ_2 of patient days (PD) relative to the multiplier μ_1 of admissions (AD) decreases from ($0.1567\mu_1$ - $1{,}694.67\mu_1$) to ($5.85\mu_1$ - $13.48\mu_1$). Similarly, the imposed range for the multiplier v_2 of cost of clerical employees (CCLR) relative to the multiplier v_1 of cost of RN services (CRNS) is set to ($1.99v_1$ - $12.54v_1$), which is higher than that originally obtained by DEA.

Table 5 -9

Hospital DEA: The Weight Restrictions

The matrix of input ratios:

$$\begin{array}{c}
\begin{array}{ccccc} v_1 & v_2 & v_3 & v_4 & v_5 \end{array} \\
R_{22} = \begin{bmatrix}
-1.99 & 1 & 0 & 0 & 0 \\
12.54 & -1 & 0 & 0 & 0 \\
-0.72 & 0 & 1 & 0 & 0 \\
7.03 & 0 & -1 & 0 & 0 \\
-0.37 & 0 & 0 & 1 & 0 \\
8.40 & 0 & 0 & -1 & 0 \\
-0.53 & 0 & 0 & 0 & 1 \\
59.82 & 0 & 0 & 0 & -1 \\
0 & -0.17 & 1 & 0 & 0 \\
0 & 2.40 & -1 & 0 & 0 \\
0 & -0.07 & 0 & 1 & 0 \\
0 & 2.71 & 0 & -1 & 0 \\
0 & -0.22 & 0 & 0 & 1 \\
0 & 19.74 & 0 & 0 & -1 \\
0 & 0 & -0.09 & 1 & 0 \\
0 & 0 & 3.24 & -1 & 0 \\
0 & 0 & -0.37 & 0 & 1 \\
0 & 0 & 21.18 & 0 & -1 \\
0 & 0 & 0 & -0.13 & 1 \\
0 & 0 & 0 & 93.32 & -1
\end{bmatrix}
\end{array}$$

The matrix of output ratios:

$$\begin{array}{c}
\begin{array}{ccc} \mu_1 & \mu_2 & \mu_3 \end{array} \\
P_{11} = \begin{bmatrix}
-5.85 & 1 & 0 \\
13.48 & -1 & 0 \\
-5.32 & 0 & 1 \\
48.44 & 0 & -1 \\
0 & -0.57 & 1 \\
0 & 5.31 & -1
\end{bmatrix}
\end{array}$$

Note: The two matrices (P_{11}, R_{22}) form the Q matrix with dimensions 2(s+m-2) x (s+m).
The coefficients : v_1 =crns, v_2 =cclr, v_3 =csup, v_4 =cser, v_5 =cdfi,
μ_1 =admissions, μ_2 =patient days, μ_3 =outpatient visits

The weight restriction matrices of the hospital function are entered in estimation following the specification 2.5-9. The results of the restricted function are presented below. Compared to efficiency levels of the unrestricted model, the restricted model yielded lower levels of efficiency, table (5-10). The area of search for the optimal solutions has been decreased and the efficiency scores on average are lower. The multiplier bounds, derived empirically, are consistent with the actual importance of factors of production or consistent with the underlying objectives of each DMU. The restricted

DEA estimates reflect an overall technical efficiency assessment [Charnes et al., 1990; Allen et al., 1997].

Table 5 –10 Hospital DEA: Weight Restricted Efficiency Estimates

Model		All Hospitals Mean Efficiency	Min	Max	Inefficient Hospitals Mean Efficiency	Min	Max	Number	Efficient Hospitals Number	(% of All)
CRS	(I)	0.7974	0.29	1.00	.7697	.29	.98	73	10	(12.05)
	(θ)	0.8167	0.30	1.00	.7916	.30	1.0	50		
VRS	(I)	0.8486	0.33	1.00	.8036	.33	.99	64	19	(22.89)
	(θ)	0.8618	0.35	1.00	.8208	.35	1.0	64		

The interpretation of the efficiency scores derived from a binding weight restricted model differs from the interpretation of the unrestricted model. The efficiency score does not reflect the radial reduction of inputs necessary to move the inefficient DMU to its optimal location on the frontier (Allen et al., 1997). The potential improvement of inputs is given in the following table.

Table 5 -11 Hospital DEA: Weight Restricted Excess Inputs

Model	Hospitals	RNS	CLR	CSUP	CSER	CDFI
CRS	All	3,599.83	372.09	3,914.03	1,703.32	2,173.45
	Ineff 73	4,092.96	423.06	4,450.19	1,936.66	2,471.18
VRS	All	2,624.62	29.98	3,412.73	2,142.06	1,430.23
	Ineff 64	3,403.81	38.89	4,425.88	2,777.99	1,854.83

The input adjustments have change dramatically. All input targets (but the CLR, under VRS) are much higher indicating increased opportunities for savings. The CRS model implies a potential improvement of $11,762.72 thousand and the VRS a potential improvement of $9,639.62 thousand. As noted by Allen et al., 1997 the weight restricted DEA can yield a substantially different input and output mix. How the estimated DEA inefficiencies, obtained from both the restricted and unrestricted specifications, are related to that obtained form the stochastic frontier will be investigated in the following section.

5.3 Administrative Hospital Cost Efficiency

The administrative performance of hospitals is evaluated in this section with the DEA methodology. The number of admissions (AD), and the number of outpatient visits (VIS) are the two variables that approximate the administrative output (the number of patients served). The administrative function includes six inputs. Four are considered discretionary and two non-discretionary.

The discretionary inputs are: The cost of administrative personnel (EC); the total cost of supplies and other expenditures (WSUP); the total cost of contract and lease services (WCON); and the total cost of capital (WCAP), measured as annual depreciation and interest of all administrative sections. The cost associated with Physicians on administrative tasks (CPHY) and the number of maintained beds (BED) are entered as non-discretionary inputs and reflect the size of the hospital, which is closely related to administrative complexity.

Table: 5-12

Descriptive Statistics: The Administrative DEA Model

		Variable	Mean	Std. Dev.	Minimum	Maximum	Description
Outputs	(y_1)	ADTOT	13786.4	7628.8	2028.0	39206.0	Admissions
	(y_2)	VNATOT	145741.0	119484.1	10896.0	769918.0	Outp.Visits
Inputs	(x_1)	EC	7207.6	4280.7	1315.0	29281.0	Cost (Employees)
	(x_2)	WSUP	3995.2	3169.3	693.0	17306.0	Cost (Supplies)
	(x_3)	WCON	2674.7	2445.4	324.0	15746.0	Cost (Contr. Serv)
	(x_4)	WCAP	760.4	480.4	14.1	2019.4	Cost (Capital)
	(x_5)	CPHYS	202.5	457.7	0.0	2781.0	Cost (Phy/Admin.)
	(x_6)	MBEDTOT	355.8	161.5	86.0	799.0	Number of Beds

The two uncontrollable factors do not affect the efficiency rating of the hospital but the selection of the peer group (Morey and Dittman, 1996).

The two-staged, input-oriented, and unit invariant model (models 2.5-7 and 2.5-8) is estimated for both CRS and VRS surfaces. As the measurement of inputs reflects, also, the choice of input-prices (and not only amounts), the estimated efficiency incorporates elements of allocative and not only technical efficiency.

Table 5 -13 Administrative DEA: Efficiency Estimates[2]

		All Hospitals			Inefficient Hospitals				Efficient Hospitals	
		Mean			Mean					
Model		Efficiency	Min	Max	Efficiency	Min	Max	Hospitals	Hospitals	(% of All)
CRS	(I)	0.8297	0.44	1.00	.7562	.44	.989	58	25	(30.12)
	(θ)	0.8642	0.44	1.00	.8057	.44	.998	58	25	
VRS	(I)	0.8757	0.44	1.00	.7895	.44	.985	49	34	(40.96)
	(θ)	0.8955	0.44	1.00	.8229	.44	.996	49	34	

The results indicate that 30 percent of hospital administrative departments are technically efficient. Under a VRS evaluation the efficient portion is 41 percent (pure technical efficiency). The constant returns to scale envelopment form identifies 25 efficient hospitals and the variable returns to scale identifies 34, with mean efficiencies 0.8297 and 0.8757, respectively. The CRS model indicates that inputs can be proportionately reduced by 17 percent and still produce the same output levels. Scale inefficiency accounts for a large portion of this percentage. The analysis of efficiency reveals that the

[2] Note: θ (theta), the measure of radial efficiency, indicates the proportional reduction of inputs necessary to reach the frontier.

I (Iota) measures total efficiency since takes into account relative prices and residual changes (entire "facet-defining plane") as obtained from the two-staged approach (equations 2.5-7 and 2.5-8).

majority of hospitals experience increasing returns to scale. The following table 5-13 summarizes the results.

Table 5 -14 Administrative DEA: Returns to Scale[3]

Type	Ave. Eff/cy	No of Hospitals	AD	VIS	BEDS	Cost per Admission	Visit	Bed
IRS	0.87	38	9,292	78,169	259.0	$1,136.7	$106.9	$42,908.6
CRS	1.00	21	14,668	182,748	339.7	927.5	96.9	37,275.3
DRS	0.86	24	20,131	220,348	523.4	1,112.9	141.4	38,170.9

The VRS surface indicates that 24 hospitals operate under decreasing returns to scale (mean efficiency 0.86), 38 under increasing returns to scale (mean efficiency 0.87) and 21 under constant returns to scale.

The administrative hospital function indicates a U-shaped average cost path. The administrative cost per admission, outpatient visit, and bed of hospitals operating under constant returns to scale averages $927.5, $96.9 and $37,275.3, respectively. Hospitals operating under decreasing or increasing returns to scale face a higher average cost.

The relationship between scale efficiency and levels of hospital variables that indicate size is the expected one. The hospital specific returns to scale evaluation is an additional tool for decision-makers provided by DEA.

[3] The function includes 5 inputs; the cost of employees, the cost of supplies and other expenditures, the cost of contract and lease services, and the number of beds. All inputs and outputs are considered discretionary.

Table 5 -15 Administrative DEA: Average Output Slacks

Model		Hospitals	Admissions	Visits
CRS	All	83	0.00	832.73
	Ineff	58	0.00	1,191.66
VRS	All	83	0.00	1,751.18
	Ineff	49	0.00	2,966.28

Table 5-15 presents the output targets. Hospitals produce the maximum possible amount of the first proxy administrative output, admissions but a lower amount of the second one, outpatient visits. On average, the hospital production could increase by 832.73 and by 1751.18 visits for the CRS and VRS surfaces respectively; a potential improvement of 0.57 percent and 1.2 percent respectively. The production of admissions is efficient.

Table 5 -16 Administrative DEA: Average Excessive Inputs

Model	Hosp		EC	WSUP	WCON	WCAP	CPHY	BED
CRS	All	83	1,220.70	981.57	969.16	219.63	144.04	45.59
	Inef	58	1,746.87	1,404.65	1,386.90	314.30	206.12	65.24
VRS	All	83	1,094.38	804.07	742.54	174.32	144.82	42.55
	Inef	49	1,853.74	1,362.00	1,257.77	295.28	245.31	72.08

Table (5-16) presents the analysis of potential improvement of inputs. The average hospital, for example, could save $1,220.7 and $1,094.38 thousand from the efficient employment of the administrative personnel under the CRS and VRS surfaces respectively.

The actual levels of inputs and outputs, the potential levels of operation under efficiency, and their difference labeled potential improvement are presented in table 5-17.

The results indicate that the average hospital spends $3,535.1 thousand (CRS surface) on administration above the optimal level ($2,960.13 for the VRS surface). The CRS model indicates a 24.68 percent overall potential improvement (input savings) from the movement to efficient frontier, while the VRS indicates a 20.67 percent.

Table 5 -17 Administrative DEA: Efficiency Analysis (Means)

	Actual Value	Projected Efficient Value		Potential Improvement (Slacks)	
		CRS	VRS	CRS	VRS
Outputs					
Admissions	13,786.4	13,786.5	0.0	0.0	0.0
Visits	145,741.0	146,573.7	147,492.2	832.7	1,751.2
EC	7,207.6	5,986.9	6,113.2	1,220.7	1,094.2
WSUP	3,995.2	3,013.6	3,191.1	981.6	804.2
WCON	2,674.7	1,705.5	1,932.2	969.2	742.5
WCAP	760.4	540.8	586.1	219.6	174.3
CPHY	202.5	58.5	57.7	144.0	144.8
BED	355.8	310.2	313.3	45.6	42.6

5.3.1 The TC-AR Extension: Weight restricted DEA and Administrative Efficiency

For the administrative function of the previous model DEA freely assigns the input and output multipliers. The following table presents descriptive statistics of multipliers .

Table 5 –18 Administrative DEA: Input and Output multipliers

	CRS			VRS		
Variable	Mean	Min	Max	Mean	Min	Max
AD	0.0016	0.0001	0.0233	0.0042	0.0000	0.0668
VIS	0.0000	0.0000	0.0004	0.0001	0.0000	0.0010
EC	0.0018	0.0000	0.0169	0.0092	0.0000	0.1387
WSUP	0.0029	0.0001	0.0421	0.0048	0.0001	0.1839
WCON	0.0009	0.0001	0.0106	0.0014	0.0001	0.0372
WCAP	0.0144	0.0005	0.3210	0.0114	0.0005	0.3025

The range of multipliers in ratio form is presented below. The ratio of output weights, admissions to visits, for example, which reflects the marginal rate of output transformation ranges between 1.64 and 462.6, (table 5-19). As illustrated in previous sections for the hospital cost function, the weights obtained sometimes do not reflect the actual importance of factors in production or exhibit considerable flexibility, which is considered inappropriate.

Following the same methodology, weight bounds are developed and a weight restricted DEA model is estimated for the administrative hospital function.

The construction of bounds presents the most difficult empirical issue in restricted DEA analysis. The popular choice in the literature is the selection of bounds based on existing "price/cost" information or based on expert opinions about optimal importance of factors in production (Thompson et al., 1996).

Table 5-19

Administrative DEA: Obtained Range of DEA Multipliers

CRS: The matrix of output ratios:

$$\begin{array}{cc} \mu_1 & \mu_2 \end{array}$$

$$P_{11} = \begin{bmatrix} -1.6402 & 1 \\ 462.8621 & -1 \end{bmatrix}$$

CRS: The matrix of input ratios:

$$R_{22} = \begin{array}{c} \begin{array}{cccc} v_1 & v_2 & v_3 & v_4 \end{array} \\ \begin{bmatrix} -0.0041 & 1 & 0 & 0 \\ 47.5381 & -1 & 0 & 0 \\ -0.0864 & 0 & 1 & 0 \\ 18.6935 & 0 & -1 & 0 \\ -0.0108 & 0 & 0 & 1 \\ 1.5113 & 0 & 0 & -1 \\ 0 & -0.1507 & 1 & 0 \\ 0 & 115.8683 & -1 & 0 \\ 0 & -0.0046 & 0 & 1 \\ 0 & 35.3389 & 0 & -1 \\ 0 & 0 & -0.0012 & 1 \\ 0 & 0 & 3.5766 & -1 \end{bmatrix} \end{array}$$

VRS: The matrix of output ratios:

$$\begin{array}{cc} \mu_1 & \mu_2 \end{array}$$

$$P_{11} = \begin{bmatrix} -0.7346 & 1 \\ 1187.4813 & -1 \end{bmatrix}$$

VRS: The matrix of input ratios:

$$R_{22} = \begin{array}{c} \begin{array}{cccc} v_1 & v_2 & v_3 & v_4 \end{array} \\ \begin{bmatrix} -0.0097 & 1 & 0 & 0 \\ 113.0281 & -1 & 0 & 0 \\ -0.0470 & 0 & 1 & 0 \\ 523.8543 & 0 & -1 & 0 \\ -0.0032 & 0 & 0 & 1 \\ 116.4976 & 0 & 0 & -1 \\ 0 & -0.0356 & 1 & 0 \\ 0 & 694.6103 & -1 & 0 \\ 0 & -0.0044 & 0 & 1 \\ 0 & 154.4712 & 0 & -1 \\ 0 & 0 & -0.0080 & 1 \\ 0 & 0 & 3.5249 & -1 \end{bmatrix} \end{array}$$

The TC-AR incorporates weight restrictions in DEA Analysis based on the empirical results obtained from the stochastic administrative cost frontier (parametric model). Specifically, the ratios of marginal costs of inputs and outputs evaluated at their actual levels (every hospital) are obtained. The multiplier bounds are defined as the 10th and 90th percentiles of the marginal cost ratios.

Table:5 -20.

Administrative DEA: The Set Weight Restrictions

CRS: The matrix of output ratios:

$$
\begin{array}{cc}
 & \begin{array}{cc} \mu_1 & \mu_2 \end{array} \\
P_{11} = & \begin{bmatrix} -4.72 & 1 \\ 16.48 & -1 \end{bmatrix}
\end{array}
$$

CRS: The matrix of input ratios:

$$
\begin{array}{cc}
 & \begin{array}{cccc} v_1 & v_2 & v_3 & v_4 \end{array} \\
R_{22} = & \begin{bmatrix}
-0.27 & 1 & 0 & 0 \\
0.79 & -1 & 0 & 0 \\
-0.16 & 0 & 1 & 0 \\
0.67 & 0 & -1 & 0 \\
-7.21 & 0 & 0 & 1 \\
49.10 & 0 & 0 & -1 \\
0 & -0.25 & 1 & 0 \\
0 & 1.63 & -1 & 0 \\
0 & -10.68 & 0 & 1 \\
0 & 113.95 & 0 & -1 \\
0 & 0 & -14.76 & 1 \\
0 & 0 & 207.13 & -1
\end{bmatrix}
\end{array}
$$

The introduction of weight restrictions in DEA is expected to discriminate among otherwise relatively efficient hospitals. Hospitals that appear efficient based on favorably selected weights will be reassessed with the imposed bounds. The obtained set of efficient hospitals will reflect the desired evaluative standards.

Table 5-21 Administrative DEA: Weight Restricted Efficiency Estimates

Model		All Hospitals Mean Efficiency	Min	Max	Inefficient Hospitals Mean Efficiency	Min	Max	Hospitals	Efficient Hospitals Hospitals	(% of All)
CRS	(I)	0.5724	0.22	1.00	.5563	.22	.903	80	3	(3.61)
	(θ)	0.5728	0.22	1.00	.5567	.22	.905	80	3	
VRS	(I)	0.6633	0.25	1.00	.6119	.25	.962	72	11	(13.25)
	(θ)	0.6633	0.25	1.00	.6119	.25	.962	72	11	

Both the number of efficient hospitals and the efficiency scores are significantly lower compared to unrestricted model. However, the effectiveness of the new model will be considered in the next section that provides efficiency analysis and comparison of the alternative models.

The potential improvement of inputs appears, also, significantly higher. The amounts of input contraction necessary for efficient operation have almost doubled.

Table 5 -22 Administrative DEA: Weight Restrictive Excessive Inputs

Model	Hosp		EC	WSUP	WCON	WCAP	CPHY	BED
CRS	All	83	2,961.56	1,631.27	1,753.00	292.52	183.35	108.15
	Inef	80	3,072.61	1,692.44	1,818.74	303.48	190.23	112.21
VRS	All	83	2,427.83	1,441.08	1,559.28	334.81	169.22	103.08
	Inef	72	2,798.75	1,661.25	1,797.51	385.96	195.07	118.83

Hospitals can save on average from $2,961.56 thousand on employees to $183.35 thousand on physician costs. The total savings equal $6,821.1 and $5,932.22 under the CRS and VRS formulations, respectively.

5.4 The Hospital Cost-minimizing DEA Function

In this analysis an alternative non-parametric DEA formulation will be used. This method is based on Fare et al., (1994), as described in the appendix 2.5.2, and involves the estimation of a cost function via linear programming. However, except the levels of outputs and levels of inputs, input prices must be entered into estimation. The procedure involves the estimation of overall cost efficiency the analog of the stochastic cost frontier. The variables used in this hospital specification include:

a) The set of outputs; Admissions, Patient Days, and Outpatient Visits.
b) The set of inputs; Hours of service of Registered Nurses, hours of service of Clerical personnel, hours of service of physicians, the number of beds, and a proxy of capital input constructed from the total cost of depreciation and interest and the price level depreciation allowance.
c) The set of input prices; the wage of RN, the wage of clerical personnel, the wage of physicians, a proxy price for supplies and contact services, a proxy price for capital.

The input prices are calculated given the total cost of each input. The additional information required over and above even a regression cost analysis is the set of both input levels and input prices. The number of beds is used as an input in this analysis and its price is the ratio of cost of supplies and contract services to beds. Other studies used the number of beds as a proxy of the capital input [Grosskopf and Valdmanis, (1987); Ferrier and Valdmanis, (1996)].

The overall cost efficiency is obtained as the ratio of the minimum cost of operation to actual cost:

$$OE(y, x, w) = MinCost(y, x, w)/ObservedCost(x, w)$$

So the estimation of overall cost efficiency is more demanding in terms of data requirements but yields technical and allocative efficiencies.

The minimum cost necessary to produce the observed set of outputs can be obtained using a cost minimization linear programming problem.

$$\mathrm{Min}_{x,\lambda} \quad \mathbf{x}^{\#}\,\mathbf{w}$$

$$\text{s.t. } \mathbf{y}\lambda - \mathrm{y} \geq 0$$

$$-\mathbf{x}\lambda + \mathbf{x}^{\#} \geq 0$$

Where $\mathbf{x}^{\#}$ is the obtained set of cost minimizing input quantities given the input prices and the output levels.

The overall efficiency can be decomposed into its technical and allocative components. The technical efficiency TE(y, x) is provided by the solution of the CRS model. The ratio of the overall cost to technical efficiency provides the allocative efficiency AE(y, x, w). This alternative DEA specification takes into account the fact that a technically efficient DMU may be allocatively inefficient utilizing the wrong mix of inputs.

The technical efficiency gives the proportion that inputs can be reduced and still produce the given levels (observed) of outputs. Scale inefficient DMUs produce beyond the most productive scale size (decreasing returns to scale) or produce below the most productive scale size while not taking full advantage of the most productive scale size. The appendix 2.1 illustrates the computation of scale efficiencies using DEA.

Descriptive statistics follow (table 5-23).

Table 5-23
Descriptive Statistics: The Hospital Cost-Minimizing DEA Model

Variable	Mean	Std. Dev.	Minimum	Maximum	Description
ADTOT	13786.4458	7628.88	2028.00	39206.00	Admissions
PDTOT	95543.7590	47782.99	17109.00	228331.00	Patient Days
VNATOT	145741.0000	119484.08	10896.00	769918.00	Outpatient Visits
HRNSE	530473.1325	322184.23	89700.00	1478990.00	RNS Hours
HCLRE	95309.6747	69802.16	9259.00	372882.00	CLR Hours
HPHY	138107.7108	171950.52	3007.00	794508.00	Physician Hours
MBEDTOT	355.8554	161.52	86.00	799.00	Number of Beds
H_CAP	32.1038	12.39	12.06	73.27	Capital Input
WRNS	0.0231	0.0065	0.0168	0.0769	RNS Wage ($000)
WCLR	0.0122	0.0054	0.0074	0.0423	CLR Wage ($000)
WPHY	0.0432	0.0125	0.0237	0.0743	Physician Wage ($000)
W_SUPCON	58.3043	19.59	33.17	149.26	Suppl etc Price ($000)
PLDA	241.2530	162.69	8.00	769.00	Capital Price ($000)
CRNSE	12114.9759	7589.27	1712.00	35320.00	RNS Cost ($000)
CCLRE	1187.2048	988.26	98.00	4956.00	CLR Cost ($000)
CPHY	5000.9759	6200.12	147.00	42870.00	Physician Cost ($000)
CSUP_CON	21325.1928	13542.94	4060.00	66008.00	Suppl etc Cost ($000)
CDFI	7289.5422	4470.07	373.00	18662.00	Capital Cost ($000)

The following table presents the empirical results for the hospital cost-minimizing DEA function.

Table 5-24 Hospital Cost-DEA: Efficiency Estimates

Description	Mean	Std. Dev.	Minimum	Maximum
CRS				
Technical Efficiency	0.9220120	0.0831634	0.6810000	1.0000000
Allocative Efficiency	0.8509759	0.0775591	0.6380000	1.0000000
Cost Efficiency	0.7845904	0.1027437	0.5530000	1.0000000
VRS				
Technical Efficiency	0.9426747	0.0724857	0.7180000	1.0000000
Allocative Efficiency	0.8836145	0.0817906	0.6710000	1.0000000
Cost Efficiency	0.8332892	0.1054963	0.5560000	1.0000000

On average the technical efficiency, which measures the proportion that inputs could be reduced and still produce the same output levels, is 0.92 and 0.94 under the CRS and VRS, respectively. The allocative efficiency, which indicates the departure from the optimal mix of inputs, is lower than the technical and averages 0.85 and 0.88, respectively. The cost efficiency, which indicates the departure from the minimum possible cost of operation, averages 0.78 and 0.83 for the CRS and VRS, respectively.

The technical efficiency score (CRS) implies an 8.45 percent of excess inputs. The allocative efficiency (CRS) score indicates that 17.5 percent of the cost can be avoided with the right input mix. Finally, the cost efficiency (CRS) implies that on average the observed cost exceeds the minimum cost by 27.45 percent.

The cost minimizing levels of inputs derived from the solution of the DEA model are given below:

Table 5-25 Hospital Cost-DEA: The Cost Minimizing Input Levels

	Mean	Std. Dev.	Minimum	Maximum	Description
Actual					
HRNSE	530473.13	322184.23	89700.00	1478990.00	RNS Hours
HCLRE	95309.67	69802.16	9259.00	372882.00	CLR Hours
HPHY	138107.71	171950.52	3007.00	794508.00	Physician Hours
MBEDTOT	355.86	161.52	86.00	799.00	Number of Beds
H_CAP	32.10	12.39	12.06	73.27	Capital Input
CRS Potential					
HRNS	463953.82	260123.03	53998.84	1190882.78	RNS Hours
HCLR	78070.31	45462.42	8874.95	225895.00	CLR Hours
HPHY	33899.09	47619.05	3249.70	332019.00	Physician Hours
BEDS	317.45	157.00	58.56	734.31	Number of Beds
H_CAP	17.36	8.94	2.47	40.76	Capital Input
VRS Potential					
HRNS	469830.91	299652.86	89700.00	1405710.00	RNS Hours
HCLR	81545.55	53626.31	9259.00	314162.00	CLR Hours
HPHY	37697.84	47562.10	3007.00	332019.00	Physician Hours
BEDS	328.45	157.48	86.00	799.00	Number of Beds
H_CAP	22.52	4.67	12.07	46.63	Capital Input

5.5 The Administrative Cost-minimizing DEA Function

In this section the administrative hospital function will be estimated via the cost-minimizing DEA formulation. The variables used in this specification include:

d) The set of outputs; Admissions, and Outpatient Visits.

e) The set of inputs; hours of service of administrative employees, hours of service of physicians in administrative positions, the number of beds, and a proxy of capital input the administrative area as a percentage to total plant.

f) The set of input prices; the wage of administrative employees, the wage of administrative physicians, a proxy price for supplies, contact services, lease services and other services, a proxy price for capital.

The input prices are calculated given the total cost of each input. Using the same methodology for the administrative function, the overall cost efficiency is obtained as the ratio of the minimum cost of operation to actual cost:

$$OE(y, x, w) = MinCost(y, x, w)/ObservedCost(x, w)$$

And its two components the technical and allocative efficiencies as described above.

The technical efficiency $TE(y, x)$ is provided by the CRS model, which includes levels of outputs and inputs, and the allocative efficiency from the ratio of the overall cost to technical efficiency $AE(y, x, w) = OE(y, x, w)/TE(y, x)$.

Descriptive statistics for the administrative hospital cost-minimizing function are presented below, table 5-26.

Table 5-26
Descriptive Statistics: The Administrative Cost-Minimizing DEA Model

Variable	Mean	Std. Dev.	Minimum	Maximum	Description
ADTOT	13786.4	7628.9	2028.0	39206.0	Admissions
VNATOT	145741.0	119484.1	10896.0	769918.0	Outpatient Visits
EH	460571.9	225567.8	94624.0	1151835.0	Employee Hours
HPHY	4175.7	11000.7	0.0	63374.0	Physician Hours
MBEDTOT	355.8	161.5	86.0	799.0	Number of Beds
PLT	15.3	6.7	2.2	35.0	Capital Input
WEMP	0.0153	0.0025	0.0103	0.0332	Employee Wage ($000)
WPHY	0.0518	0.0517	0.0000	0.4510	Physician Wage ($000)
W_OTHER	18.2	6.9	10.9	56.3	Supplies etc. Price ($000)
WCAP	5719.7	4344.8	149.6	24921.3	Capital Price ($000)
EC	7207.5	4280.7	1315.0	29281.0	Employee Cost ($000)
CPHY	202.6	457.7	0.0	2781.0	Physician Cost ($000)
CAP	760.4	480.4	14.1	2019.4	Supplies etc, Cost ($000)
C_OTHER	6669.9	4846.9	1168.0	31010.0	Capital Cost ($000)

The empirical results indicate that the cost efficiency averages 0.3 and 0.41 for the CRS and VRS models, respectively. Allocative efficiency accounts for a very large portion of the total cost efficiency.

Table 5-27 Administrative Cost-DEA: Efficiency Estimates

Description	Mean	Std. Dev.	Minimum	Maximum
CRS				
Technical Efficiency	0.805024	0.148341	0.508	1.00
Allocative Efficiency	0.354675	0.150630	0.147	1.00
Cost Efficiency	0.287988	0.146327	0.105	1.00
VRS				
Technical Efficiency	0.881602	0.115739	0.583	1.00
Allocative Efficiency	0.469867	0.206508	0.193	1.00
Cost Efficiency	0.421265	0.216812	0.148	1.00

The technical efficiency is comparable to that obtained from the previous models. Even if the construction of input prices is based on proxy input units (beds and the capital input), the magnitude of allocative inefficiency can not be attributed solely to specification error. In addition, the technical efficiency, which is based on the same proxy inputs, falls into the range obtained from alternative models estimated in section 5.3.

One of the disadvantages of this model is the data requirements. Except for the level of inputs, the prices of inputs must be available, which makes the construction of health care models prohibitively difficult.

Data Envelopment Analysis provides a variety of alternative models and yields a detailed record of performance for each hospital. The results provide hospital administrators with valuable information about overall performance as well as information by functional component.

However, modeling the efficiency score in a second stage will enable decision-makers to identify potential determinants of performance and will provide an additional managerial tool. The results of the alternative DEA formulation (hospital and administrative) will be modeled in the following section.

6

Modeling inefficiency

6.1 Introduction

One of the objectives of this study is to model the inefficiency of hospital administration obtained from the stochastic frontier and the DEA models as well as the inefficiency of the total hospital sector. In this methodology, the first stage establishes the optimal (frontier) performance of a set of productive units while the second explains the gap between the optimal and the actual performance. Factors associated with inefficient performance are identified and their effect on the cost efficiency/inefficiency is estimated.

Modeling inefficiency enables us to identify possible determinants of inefficiency and quantify their contribution to inefficiency. Also, based on assumptions about the distribution of the efficiency index, different sets of hypotheses can be tested for a variety of DMU characteristics.

By reducing inefficiency hospitals can produce a given level of output with fewer productive resources and lower overall expenditures.

It is common in the empirical literature of efficiency analysis to employ statistical tools (regression analysis) to explain the variability of the efficiency index.

Modeling inefficiency in a second stage is a difficult task as the model of inefficiency involves the identification of factors that belong to the second stage and not in the first (Dor, 1994). In the stochastic frontier, omitted variables can upward bias the residuals and the inefficiency index. Also, correlation between the explanatory variables in the two stage model will affect the coefficients of the second stage regression. In this case, the coefficients will not be unbiased and consistent (Grosskopf, 1996).

The stochastic frontier model yields a hospital specific index of inefficiency. Specifically, the residuals of the model provide the composite error ε_i ($\varepsilon_i = u_i + v_i$) of inefficiency and noise. To isolate the inefficiency component, the expected value of u_i conditional on ε_i is obtained, which reflects the individual hospital-specific departure from the optimum frontier (Jodrow et al., 1982). The stochastic frontier yields an index that measures the degree of inefficiency. The efficient hospitals are assigned the value of zero while the inefficient ones a value above zero.

The DEA technique evaluates the hospital performance and constructs an efficiency index. Hospitals that perform efficiently have an index of performance equal to 1 and form the best practice frontier against which all other hospitals are evaluated.

This study will investigate the administrative hospital efficiency and the potential benefits of electronic data interchange (EDI). Concerns about the administrative efficiency in the hospital sector and the intensified criticism posed the following questions:

Is the administrative component of hospitals inefficient?

Does more administration increase or decrease hospital efficiency?

How efficient is the administrative function of hospitals?

Does Electronic Data Interchange improve the efficiency of administration?

The inefficiency of hospital administration is costly as it was evaluated empirically in previous sections. However, it pays to investigate its determinants.

6.2 Econometric Issues

The determinants of efficiency/inefficiency are modeled according to the following general model:

Stochastic Frontier Inefficiency Score = f (Independent Variables)

DEA Transformed Inefficiency Score = f (Independent Variables)

Studies model the inefficiency (efficiency) index using a variety of techniques. Ordinary Least Squares regression analysis is the simple and the most popular method of explaining the variations of a given dependent variable. A number of applications that analyze estimated inefficiencies employ OLS. Vitaliano and Toren, (1994), among others, used OLS regression and the residuals from the stochastic frontier as a dependent variable modeling the determinants of nursing home inefficiency.

However, since the efficiency score is constrained to fall between 0 and 1 OLS is not appropriate as it yields biased estimates. Since OLS yields biased and inconsistent estimators other studies proposed transformations of the bounded by zero or unity index to an unbounded score using a transformed variable. Other propositions involve the transformation ln(1-y/y), where y is the DEA efficiency score (Lovell, Walter and Wood, 1995). If the dependent variable is bounded below by zero then a simple logarithmic transformation can remove the OLS bias.

The DEA efficiency index is treated as a censored variable by Kooreman (1994), who employed the tobit technique. In addition, he transformed the efficiency index into a binary variable (grouping DMUs into efficient and inefficient ones) and used the probit technique. Ferrier and Valdmanis (1996) modeled rural hospital efficiency using the reciprocal of the efficiency index as dependent variable. So, they estimated a censored at

1 Tobit model since the reciprocal of the efficiency index is bounded below by 1 and it is unbounded above.

Since the dependent variable is continuous but ranges between 0 and 1, OLS estimation does not seem appropriate for estimation. Actually, for the DEA efficiency index a large percentage of observations take the value of one and the remaining form a continuous variable that is close but lower than one. Furthermore, while the dependent variable (efficiency or inefficiency index) is strictly positive and ranges between zero (0) and one (1), the whole range of the explanatory variables (X_i) is available. This combination of discrete and continuous elements form a variable that is neither normally distributed nor homoscedastic (Chilingerian, 1995).

The distribution of the DEA index is best described by a censored distribution and the most appropriate model for estimation is the Tobit, since a large number of values is censored at the value of 1 (or 0 for the inefficiency index). The Tobit model takes into account the nature of distribution of the efficiency score and in addition the interpretation of its coefficients is similar to that of an OLS model.

Chilingerian, (1995), points out that, in this case, censoring is a result of the mathematical derivation and not that of a stochastic mechanism, but is a good approximation for the nature of an efficiency score. So, he used the normalization:

$$\text{Inefficiency score} = [(1/y)-1]$$

for computational reasons following the suggestion of Greene (1993a), and employed the Tobit technique. Rosko et al., (1995), used the negative of the above transformation: Efficiency score= $-1[(1/y)-1]$. This transformation bounds the DEA score in one direction censoring it at zero. The efficient DMUs take the value of zero while the inefficient ones take negative values.

This study employs the Tobit technique to model the inefficiency index. The dependent variable is the stochastic frontier inefficiency score without any transformation or the transformed DEA efficiency score. The transformation used for the DEA type efficiency scores is that proposed by Chilingerian, (1995), DEA Inefficiency Score = [(1/y)-1].

6.3 *Data and Variables*

The additional data set used in this section were obtained from the Medicare's (HCFA) Impact file for the year 1993 and the 1993 County and City Data Book of the Bureau of Census. Also, the 1993 survey of the health care sector conducted by Response Analysis Corporation (RAC) for the state of New Jersey will be used.

Table 6-1

Descriptive Statistics: Hospital Inefficiency Model

Variable	Mean	Std. Dev.	Minimum	Maximum	Description
SAMC	0.1514	0.0236	0.0908	0.2089	The Share of Administration
SAMC2	0.0235	0.0072	0.0082	0.0436	The Share of Admin. Squared
MBEDTOT	355.8554	161.5196	86.0000	799.0000	Number of Beds
MILESTH	4.4390	4.3634	0.0000	19.0000	Miles to the Nearest Hospital
INC	17193.3012	6675.2674	7033.0000	41673.0000	Income Per Capita, County
HS	72.6506	11.6015	43.3000	93.3000	High School Educ. (%), County
OCRATE	0.7214	0.0930	0.4706	0.8920	Occupancy Rate
CMI	1.3265	0.2149	1.0864	2.6039	Case Mix Index
UNCOM_C	9965.6506	11130.7672	-388.0000	94673.0000	Uncompensated Care ($)
MALPR	444.4819	1169.5726	0.0000	9465.0000	Malpractice Cost ($)
PROFIT	4805.0723	7080.4846	-30631.0000	25915.0000	Profit ($)
HOSP	8.0241	4.0030	1.0000	16.0000	No of Hospitals in County

6.4 The Model

The first model to be estimated is an OLS corrected for heteroscedasticity.

$$y_i = \beta' x_i + u_i$$

Where : y_i is the inefficiency index

β is a k x 1 vector of parameters

x_i is a k x 1 vector of explanatory variables

u_i is the error term which by assumption is i.i.d. distributed: u ~ N(0, σ^2)

The second model follows the Tobit specification:

$$y_i = \begin{cases} \beta' x_i + u_i & \textit{if } \mathrm{y_i} > 0 \\ 0 & \textit{Otherwise} \end{cases}$$

with

$$prob(y_i > 0) = prob(y_i > 0).f(y_i|y_i > 0) = \Phi\frac{f(y_i - \beta' x_i, \sigma^2)}{\Phi}$$

$$prob(y_i = 0) = prob(u_i < -\beta' x_i) = (1 - \Phi)$$

The maximum likelihood function of this model is:

$$\ell = \prod_0 [1 - \Phi] \prod_1 f[(y_i - \beta x_i) / \sigma]$$

The log likelihood becomes:

$$L = \sum_0 \log(1 - \Phi) + \sum_1 \log \frac{1}{\sqrt{2\pi\sigma^2}} - \sum_1 \frac{1}{2\sigma^2}(y_i - \beta x_i)^2$$

Note: The dependent variable is: (1) the inefficiency index derived from the stochastic frontier model (Hospital and Administrative functions), or (2) the transformation ((1/y)-1), where y is the efficiency index obtained from Data Envelopment Analysis type of models.

6.5 Modeling Hospital Inefficiency

In this section the hospital inefficiency is modeled. The dependent variable is the inefficiency index obtained from the stochastic (6.5.1) and the transformed efficiency index obtained from the alternative DEA type of models (6.5.2). The Tobit technique is used.

6.5.1 The Stochastic Frontier

The possible influences of the hospital inefficiency are hospital characteristics (variables not included in the first stage) and hospital area characteristics. The stochastic frontier yielded the following results:

Table 6-2

Hospitals: The Stochastic Frontier Inefficiency Model

TOBIT Estimates
Dependent variable: The Stochastic Frontier INEFFCIENCY INDEX (Mean=0.04037,S.D.= 0.0417)
Log likelihood function 163.0317

Variable	Coefficient	Standard Error	z=b/s.e.	P[|Z|≥z]
Constant	-0.59852	0.17217	-3.476	0.00051
SAMC	6.3177	1.8137	3.483	0.00050
SAMC2	-19.292	5.8333	-3.307	0.00094
MBEDTOT	0.36668E-04	0.31802E-04	1.153	0.24891
MILESTH	0.48006E-04	0.35907E-04	1.337	0.18124
INC	-0.32435E-05	0.11166E-05	-2.905	0.00367
HS	0.19656E-02	0.65049E-03	3.022	0.00251
OCRATE	-0.50624E-01	0.45350E-01	-1.116	0.26430
CMI	0.49536E-01	0.29580E-01	1.675	0.09400
UNCOM_C	0.12902E-05	0.41885E-06	3.080	0.00207
MALPR	-0.68051E-05	0.44597E-05	-1.526	0.12703
PROFIT	-0.74162E-06	0.61574E-06	-1.204	0.22842
σ	0.33940E-01	0.26342E-02	12.884	0.00000

OLS Statistics:
OLS: R^2 = 0.32932 Adj-R^2 = 0.22541 Model test: F[11,71]= 3.17, Prob value = 0.00154
Breusch-Pagan chi-squared = 13.4573, (with 11 d.f.)

The results indicate that only a small portion of variation in hospital inefficiency can be explained by the available set of independent variables. The main objective of this analysis is to assess the effect of administration on hospital inefficiency. The independent variables except the administrative variable control for size, market demand, competition and other hospital or area characteristics.

It was hypothesized that hospital administration influences inefficiency. The results support this hypothesis. The effect of administration on inefficiency is positive, significant, and nonlinear. Inefficiency as a function of administration increases at a decreasing rate and reaches a maximum when the administrative share exceeds 17 percent. The percentage of administrative cost to total hospital cost serves as a proxy measure of administration. The results indicate that holding other variables constant, the larger the administrative share the more inefficient the hospital is.

The number of beds, which indicate size, also, has a positive linear and significant effect on inefficiency. Excessive growth of the firm creates inefficiency pressures. The size-caused inefficiency can be the result of exhausted gains from the division of labor, as well as reduced coordination and decision making congestion (Färe et al, 1985).

The variable "miles to the nearest" hospital is an indicator of competition in a hospital's area. It is assumed that the higher the number of miles from the nearest hospital the lower the degree of competition. The positive sign indicates that (the lower the degree of competition) the higher the number of miles the higher the inefficiency. So, competition promotes efficient operation. The relationship between efficiency and competition has been documented in the literature. Libenstein (-1966, 1976 -) among others connected competitive forces with his "X-efficiency" theory. Studies that examined the effect of competition on hospital costs reported a significant relationship. Zwanziger and Melnick (1988) analyzed the behavior of California's hospitals under different competitive regimes and found that competition lowered hospital costs significantly.

Other variables that explain overall hospital inefficiency are the per capita income, and the percentage of high school graduates. Per Capita Income has the expected sign and it is related to market demand in the area. The percentage of high school graduates in the area is another environmental factor that influences the market demand for the hospital services as well as the market for inputs. The positive sign implies the presence of educational effects on demand and a pressure for higher wages in the market.

The effect of occupancy rate (also, a market demand indicator) is negative but not significant and indicates that holding the hospital size constant, the higher the occupancy rate, the higher the efficiency level. Both, the Medicare case mix index and uncompensated care influence inefficiency. The malpractice cost was included as a proxy measure of quality. If higher levels of malpractice costs indicate lower levels of quality then the coefficient of malpractice cost implies a positive relationship of quality and inefficiency. Quality is costly to the hospital, as it requires more inputs and greater administrative effort to be produced. The frontier cost equation does not include a case mix index and a quality adjuster, so since both quality and case mix are more costly to the hospital, they are expected to have a positive effect on inefficiency.

Regulation, a major determinant of inefficiency, can not be controlled, since all hospitals operate under the same regulatory environment. Type of ownership is another suspected cause of inefficiency but its effect can not be determined in this study, since almost all hospitals are not-for-profit (there is no private hospital in the sample). However, the coefficient of profit is negative (but not significant) indicating that the profitable hospitals are more efficient.

The percentage of administrative cost to total averages 15.14 and ranges from 9.08 to 20.89. There are 31 hospitals that spend 1 percent below the mean and 33 hospitals that spend one percent above the mean. The first group of hospitals has an average inefficiency index of 1.91 while the second group's inefficiency index averages 5.19. The t-test supports the hypothesis that hospitals with a lower than average administrative share are more efficient than hospitals with a higher than average administrative share.

Table 6-3: Hospital Inefficiency and Hospital Administration

Variable	Cases	Mean	Std. Dev.	Minimum	Maximum	
Inefficiency	31	0.0191402	0.0153571	0.0028696	0.0686672	1st group
Inefficiency	33	0.0518887	0.0490808	0.0027302	0.1528228	2nd group

Hypothesis	Test	P-Value
Ho: mean(1st group)-mean(2nd group)=0	t=-3.5537	P>|t|=0.0007
Ho: Ineff Distr (1st group)=Ineff Distr (2nd group)	F=8.457	P> F =0.0000

A Test proposed by Banker, (1993), uses the half-normal or exponential distribution assumptions of the inefficiency index to test hypotheses on efficiency differences between groups (appendix 6.1). To apply this test, let's consider the above two groups of hospitals. The first group (31 hospitals) spends less than 14 percent on administration, while the second group (33 hospitals) spends more than 16 percent. Since the stochastic frontier is modeled on the assumptions of a half-normally distributed inefficiency term, the half normal distribution is the most appropriate to use. Under this assumption the Banker's test statistic is: $T = 8.457$

The test statistic follows the F-distribution with (33, 31) degrees of freedom. The test statistic is statistically significant at less than 0.01 levels of significance. The test implies that hospitals with lower levels of administration are significantly more efficient.

6.5.2 Modeling Hospital Inefficiency: The DEA Models

The second stage analysis is applied to the alternative Data Envelopment Analysis models estimated in the previous section. The main objective of this model is to test if administration influences hospital inefficiency. The Data Envelopment Analysis constructs the best practice based, not only on the sets of output and levels, but also on the model's priorities. However, it is expected to yield a relative ranking of DMUs not necessarily comparable with that obtained via the stochastic frontier. In addition, the set of DEA inefficiency determinants is expected to be different from the stochastic one. The stochastic frontier supports the hypothesis of inefficient hospital administration. The size of administration is the main determinant of the cost inefficiency.

The administrative function of hospitals is not expected to be among the main determinants of the hospital production function and the influences of its technical efficiency. The empirical results of the DEA modeling are not consistent with the results obtained from the stochastic frontier, in general. In addition, the weight restricted DEA results are more correlated with the production-optimizing behavior of hospitals than with the cost- minimizing one. However, the cost-minimizing DEA criterion, as expected, yields comparable results with the stochastic model.

The following table presents the empirical estimates of two DEA models; the constant returns to scale cost-DEA efficiency and the variable returns to scale cost-DEA efficiency. The coefficient of administration is not statistically significant but has the expected sign in both models. The remaining variables are comparable.

Table 6-4: Hospitals: The DEA Inefficiency Model

TOBIT ESTIMATES

Dependent variable: Cost Inefficiency (CRS)
Log likelihood function: 42.72806

Variable	Coefficient	Standard Error	z=b/s.e.	P[|Z|>z]
Constant	1.0997	0.66132	1.663	0.09635
SAMC	0.81531E-01	6.8905	0.012	0.99056
SAMC2	-0.75326	22.093	-0.034	0.97280
MBEDTOT	-0.69486E-04	0.12002E-03	-0.579	0.56261
HOSP	0.55363E-02	0.42176E-02	1.313	0.18930
INC	-0.52851E-05	0.43997E-05	-1.201	0.22965
HS	-0.17346E-02	0.25945E-02	-0.669	0.50376
OCRATE	-1.1124	0.17685	-6.290	0.00000
UNCOM_C	0.22112E-06	0.16445E-05	0.134	0.89304
CMI	0.14829	0.11427	1.298	0.19439
MALPR	0.12548E-04	0.17149E-04	0.732	0.46436
PROFIT	-0.14660E-05	0.23697E-05	-0.619	0.53616
σ	0.12969	0.10541E-01	12.303	0.00000

Dependent variable: Cost Inefficiency (VRS)
Log likelihood function: 18.75853

Variable	Coefficient	Standard Error	z=b/s.e.	P[|Z|>z]
Constant	-0.85360E-01	0.76853	-0.111	0.91156
SAMC	8.4039	8.0100	1.049	0.29410
SAMC2	-28.100	25.706	-1.093	0.27433
MBEDTOT	0.22001E-03	0.14293E-03	1.539	0.12373
HOSP	0.31588E-02	0.49380E-02	0.640	0.52238
INC	-0.47527E-05	0.51052E-05	-0.931	0.35188
HS	-0.26426E-02	0.30188E-02	-0.875	0.38135
OCRATE	-0.55304	0.21128	-2.618	0.00886
UNCOM_C	0.37585E-06	0.19154E-05	0.196	0.84443
CMI	0.19588	0.13264	1.477	0.13975
MALPR	-0.12367E-05	0.19911E-04	-0.062	0.95047
PROFIT	-0.29136E-05	0.27483E-05	-1.060	0.28906
σ	0.15018	0.13251E-01	11.333	0.00000

6.6 Modeling the Administrative Hospital Efficiency

The inefficiency of the administrative function, obtained from the stochastic frontier model, is explained by a set of hospital characteristics, like payer-mix, and other environmental variables that imply organizational complexity and possibly influence inefficiency. The additional data were taken from the Medicare's (HCFA) Impact files, the County and City Data Book of the Bureau of Census, and the Health Care Survey (1993) conducted by Response Analysis Corporation for the State of New Jersey.

Table 6-5

Descriptive Statistics: The Administrative Inefficiency Model

Variable	Mean	Std. Dev.	Minimum	Maximum	Description
PADMC	0.3677	0.1084	0.0965	0.6720	Medicare Admissions (%)
PADMD	0.1246	0.1005	0.0116	0.5083	Medicaid Admissions (%)
PADCHAR	0.0333	0.0485	0.0000	0.2569	Charity Care Admissions (%)
PADHMO	0.0781	0.0606	0.0000	0.2809	HMO Admissions (%)
DSH	0.1583	0.1272	0.0271	0.6274	DSH Percentage
IRB	0.0808	0.1186	0.0000	0.5220	IRB Ratio
HS	72.6506	11.6015	43.3000	93.3000	High School Grad (%), County
BS	22.6012	12.6393	5.8000	63.2000	Bachelor's Degree (%), County
POVH	10.6904	8.2103	1.8000	38.8000	Households below poverty (%)
MILESTH	4.4390	4.3634	0.0000	19.0000	Miles to the Nearest Hospital
BIRTH	659.9880	629.6005	59.0000	4992.0000	Births No.(<2500 grams), County
SIXF	7.4386	1.7502	4.4000	12.6000	Age 65-74 (%), County

The results indicate that Medicare and Medicaid admissions have a positive effect on inefficiency while HMO (excludes Medicare and Medicaid HMO) and charity related admissions have a negative effect. The IRB variable (residents to bed ratio) represents the administrative complexity of teaching hospitals, but it is not significant in this model. The "miles to the nearest hospital" variable that implies competitive pressures in the market is not significant in the Tobit specification. The coefficient tends to be negative implying that competition influences inefficient behavior. The environmental factors HS, BS, BIRTH, POVH and SIXF indicate influences on demand for hospital services and demand for hospital inputs that affect the administrative function. The variable Birth that measures low birth weight (number of cases, less than 2,500 grams) has a positive (and mostly significant) effect across equations, indicating the burden that premature births place on hospitals.

Table 6-6

Administration: The Stochastic Frontier Inefficiency Model

TOBIT Estimates

Dependent variable: The Stochastic Frontier INEFFCIENCY INDEX (Mean=0.04037,S.D.= 0.0417)

Log likelihood function 180.7159

Variable	Coefficient	Standard Error	z=b/s.e.	P[|Z|≥z]
Constant	-0.29424	0.65338E-01	-4.503	0.00001
PADMC	0.58847E-01	0.52536E-01	1.120	0.26266
PADMD	0.46389	0.12420	3.735	0.00019
PADCHAR	-0.17393	0.79217E-01	-2.196	0.02812
PADHMO	-0.62349E-01	0.65742E-01	-0.948	0.34293
DSH	-0.19810	0.10355	-1.913	0.05573
IRB	0.59821E-02	0.33821E-01	0.177	0.85961
HS	0.36189E-02	0.80002E-03	4.523	0.00001
BS	-0.14708E-02	0.54152E-03	-2.716	0.00661
POVH	0.14000E-02	0.84320E-03	1.660	0.09684
MILESTH	-0.26989E-04	0.29649E-04	-0.910	0.36268
BIRTH	0.17575E-04	0.57099E-05	3.078	0.00208
SIXF	0.44806E-02	0.19726E-02	2.271	0.02313
σ	0.27427E-01	0.21287E-02	12.884	0.00000

OLS: R^2 = 0.37813 Adj-R^2 = 0.27152 Model test: F[12,70]= 3.55, Prob value = 0.00039
Breusch-Pagan chi-squared = 39.6720, (with 12 d.f.)

The Percentage of households in the county below the poverty level and the percentage of individuals between 65 and 74 have a strong positive effect on inefficiency (stochastic and DEA). However, this effect is not consistent across all DEA surfaces. The DSH[1] variable (the disproportionate share adjustment payments), indicates the regulatory

[1] *The DSH payments compensate hospitals for serving a large proportion of low-income patients. Low-income patients are sicker than the average patient and therefore, more costly to treat. Hospitals DSH payments are made according to the sum of two percentages; the percentage of Medicare inpatient days that receive supplemental security income (SSI) payments and the percentage of Medicaid to total inpatient days.*

environment in which hospitals operate and the administrative burden that it possibly places on them. The coefficient of DSH is negative and statistically significant which indicates that the administrations of high DSH hospitals are more efficient.

The efficiency index of the alternative DEA formulations when regressed on the same set of independent variables yielded similar as well as different results. An outcome that it is expected given the assumptions and priorities of the alternative models are different. Two representative regressions are presented in appendix 6.2. The overall f it of the models is weak as most of the coefficients are insignificant. After all, the regressions have shown that the optimizing priorities of the stochastic cost frontier and DEA are different. Even within DEA there are significant differences in efficiencies.

6.7 Electronic Data Interchange

The use of computerized technology in the hospital setting is extensive and involves almost every organizational and clinical aspect. The major areas include medical education and research, patient care and medical records, medical expert systems, diagnostic support systems, and financial management. The impact of computerized medical technology on hospital and in general on health care expenditures is expected to be significant.

Hospital expenditures have consistently risen with overall health care expenditures for the last twenty years, and medical technology is considered one of the major components of hospital cost growth. However, (information) technology can be used as a cost reduction mechanism able to streamline the administrative complexity of the health care system. Among the strategies of reducing the administrative cost of a health care system is the application of electronic data interchange (EDI). Electronic Data Interchange is a unique computerized-communication system of transferring information (data) directly between computer applications of two organizations.

The electronic data interchange technology extends the boundaries of hospital's health information system and provides the link between the hospital and its trading partners (patients, employers, insurance companies, government). Electronic data interchange implies the cooperation of at least two or more geographically dispersed common systems. The physical distance becomes unimportant as the flow of information exchanged and transactions carried out involve telescopic time (Holland et al., 1992).

Adoption of EDI technology involves the use of a uniform billing and record keeping system using common formats and standards.

The Workgroup on Electronic Data Interchange (WEDI), a not-for-profit organization was established in 1991 to examine the potential effect of electronic communication technology on health care administration. The WEDI group estimated in two successive reports that the development of a national electronic communication network in health care could create significant administrative savings (WEDI, 1992 and 1993).

Electronic data interchange, in a hospital setting, can be applied to transactions that involve a variety of functions;

(a) Financial functions that include transactions such as claim submission, coordination of benefits, claims payment remittance and notice.

(b) Administrative functions that include transaction such as enrollment, eligibility verification, claims inquiry, provider referrals/authorizations, test of order and results, prescription orders, managed-care pre-authorizations, material management, and provider appointment scheduling.

(c) Clinical functions that include transactions such as prescription records, medical tests and results, and medical records.

In 1992, WEDI estimated possible annual administrative savings through automation of claims submission, claims inquiry, enrollment, eligibility verification and payment/remittance advice transactions. These five core transactions could result in savings ranged between $4 and $10 billion for a single year. In 1993, WEDI expanded the analysis to cover six more EDI applications; health care material management, prescription ordering, test ordering, results reporting, coordination of benefits, referrals and pre-authorizations, provider appointing and scheduling. As reported, total savings from the core and the six additional transactions ranged from $12.9 to $26 billion (WEDI, 1992, 1993). Other studies reported substantial savings from the implementation of a set of EDI applications. The estimates are based on different sets of applications and assumptions. However, they are not comparable but indicative of the potential savings. According to Lewin-VHI et al., (1993), the estimates of four representative studies range between $1 and $9.4 billion.

Currently market participants widely believe that the operationalization and assimilation of computerized technology can substantially reduce administrative costs.

WEDI reported that the average unit cost of electronic processing is lower than that of on paper processing which can be considered as a gain in efficiency. The philosophy of WEDI project is based on the following hypothesis: If *"on a per transaction basis, the cost to perform claims related transactions electronically is lower than the cost to perform the same transaction manually,"* then the savings from automation would be significant.

Electronic interchange of information has become a good substitute for other methods of exchanging information. In addition, the technology may be applied to patient records and to management control.

Based on the demonstrated ability of computers to influence the administrative functionality and efficiency of many administrative sections, hospital decision-makers embraced the advanced technology of electronic data interchange to streamline hospital administrative costs and seek efficient practices for the administrative problems.

The development of Electronic Data Interchange has been influenced by a variety of regulations and policies. HCFA is developing the Medicare Transaction System and by the year 1998 all Medicare claims, payments, and coordination of benefits transactions will be processed electronically (Wagner and Lynn, 1994).

The Health Information Network and Technologies (HINT) project investigated the degree of implementation of electronic data interchange (EDI) technology in the state of New Jersey. The survey conducted by Response Analysis Corporation (RAC) involved three major areas (administrative functions); eligibility, claims processing, and medical information communication and storage (medical records).

The sample size is too small to be representative at the national level but it is indicative of the trends of computerization of the hospital sector. Hospital administrators answered two different questionnaires. One involved eligibility and claim processing and the second the medical record department. However, the response rate is very low and limits the objectives for this study. Basically, the survey focuses on three administrative functions: Insurance eligibility verification, health insurance claims processing and communicating and storing other medical information. The main findings of the survey for claims processing and medical records are discussed below.

6.7.1 Hospital Claims Processing and Administrative efficiency

The majority of hospitals process claims on paper (includes telephone and fax) and a relatively smaller proportion use both means, paper and electronic (EDI). In 1993, 76 % of hospitals use telephone to confirm insurance eligibility and only 15 % use electronic methods, while devoting approximately 66 staff hours per week to conduct this volume at an average total cost of $3.81 (per check).

The majority of hospitals (81%) process health insurance claims both on paper and electronically. Approximately 14% of hospitals process claims only on paper and there is no hospital that processes claims electronically only.

The average number of claims processed per week is 600. It takes 116 staff hours per week to process the above volume on paper and only 82 electronically. However, the cost per claim does not differ substantially ($0.67 or 15%). Electronic processing costs less ($3.80) than on paper ($4.50). Other sectors report gains form conversion to electronic processing that range from 24% (pharmacies) to 37% (payers). The average rejection rate of initial claims is substantially lower, (47%), for electronic than for paper transactions as well as for follow-up claims, (45%).

Another cost advantage of electronic processing in this survey is the turnaround of payments. The average age of accounts receivable is 66 days for paper claims and 37 for electronic. However, it is not clear if hospitals decide the method of processing claims according to the complexity of a claim to be processed, or according to the fact that the second entity does not accept electronic processed claims.

Modeling the effect of electronic data interchange and specifically the claims processing function is a difficult task because of the very limited number of observations (maximum 15). However even if a model can not be completely specified, the results are indicative of the true EDI effect on administrative inefficiency.

Only the OLS estimates are presented because of the limited data set. The first two models explain the inefficiency score of the stochastic frontier. Controlling for the effect of payer-mix; the percentage of Medicare claims, the percentage of Medicaid claims and the percentage of HMO claims, the percentage of insurance eligibility checks confirmed electronically has a negative and significant effect on administrative inefficiency. Only 15 percent of hospitals use EDI for insurance eligibility checks and 76 percent of hospitals use Paper processing which includes phone and fax equipment. In the second specification the coefficient of the percentage of insurance eligibility checks performed by phone is positive and significant implying that paper processing influences the inefficiency of administration. The results are consistent and relatively stable across the different DEA formulations. The weight restricted DEA as well as the Cost-minimizing DEA yield similar results.

Other variables that indicate the effectiveness of Electronic Data interchange in this function is the price per claim (paper or electronic). The reported average cost per electronic claim processing is negatively related to inefficiency while the average cost per paper claim processing is positively related. The results are similar for the hours spent on the claims processing variable.

EDI is an organizational tool with strategic advantages. The EDI transactions are subject to high quality standards since the information keyed only once at the beginning of the function can be translated, checked in syntax and accuracy of information, and outperforms any manual operation. The regressions confirm the advantages of EDI.

Table 6-7

Modeling the effect of EDI: Claims Processing

(The Stochastic Frontier Inefficiency)

OLS Estimates

Dependent variable: The Stochastic Frontier INEFFCIENCY INDEX

OLS: R^2 = 0.8351 Adj-R^2 = 0.5466 Model test: F[7,4]= 2.894, Prob value = 0.1606

Variable	Coefficient	Standard Error	t-ratio	P[|T|≥t]	Description
INTERCEP	-0.031816	0.05880274	-0.541	0.6172	
MCAID	0.006437	0.00236061	2.727	0.0526	Medicaid Claims
MCARE	0.000066584	0.00079045	0.084	0.9369	Medicare Claims
HMO	-0.001757	0.00136545	-1.287	0.2677	HMO Claims
HIEC	0.000517	0.00025888	1.999	0.1163	Hours on IEC
ACP	0.006703	0.00470070	1.426	0.2270	Ave Cost on Paper
ACE	-0.005943	0.00466075	-1.275	0.2713	Ave Cost Elect Claim
IECEL	-0.001192	0.00045466	-2.621	0.0588	IEC Electronically

OLS Estimates

Dependent variable: The Stochastic Frontier INEFFCIENCY INDEX

OLS: R^2 = 0.8063 Adj-R^2 = 0.6402 Model test: F[6,7]= 4.855, Prob value = 0.0286

Variable	Coefficient	Standard Error	t-ratio	P[|T|≥t]	
INTERCEP	0.007732	0.06530711	0.118	0.9091	
MCAID	0.003889	0.00218003	1.784	0.1177	Medicaid Claims
MCARE	-0.000750	0.00066519	-1.127	0.2968	Medicare Claims
HMO	-0.002718	0.00119351	-2.277	0.0569	HMO Claims
HPC	0.000114	0.00011094	1.029	0.3376	Hours Paper Claims
HEC	-0.000340	0.00010977	-3.094	0.0175	Hours Electr Claims
IECPH	0.000960	0.00038728	2.479	0.0423	IEC by phone

Table 6-8

Modeling the effect of EDI: Claims Processing (The DEA Inefficiency)

OLS Estimates

Dependent variable: The Weight Restricted (TCAR) DEA, VRS transformed Inefficiency

OLS: R^2 = 0.6767 Adj-R^2 = 0.2887 Model test: F[6,5]= 1.744, Prob value = 0.2790

Variable	Coefficient	Standard Error	t-ratio	P[|T|≥t]	
INTERCEP	-0.103618	0.62105023	-0.167	0.8740	
MCAID	0.057196	0.02466464	2.319	0.0681	Medicaid Claims
MCARE	0.007437	0.00834626	0.891	0.4137	Medicare Claims
HMO	-0.019024	0.01382974	-1.376	0.2274	HMO Claims
HIEC	0.003401	0.00211888	1.605	0.1694	Hours on IEC
ACP	-0.041378	0.03566623	-1.160	0.2984	Ave Cost on Paper
IECEL	-0.005864	0.00459902	-1.275	0.2584	IEC Electronically

OLS Estimates

Dependent variable: The Cost Efficiency Cost-DEA, CRS transformed

OLS: R^2 = 0.8378 Adj-R^2 = 0.6431 Model test: F[6,5]= 4.303, Prob value = 0.0654

Variable	Coefficient	Standard Error	t-ratio	P[|T|≥t]	
INTERCEP	0.171714	1.76716326	0.097	0.9264	
MCAID	0.041359	0.07149799	0.578	0.5880	Medicaid Claims
MCARE	0.090655	0.02396641	3.783	0.0129	Medicare Claims
HMO	-0.072587	0.04118388	-1.762	0.1383	HMO Claims
ACE	-0.115049	0.10960173	-1.050	0.3419	Ave Cost Elect
ACP	0.153785	0.13822205	1.113	0.3165	Ave Cost on Paper
IECEL	-0.038138	0.01371022	-2.782	0.0388	IEC Electronically

6.7.2 Hospital Medical Records and Administrative efficiency

Information is recorded and stored on paper during the period of encounter by the majority of hospitals. This information is recorded and stored mainly using a paper system (86% on paper, 2% electronically). 94% of medical records are stored on paper in the short-run (first year). Other medical information like admissions and lab tests is more likely to be stored on a computerized system. 75% of hospital computerized medical records allow intra-hospital access but fewer than 50% allow inter-hospital access. The level of computerization is 59% for hospital records (59% of hospitals have computerized medical records).

The response rate for the survey is higher for the medical records departments (35 observations) but the information from the types of the questions asked is limited.

The results, however, are mixed. A large percentage of hospitals records and stores the information on paper initially and after some period of time the records are computerized. The majority of hospitals have computerized medical records and the number is increasing but the level of accessing and communicating the information within or outside is not clear. The stochastic frontier inefficiency is regressed on a set of payer-mix variables and selected variables from the medical records questionnaire. The percentages of Medicare, Medicaid confirm the results obtained above. They have a positive and significant effect on inefficiency. The coefficient of the HMO is insignificant.

The entry and storage of information during the period of encounter (on paper or on computer) is one set of variables included in the model. The second set involves electronic access to computerized information (admissions) from locations in the hospital or outside the hospital. The vast majority of hospitals store the records on paper, so the paper storage appears to influence efficiency. The entry of information on paper is positively related to inefficiency while on computer it is negatively related, but the coefficients are not significant. Both electronic access from locations within the hospital and electronic access from remote locations influence efficient performance. However, their effect is not significant.

Table 6-9

Modeling the effect of EDI: Medical Records

OLS Estimates
Dependent variable: The Stochastic Frontier INEFFCIENCY INDEX
OLS: R^2 = 0.6045 Adj-R^2 = 0.4350 Model test: F[6,14]=3.567, Prob value = 0.0234

Variable	Coefficient	Standard Error	t-ratio	P[|T|≥t]	
INTERCEP	0.017910	0.14172814	0.126	0.9012	
PADMC	0.342486	0.08442330	4.057	0.0012	% Adm Medicare
PADMD	0.188292	0.08762404	2.149	0.0496	% Adm Medicaid
PADHMO	0.095773	0.10977793	0.872	0.3977	% Adm HMO
COMP	-0.000922	0.00121342	-0.759	0.4602	Comput storage
STOREP	-0.001346	0.00120523	-1.117	0.2827	Stored on Paper
X34	-0.014219	0.03191893	-0.445	0.6628	Elect Acc to Adm In

OLS Estimates
Dependent variable: The Stochastic Frontier INEFFCIENCY INDEX
OLS: R^2 = 0.6239 Adj-R^2 = 0.4044 Model test: F[7,12]= 2.843, Prob value = 0.0538

Variable	Coefficient	Standard Error	t-ratio	P[|T|≥t]	
INTERCEP	-0.081760	0.06651140	-1.229	0.2425	
PADMC	0.327792	0.11394900	2.877	0.0139	% Adm Medicare
PADMD	0.183255	0.08632075	2.123	0.0552	% Adm Medicaid
PADHMO	0.071573	0.11860512	0.603	0.5574	% Adm HMO
RESTADC	0.007942	0.05101281	0.156	0.8789	Residents (ADC)
PAPER	0.000974	0.00119579	0.815	0.4310	Entered on Paper
STOREP	-0.001333	0.00118014	-1.129	0.2809	Stored on Paper
X39	-0.014611	0.01714133	-0.852	0.4107	Elect Acc to Adm out

Appendix 6.1 Hypothesis Testing:

Banker (1993) developed a statistical test for the efficiency/inefficiency evaluation of DEA. He showed that the efficiency of two groups of DMUs can be statistically compared. First, some distributional assumptions must be made about the inefficiency index. Specifically, the inefficiency index can be considered as a "stochastic variable with a monotone decreasing probability function." Given that the sample size is sufficiently large, the derived inefficiency component approximates the probability distribution of the true but unknown inefficiency. This probability distribution can be the half normal or the exponential.

Let's consider two groups of hospitals (G1 and G2). To test if the inefficiency of one group is statistically different from the other, the null hypothesis is formed:

$H_0 : \sigma_1 = \sigma_2$ $\qquad$ $H_1 : \sigma_1 > \sigma_2$

Under the assumption of exponentially distributed observations the test statistic is:

$$\frac{\left[\sum_{j \in G_1} \varepsilon_j / G_1\right]}{\left[\sum_{j \in G_2} \varepsilon_j / G_2\right]}$$

Which follows the F-distribution with ($2G_1$, $2G_2$) degrees of freedom.

Under the assumption of half normal distribution the test statistic is:

$$\frac{\left[\sum_{j \in G_1} (\varepsilon_j)^2 / G_1\right]}{\left[\sum_{j \in G_2} (\varepsilon_j)^2 / G_2\right]}$$

Which follows the F-distribution with (G_1, G_2) degrees of freedom. The decision rule rejects the null if the test statistic exceeds the F-critical value (at a given level of significance). That means the G_2 group is more efficient than the G_1 group or the inefficiency of the G_1 group exceeds the inefficiency of the G_2 group.

Appendix 6.2 Administration: The DEA Inefficiency Models

TOBIT Estimates

Dependent variable: The Weight Restricted (TCAR) DEA (CRS) INEFFCIENCY INDEX

Log likelihood function -63.92243

Variable	Coefficient	Standard Error	z=b/s.e.	P[|Z|≥z]
Constant	-0.38068E-02	1.1475	-0.003	0.99735
PADMD	-3.4596	2.3209	-1.491	0.13606
PADCHAR	1.6869	1.4823	1.138	0.25509
PADHMO	-1.2749	1.0401	-1.226	0.22030
DSH	2.3533	1.8267	1.288	0.19765
IRB	1.0759	0.60425	1.781	0.07499
HS	0.15199E-01	0.14942E-01	1.017	0.30905
BS	-0.15575E-01	0.93202E-02	-1.671	0.09469
POVH	0.14015E-01	0.15674E-01	0.894	0.37122
MILESTH	-0.42251E-03	0.55172E-03	-0.766	0.44380
BIRTH	0.10836E-03	0.10298E-03	1.052	0.29265
SIXF	-0.11087E-01	0.36678E-01	-0.302	0.76243
σ	0.51205	0.40927E-01	12.511	0.00000

TOBIT Estimates

Dependent variable: DEA VRS INEFFCIENCY INDEX (Transformed)

Log likelihood function -31.87259

Variable	Coefficient	Standard Error	z=b/s.e.	P[|Z|≥z]
Constant	0.39476	0.65920	0.599	0.54928
PADMD	1.0341	1.3534	0.764	0.44482
PADCHAR	0.24978	0.85901	0.291	0.77122
PADHMO	-0.98248	0.62271	-1.578	0.11462
DSH	-0.69811	1.0467	-0.667	0.50481
IRB	1.3091	0.35080	3.732	0.00019
HS	-0.33464E-02	0.86587E-02	-0.386	0.69915
BS	-0.50892E-02	0.55725E-02	-0.913	0.36110
POVH	-0.12086E-01	0.90754E-02	-1.332	0.18293
MILESTH	-0.25326E-03	0.30851E-03	-0.821	0.41170
BIRTH	0.15940E-03	0.58603E-04	2.720	0.00653
SIXF	0.24480E-02	0.22250E-01	0.110	0.91239
σ	0.28152	0.30678E-01	9.177	0.00000

7

Conclusions and Implications

The administrative expenditures of hospitals grew faster than any other component of hospital costs the last decade (Shulkin et al., 1993) and its share reached an average of 26 percent ranging between 22.9 and 34 percent in 1994 (Woolhandler and Himmelstein, 1997). To address the question of efficiency a comprehensive empirical investigation was undertaken. The state of the art techniques on efficiency measurement, both parametric and non-parametric, were employed.

Hospital efficiency and administrative efficiency were estimated and evaluated.

The hospital average inefficiency was found to be 4.04 percent, a dollar equivalent of $4,293 thousand. The mathematical programming technique yielded comparable results. The average potential cost improvement amounted to $4,273.98 for the VRS and $7,516.22 for the CRS formulations.

In an integrated framework, an improved Assurance Region/Cone Ratio model was estimated using the empirical estimates of the stochastic frontier to construct the weight bounds in an attempt to bring the DEA estimates (technical efficiency) closer to an overall cost efficiency.

Specifically the marginal rate of output transformation and the marginal rate of input substitution formed the "Technologically Consistent Assurance Region."

The restricted model 's inefficiency estimates were much higher. The potential cost savings for the average hospital amounted to $9,639 and $11,762 thousand for the VRS and CRS surfaces, respectively.

The results indicated that the weight restricted DEA score was correlated more with the DEA initial estimates than the overall cost frontier estimates. The weight bounds that incorporate additional information into the model (price information) do not necessarily yield overall cost efficiency as many recent studies claim (Thompson et al., 1990).

Table 7-1

Hospital Efficiecy

Model		Inefficiency	Efficiency	Av.Savings ($000)
Stochastic Frontier		0.0404		$4,293
Stochastic Frontier (CMI adj)		0.0339		$3,820
Data Envelopment Analysis	CRS		0.8619	$7,516
	VRS		0.9287	$4,273
Weight Restricted DEA	CRS		0.7974	$11,762
	VRS		0.8167	$9,639
Cost Minimizing DEA	CRS	Technical	0.9220	
		Allocative	0.8509	
		Cost	0.7845	
	VRS	Technical	0.9427	
		Allocative	0.8836	
		Cost	0.8333	

However, another nonparametric approach, the cost-minimizing DEA, was estimated. This is a DEA cost minimization approach to efficiency measurement or the nonparametric analog of the stochastic frontier.

Even if the data requirements of this technique are enormous, the results are in line with those of the stochastic frontier. The cost-minimizing DEA inefficiency and the stochastic cost frontier inefficiency are correlated.

Inefficiency was modeled in a second stage. Administration was found the most important determinant of hospital inefficiency. The results support the hypothesis that hospital administration is inefficient and also support the notion of Himmelstein et al., (1996), that "more administration waste time and trees."

The administrative function of the hospital, also, was specified and estimated using the techniques mentioned above. The average administrative inefficiency, (estimated parametrically), was found to be 3.34 percent, which translated into dollars yielded an average of $470.28 thousand per hospital. The DEA estimates amounted to $2,960 and $3,535 thousand for the two surfaces (VRS and CRS respectively).

A weight-restricted model, also, was estimated with bounds obtained from the administrative stochastic frontier model, which yielded much higher potential savings for producers. Specifically, hospital could save from $5,932 to $6,821 thousand under the CRS and VRS formulations, respectively.

Table 7-2

Administrative Efficiecy

Model		Inefficiency	Efficiency	Av.Savings ($000)
Stochastic Frontier		0.0334		$470
Data Envelopment Analysis	CRS		0.8297	$3,535
	VRS		0.8757	$2,960
Weight Restricted DEA	CRS		0.5724	$6,821
	VRS		0.6633	$5,932
Cost Minimizing DEA	CRS	Technical	0.8050	
		Allocative	0.3547	
		Cost	0.2879	
	VRS	Technical	0.8816	
		Allocative	0.4698	
		Cost	0.4213	

The cost–minimizing DEA function, also, was estimated, which indicated a large proportion of allocative and cost inefficiencies. However, the construction of input variables (prices and quantities) of this type of models involves an additional problem to estimation.

The most significant determinants of hospital inefficiency include the administrative hospital function, hospital size, competition in the local market, quality, and case mix. Among the determinants of administrative inefficiency are the payer mix, teaching status, and hospital area characteristics.

Hospitals, like any other firm, have invested billions of dollars in computer information systems. This paper provides a different approach for assessing the economic contribution of information technology based on the foundations of microeconomic theory of the cost and production functions. The results strongly support the wide application of Electronic Data Interchange.

There are several limitations regarding the data set employed in this analysis. The number of observations does not allow an actual model to be developed and estimated. However, the regressions confirm that information technology and specifically Electronic Data Interchange could reduce administrative costs and improve efficiency.

Finally, in addition to the limitations of the data set, a number of caveats of this study and suggestions for future research should be mentioned.

An Assurance Region, which is based on empirically obtained productive characteristics of a cost function, could be proved the best approach of setting weight bounds, limiting weight flexibility and estimating an overall cost efficiency through a production function. However, this is at the expense of a rich data set that would allow a cost function to be estimated. The cost-minimizing DEA proves to be the nonparametric analog of the stochastic cost frontier, but its data requirements exceed even the requirements of the stochastic frontier.

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