10-24-2011

Three Essays on Hospital Efficiency

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DOI: 10.25148/etd.FI11120201

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THREE ESSAYS ON HOSPITAL EFFICIENCY

A dissertation submitted in partial fulfillment of the

requirements for the degree of

DOCTOR OF PHILOSOPHY

in

ECONOMICS

by

Alfonso Rodriguez

2011

To: Dean Kenneth Furton
College of Arts and Sciences

This dissertation, written by Alfonso Rodriguez, and entitled Three Essays on Hospital Efficiency, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend it be approved.

Cem Karayalcin

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Florida International University, 2011

DEDICATION

To my my parents , Alfonso, and Adela, your incredible sacrifice has made all my hopes and dreams possible. To the loving memory of my grandmother, Mama, whose smile, grace, and love continues to live on. Finally, to my wife, Carmen, my best friend and voice of reason, I knew I loved you before I met you.

ACKNOWLEDGMENTS

To my advisor Peter Thompson, a gracious mentor whose wise council, words of encouragement, and gentle persistence kept me focused and on track while writing this dissertation. Without your guidance, Peter, my path would of been filled with many more obstacles. To my committee members Cem Karayalcin, Sheng Guo, and Timothy Page, for their invaluable feedback, support, and time and attention during busy semesters. To all my professors for ensuring I received the best possible education, and for imparting upon me the gift of critical thought. To the Department of Economics staff for assisting me with the administrative tasks necessary for completing my doctoral program. Finally, I'd like to extend a special thanks to the late Dr. Jeffrey Bernstein, who guided me in the initial stages of my dissertation and got me interested in health care research.

ABSTRACT OF THE DISSERTATION

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This dissertation analyzes hospital efficiency using various econometric techniques. The first essay provides additional and recent evidence to the presence of contract management behavior in the U.S. hospital industry. Unlike previous studies, which focus on either an input-demand equation or the cost function of the firm, this paper estimates the two jointly using a system of nonlinear equations. Moreover, it addresses the longitudinal problem of institutions adopting contract management in different years, by creating a matched control group of non-adopters with the same longitudinal distribution as the group under study. The estimation procedure then finds that labor, and not capital, is the preferred input in U.S. hospitals regardless of managerial contract status. With institutions that adopt contract management benefiting from lower labor inefficiencies than the simulated non-contract adopters. These results suggest that while there is a propensity for expense preference behavior towards the labor input, contract managed firms are able to introduce efficiencies over conventional, owner controlled, firms.

Using data for the years 1998 through 2007, the second essay investigates the production technology and cost efficiency faced by Florida hospitals. A stochastic frontier multiproduct cost function is estimated in order to test for economies of scale, economies of scope, and relative cost efficiencies. The results suggest that small-sized hospitals ex-

perience economies of scale, while large and medium sized institutions do not. The empirical findings show that Florida hospitals enjoy significant scope economies, regardless of size. Lastly, the evidence suggests that there is a link between hospital size and relative cost efficiency. The results of the study imply that state policy makers should be focused on increasing hospital scale for smaller institutions while facilitating the expansion of multiproduct production for larger hospitals.

The third and final essay employs a two staged approach in analyzing the efficiency of hospitals in the state of Florida. In the first stage, the Banker, Charnes, and Cooper model of Data Envelopment Analysis is employed in order to derive overall technical efficiency scores for each non-specialty hospital in the state. Additionally, input slacks are calculated and reported in order to identify the factors of production that each hospital may be over utilizing. In the second stage, we employ a Tobit regression model in order to analyze the effects a number of structural, managerial, and environmental factors may have on a hospital's efficiency. The results indicated that most non-specialty hospitals in the state are operating away from the efficient production frontier. The results also indicate that the structural make up, managerial choices, and level of competition Florida hospitals face have an impact on their overall technical efficiency.

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CHAPTER 1

CONTRACT MANAGEMENT IN U.S. HOSPITALS

1.1 Introduction

The subletting of an institution's management to a third-party firm has been around for many years. This is known as contract management and it has been gaining traction in the hospital industry in recent years. Contract management is the act of turning over the day to day operations of an institution to a third-party firm which reports directly to the institution's board of directors or trustees (Brown & Money, 1976). However, the third-party managers may or may not pursue the same objectives as the controllers of the institution. For instance, the owners or controllers of an institution may be profit maximizers, while the third-party managers may not be. Instead, the third-party managers may have positive preferences for staff levels or wages well above the profit maximizing amount. The idea that third-party managers may not have the same goals as an institution's controllers is know in the incentives literature as expense preference.

Expense preference is the notion that third-party managers are out to maximize their utility instead of the institution's profits. That is, third-party managers may have preferences for inputs above and beyond the profit maximizing, or cost minimizing, amount. Oddly enough, in the last two decades, contract management of U.S. hospitals has been steadily rising. From 1980 to 2007, the share of U.S. hospitals under contract management has increased around 70%, with roughly 18% of all current U.S. hospitals choosing to outsource their management (See Figure 1.1).

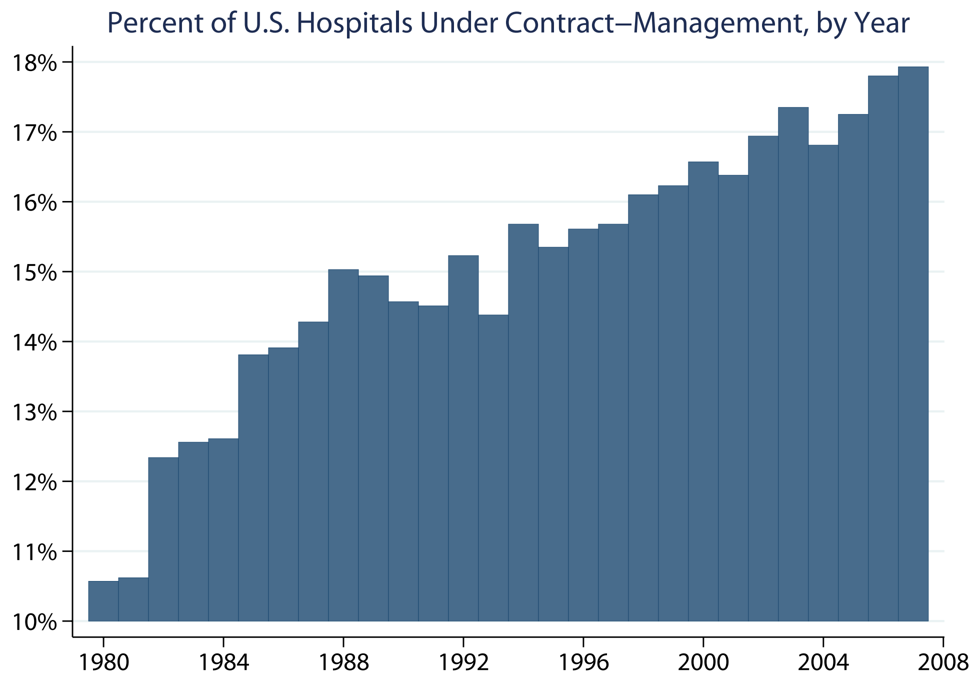

Figure 1.1: Percent of Non-Federal, Non-Specialty U.S. Hospitals Under Contract Management

The question that comes readily to mind then is, has this increase in the adoption of contract management by the U.S. hospital industry lead to expense preference behavior? And has it lead to greater inefficiency when compared to non-contract managed hospitals?

This paper, thusly, sets out to test whether the adoption of contract management, by U.S. hospitals, has lead to expense preference behavior and therefore to a higher degree of inefficiency than conventionally managed hospitals. The paper continues as follows: section two reviews the related literature; a test for expense preference is presented in section three; section four describes the data and outlines the creation of the different samples used in the study; results are discussed in section five; and the paper concludes in section six.

1.2 Background

An alternative to the standard profit maximization theory is that of expense preference behavior. The expense preference behavior theory hypothesizes that a firm's third-party manager may not have the goal of maximizing the firm's profits. Instead, expense preference suggests that the third-party manager may be a utility maximizer with preferences for expenses above the profit maximizing level. That is, the separation of ownership from control permits third-party managers to pursue non-profit maximizing objectives such as higher salaries, job security, prestige, etc. The idea of expense preferences has been around in the economic literature for some time and is one of that has been the foundation for very interesting work (e.g., Baumol, 1957; Alchian & Kessel, 1962). However, in the hospital industry this theory has been rarely examined, even though the majority of institutions are not-for-profit and are rarely owned and managed by the same agents (Carey & Dor, 2008).

The idea that utility maximizing managers indulge in excessive spending was first suggested by Becker (1971). But, Baumol (1957); Marris (1957); Williamson (1963) took the first steps in pioneering the theory of expense preference behavior. In particular, Williamson (1963) was the first to argue that third-party managers derive additional some sort of positive utility from expenditures above cost minimizing levels. Williamson theorized that third-party managers derived utility from expenditures on salaries, additional staff, or other fringe benefits for which the third-party managers may have a positive preference. Williamson was also one of the first to argue for the importance of empirical work in order to test for the existence of expense preference behavior.

Yet, very few studies have been done in this field. The studies that have tested for the existence of expense preference have mainly been in the banking and saving-and-loans industry with results that have been somewhat mixed.

The first empirical framework capable of testing for the presence of expense preference behavior was developed by Edwards (1977). Edwards postulated that the existence of expense preference behavior was readily distinguishable in the institution's demand for labor. If an institution's demand for labor was above the profit maximizing level, then expense preference behavior was present. Applying his framework to the banking industry, Edwards found that banks in his sample showed evidence of expense preference behavior. Adding to Edwards, Hannan (1979) argued that the organizational structure of the firm is an important element in determining the level of separation between an institution's owners and its third-party managers. Taking this into account, Hannan and Mavinga (1980), along with Verbrugge and Jahera Jr (1981) used a similar test as that proposed by Edwards, but incorporated more detailed information on the dispersion of firm ownership in their model. They found that banks controlled by third-party managers exhibited a tendency to spend more on items likely to be preferred than managers from owner-controlled banks; thus, exhibiting expense preference behavior and lending support to Edward's results.

However, subsequent studies focusing on expense preference behavior in the banking industry, by Rhoades (1980), and Smirlock and Marshall (1983) found conflicting evidence. Rhoades argued that Edward's test was too limiting in just focusing on the excess of labor and wages. Instead, Rhoades incorporated a greater number of variables in Edward's labor demand function, and used a much broader data set than previous studies. Rhoades found no support for the expense preference hypothesis. Similarly, using data on the banking industry Smirlock and Marshall conclude that Edward's test was too narrow and also focused on a broader labor demand equation. After running several hypothesis tests, Smirlock and Marshall reject the existence of expense preference behavior in the banking industry. In a similar study, Awh and Primeaux Jr (1985) applied an intercept test similar to Edward's and came to the conclusion that there was no evidence of expense preference behavior in the U.S. electricity industry. Likewise, Blair and Placone (1988) found no evidence of expense preference behavior in the U.S. savings and loans industry.

In a departure from Edward's test, Mester (1989) derived a more general test for expense preference. She argued that Edward's intercept test would be valid only if the firms in question all shared the same Cobb-Douglas type production function. So, Mester derived a test that only took into account the firm's cost function, and set out to test for expense preference via an input specific parameter included in the cost function. Applying this new general approach to the U.S. savings and loans industry, Mester found no evidence of expense preference behavior, lending evidence to the results in Blair and Placone (1988).

Following Mester, Dor, Duffy, and Wong (1997) studied whether hospitals that became contract managed, during a well-defined period, employed managers who used more than the cost-minimizing amounts of labor and capital. Dor *et al.* added to Mester's framework by including the input demand functions in the estimation procedure. They found that expense preference behavior is present in contract managed hospitals, but the behavior depends on the discretionary input being studied. A limiting factor of Dor *et al.*, however, is that the study was applied to a conditional sample of U.S. hospitals; only those hospitals that adopted third-party contract management agreements in the time period studied. Therefore, making cost comparisons with owner controlled hospitals impossible.

This paper builds on Dor, *et al.* with an attempt to provide additional and recent evidence to the presence of expense preference behavior in U.S. hospitals. In particular, it adds a control group in order to make reasonable cost comparisons between hospitals that contracted third-party management firms to run the day to day operations of the hospitals and those hospitals that did not.

1.3 A Test for Expense-Preference Behavior

Firms in the industry produce a vector, y, of n outputs using m inputs. A firm exhibiting expense preference behavior prefers the first k inputs. The expense preferring manager first selects the cost-minimizing level of output and inputs $(x_{k+1}, \ldots, x_m)$ from which she does not derive any utility. Then, the expense preferring manager increases spending on the inputs she prefers, the first k inputs $(x_1, \ldots, x_k)$, above their cost-minimizing levels. Let, x^* denote the cost-minimizing input level, while z denotes the expense preference or inefficiency parameter (e.g. Edwards, 1977; Mester, 1989; Dor et al., 1997). So, the expense-preferring firm demands $x_i^0 = (1 + z_i)x_i^*, \quad i \in (1, \ldots, k)$ of the preferred input, and demands $x_j^*, \quad j \in (k + 1, \ldots, m)$ of the cost-minimizing input.

The observed costs for the expense-preferring firm can then be written as,

$$
\begin{aligned}
C &= \sum_{i=1}^{k} w_i^* x_i^0 + \sum_{j=k+1}^{m} w_j^* x_j \\
&= \sum_{i=1}^{k} z_i w_i^* x_i^* + \sum_{i=1}^{k} w_i^* x_i^* + \sum_{j=k+1}^{m} w_j^* x_j^* \\
&= \sum_{i=1}^{k} z_i w_i^* x_i^* + C^* \qquad (1.1)
\end{aligned}
$$

where w^* is a vector of exogenously determined input prices and C^* is the cost-minimizing cost level. Using the cost-minimizing cost share of input i, $S_i^* = w_i^* x_i^* / C^*$, in (1.1) we can write observed costs for the expense-preferring firm as,

$$
C = C^* \left(1 + \sum_{i=1}^{k} z_i S_i^* \right) \qquad (1.2)
$$

and using Shephard's lemma, we have that the observed cost share is,

$$
S_i = \frac{w_i^* x_i^* \left(1 + z_i\right)}{C}. \qquad (1.3)
$$

Plugging (1.2) into (1.3) and rewriting, we have that the observed cost share is given by,

$$
S_i = S_i^* \, \frac{1 + z_i}{1 + \sum_{i=1}^{m} z_i S_i^*}. \qquad (1.4)
$$

We can now see that if $z_i = 0$, then $C = C^*$ and $S_i = S_i^*$ and no expense preference behavior occurs, i.e., the observed costs and observed input shares are equal to their cost-minimizing values.

In modeling the cost function, the translog (dual) cost function is used. The translog can be regarded as a quadratic approximation to the unspecified cost function and is a widely used functional form in the hospital efficiency literature (e.g. Vita, 1990; Chirikos & Sear, 2000; Ludwig, Groot, & Van Merode, 2009). A general form translog cost function is given by,

$$\begin{aligned}\ln C =& \alpha_0 + \alpha_1 \ln y + \alpha_2 (\ln y)^2 + \sum_{i=1}^{n} \beta_i \ln w_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} \ln w_i \ln w_j \\ &+ \sum_{i=1}^{n} \gamma_i \ln w_i \ln y, \end{aligned} \tag{1.5}$$

where C is total cost, y is output, and w_i is the factor price of the ith input. From the translog cost function and Shephard's lemma, the share of input j in costs is given by,

$$S_i = \frac{\partial \ln C}{\partial \ln w_i} = \beta_i + \beta_{ii} \ln w_i + \sum_{j \neq i}^{n} \beta_{ji} \ln w_j + \gamma_i \ln y. \tag{1.6}$$

Berndt and Christensen (1973) showed that estimating the full dual system (i.e., cost and share equations together), via the method of seemingly unrelated regressions, leads to much higher efficiency than just estimating the single cost function.

Using equations (1.5) and (1.6) along with equations (1.2) and (1.4) gives us the following testable specification,

$$\begin{aligned}\ln C =& \alpha_0 + \alpha_1 \ln y + \alpha_2 (\ln y)^2 + \sum_{i=1}^{n} \beta_i \ln w_i \\ &+ \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} \ln w_i \ln w_j + \sum_{i=1}^{n} \gamma_i \ln w_i \ln y \\ &+ \ln \left[1 + \sum_{i=1}^{n} z_i \left(\beta_i + \beta_{ii} \ln w_i + \sum_{j \neq i}^{n} \beta_{ji} \ln w_j + \gamma_i \ln y \right) \right] \end{aligned} \tag{1.7}$$

$$S_i = \frac{(1+z_i)\left(\beta_i + \beta_{ii}\ln w_i + \sum_{j\neq i}^{n}\beta_{ji}\ln w_j + \gamma_i \ln y\right)}{1+\sum_{i=1}^{n} z_i\left(\beta_i + \beta_{ii}\ln w_i + \sum_{j\neq i}^{n}\beta_{ji}\ln w_j + \gamma_i \ln y\right)}. \tag{1.8}$$

Parameter estimates in the above system of equations can be obtained via the method of iterative seemingly unrelated non-linear regressions (NLSUR). This method has been shown to be equivalent to maximum likelihood estimation (Gallant, 1986). In estimating this system of equations, the normal symmetry condition ($\beta_{ij} = \beta_{ji}\ \forall\ i,j$) is imposed on the coefficients. Furthermore, in order for the translog cost function to be homogeneous of degree 1 in input prices the following restriction are also compulsory,

$$\sum_{i=1}^{n}\beta_i = 1, \qquad \sum_{i=1}^{n}\beta_{ij} = 0 \ \text{ for all } \ j, \qquad \sum_{i=1}^{n}\gamma_i = 0.$$

Since the cost shares sum to unity, in estimating the system of equations one cost share must be dropped to avoid a singular covariance matrix.

1.4 Data and Sample Creation

1.4.1 Data

The bulk of the data for this paper come by way of the American Hospital Association (AHA) Annual Survey Database. The AHA database contains hospital specific data on over 6,000 hospitals with variables covering organizational structure, personnel, hospital facilities and services, and financial performance. My analysis uses data for the years 1984 to 2007. Patient case-mix data comes from the Center for Medicare and Medicaid Services, and inflation data from the Bureau of Labor Statistic's Hospital Producer Price Index.

The AHA reports total cost as a measure that incorporates all hospital operating expenses, including interest and depreciation expenses. This variable was used as the dependent variable representing total cost. Cost data in the survey is disaggregated into labor costs and other costs. Thus, two inputs were used; labor and non-labor (hereafter referred to as capital). Input prices were unfortunately not readily available in the AHA survey data set, but, following previous studies using a similar data set, reasonable measures were created. Wages, the measure of labor costs, was created by dividing labor costs by full-time equivalent employees. While the rental rate of capital, the measure of capital costs, was created by dividing capital costs by the total number of hospital beds.

Since this study was not interested in looking at specific output inefficiencies, a single output variable was chosen. Adjusted patient days, transforms outpatient services into inpatient day unit equivalents via formula documented in the AHA codebook (e.g., see AHA Annual Survey Database Documentation), and takes into account total hospital output. Hospitals coordinate care for patients across many departments, including intensive care units, emergency departments, surgical wards, and diagnostic services. So, a control for differentiated product mix across hospitals was needed to account for a varying hospital output. To control for product heterogeneity, the Medicare diagnosis related group (DRG) case-mix index was added to the cost function along with patient average length of stay. The DRG was used as it measures the complexity of both inpatient stays and outpatient visits in such a way that can be aggregated into an index. In addition to the case-mix index and average length of stay, other commonly used control variables were included in the cost function (e.g. Vita, 1990; Dor et al., 1997; Li & Rosenman, 2001); hospital size as determined by the number of hospital beds, whether the hospital is public or private, hospital profit status, whether or not the hospital was part of a larger multi-system of hospitals, and a set of binaries to control for year of observation.

1.4.2 Sample Creation

My study examines hospitals that made the transition from an owner controlled management system to contract management between 1984 and 2007. Since the goal of the paper is to compare the estimates for both the hospitals that chose to outsource their management and the hospitals that did not, two group samples were created; a treatment group, and a control group. The treatment group of hospitals were those which went from being conventionally managed to contract managed in the time frame under study. A binary variable available in the AHA survey was used in selecting institutions that made the transition from a conventional management system to contract management.

Given that both pre-contract management estimates and post-contract management estimates were of interest, the treatment group was divided into two subsampless; a pre-contract sample and a post-contract sample. The pre-contract samples include data for the year falling two years before the year of adopting contract management. While the post-contract samples include data for the year following two years after adoption of contract management. A two year lag, before and after contract management, was used in order to allow the effects of a change in management to fully appear in the data.

Hospitals with contracts shorter than three years were dropped from the samples, along with hospitals with incomplete or missing data. In addition, given that specialty hospitals and Federal hospitals produce different products, they too were dropped from the samples.

Institutions that adopted contract management differed from those that did not, so a random selection of conventionally managed hospitals did not produce an adequate match for the control group. Therefore, a control group of hospitals was selected using the Mahalanobis matching propensity score (conditional treatment probability) matching method, following Rosenbaum and Rubin (1985) and using the Stata matching algorithm provided in Leuven and Sianesi (2003). Hospitals with similar adjusted patient days, labor expenses, capital expenses, case-mix index, average patient length of stay, government control, and profit status were used for each year as the main criterion for the matching algorithm. The matching algorithm allowed for a selection of non-adopters, the control group, that shared the same longitudinal distribution as the treatment group. And just like the process for the treatment group, the control group was divided into pre-contract and post-contract subsamples. Summary statistics for both the treatment group and the control group can be found on the following page in Table 1.1.

Table 1.1: Summary Statistics

Variable	Definition	Treatment		Control	
		Pre	Post	Pre	Post
Dependent					
ln cost	Total cost	16.22(1.29)	16.21(1.06)	16.21(1.31)	16.18(1.06)
share 1	Labor cost/TC	0.54(0.07)	0.52(0.06)	0.54(0.06)	0.55(0.07)
share 2	Capital cost/TC	0.45(0.08)	0.47(0.07)	0.45(0.06)	0.44(0.07)
Independent					
$\ln y$	Adj. patient days	9.97(1.11)	9.88(1.01)	9.90(1.16)	9.82(0.97)
$\ln w_1$	Labor cost per FTE	10.31(0.29)	10.36(0.26)	10.32(0.29)	10.37(0.29)
$\ln w_2$	Capital cost per bed	11.09(0.79)	11.28(0.67)	11.14(0.72)	11.20(0.67)
cmi	Medicare case-mix index	1.15(0.19)	1.12(0.15)	1.14(0.19)	1.12(0.13)
los	Avg. length of stay	21.48(28.2)	21.77(30.3)	23.21(36.4)	26.99(58.14)
govt	Govt control binary	0.43(0.50)	0.43(0.49)	0.45(0.50)	0.41(0.49)
nprof	Nonprofit status binary	0.47(0.22)	0.51(0.24)	0.49(0.22)	0.53(0.25)
system	System status binary	0.25(0.43)	0.31(0.47)	0.27(0.44)	0.31(0.46)
church	Church operated binary	0.07(0.25)	0.04(0.19)	0.11(0.31)	0.08(0.27)
large	>100 beds binary	0.37(0.48)	0.29(0.45)	0.34(0.48)	0.27(0.45)
n		886	664	875	657

Standard deviations in parentheses. All values in 1998 dollars.

1.5 Estimation Results

Results for the estimation of the system of equations found in (1.7) and (1.8) were derived via non-linear iterative seemingly unrelated regressions (ITSUR). Starting values were obtained from the linear ITSUR model wherein the parameter z_i is set to zero, with all iterations taking 8-14 interactions to converge. Considering that all input shares add up to one, one input demand equation must always be dropped to avoid multicollinearity. Given the aforementioned and that no a priori assumption was made as to which input would be the preferred input, the expense preference parameter was allowed to differ for the two inputs. The first step in the estimating procedure was to include the labor share equation in the cost function and drop the capital share equation. The process was then repeated but with the capital share equation in the cost function and then dropping the labor share equation. This procedure was followed for both the pre-contract and post-contract samples for both the control group and the treatment group. Tables 1.2 and 1.3 report the full estimation results for the labor share equation and the capital share equation, respectively.

Comparing the inefficiency results from Tables 1.2 and 1.3 it becomes apparent that labor is the preferred input, with all inefficiency parameters greater than zero. For contract adopters there was an 18% increase in labor inefficiency from the pre-contract period to the post-contract period, z_1 increased from 1.682 to 1.99. While for the control group, there was a 97% increase in labor inefficiency between the pre-contract and post-contract period, z_1 increased from 2.815 to 5.57. For the control group in particular, the increase in z_1 indicates a strong propensity towards labor inputs.

Table 1.2: Nonlinear ITSUR Regressions Results for ln Cost, Labor Share

Coefficient	Variable	Treatment		Control	
		Pre	Post	Pre	Post
α_0	Constant	3.359(0.834)	–2.983(1.367)	1.345(0.743)	1.244(1.35)
α_1	$\ln y$	–0.536(0.173)	0.846(0.288)	–0.090(0.150)	–0.170(0.280)
α_2	$\ln y \cdot \ln y$	0.060(0.009)	–0.013(0.015)	0.036(0.008)	0.040(0.015)
β_1	$\ln w_1$	–0.054(0.095)	0.017(0.123)	–0.166(0.076)	–0.195(0.075)
β_2	$\ln w_2$	1.054(0.096)	0.983(0.123)	1.166(0.076)	1.195(0.075)
β_{11}	$\ln w_1 \cdot \ln w_1$	0.055(0.006)	0.050(0.008)	0.046(0.006)	0.039(0.009)
β_{22}	$\ln w_2 \cdot \ln w_2$	0.018(0.005)	0.018(0.007)	0.001(0.004)	0.001(0.004)
β_{12}	$\ln w_1 \cdot \ln w_2$	–0.073(0.006)	–0.068(0.009)	–0.047(0.006)	–0.040(0.009)
γ_1	$\ln y \cdot \ln w_1$	0.005(0.003)	–0.002(0.003)	–0.003(0.002)	–0.000(0.003)
γ_2	$\ln y \cdot \ln w_2$	–0.005(0.003)	0.002(0.003)	0.003(0.002)	0.000(0.003)
δ_1	cmi	0.612(0.098)	0.656(0.142)	0.777(0.107)	0.946(0.167)
δ_2	los	–0.006(0.001)	–0.005(0.001)	–0.004(0.000)	–0.001(0.000)
δ_3	govt	0.015(0.028)	–0.032(0.034)	–0.008(0.029)	–0.018(0.037)
δ_4	nprof	–0.035(0.057)	–0.050(0.071)	–0.144(0.062)	–0.062(0.069)
δ_5	system	0.035(0.032)	–0.016(0.038)	–0.025(0.033)	–0.010(0.040)
δ_6	church	0.002(0.051)	–0.006(0.085)	0.039(0.045)	–0.009(0.067)
δ_7	large	0.237(0.041)	0.368(0.057)	0.298(0.042)	0.314(0.059)
z_1		1.682(0.460)	1.99(0.814)	2.815(0.728)	5.57(2.023)
n		886	664	875	657
Adj R^2 (ln cost)		0.972	0.9534	0.970	0.9466
Adj R^2 (ln share 1)		0.458	0.453	0.304	0.393

Standard errors in parentheses. All values in 1998 dollars.

This is consistent with studies in the literature that find a direct correlation between staffing level of nurses and health outcomes (e.g. Mobley & Magnussen, 2002; Mark, Harless, & McCue, 2005; Kane, Shamliyan, Mueller, Duval, & Wilt, 2007). These results lead one to the conclusion that absent contract adoption, the degree of labor inefficiency would of have been more pronounce over the same time period.

Table (1.3) summarizes the results for the capital inefficiency parameter. Interpretation of these results, however, needs to be treated with caution. The estimates are a result of the aggregation of non-labor and "other" inputs that could not be readily identified in the data. This was, as discussed in the previous section, due to the nature in which the AHA survey presents the data. It is likely that some disaggregated categories may have resulted in positive values for the inefficiency parameter.

Table 1.3: Nonlinear ITSUR Regressions Results for ln Cost, Capital Share

Coefficient	Variable	Treatment		Control	
		Pre	Post	Pre	Post
α_0	Constant	4.400(0.894)	–2.282(1.405)	2.096(0.747)	2.298(1.362)
α_1	$\ln y$	–0.584(0.179)	0.820(0.291)	–0.102(0.149)	–0.184(0.280)
α_2	$\ln y \cdot \ln y$	0.063(0.009)	–0.012(0.016)	0.037(0.008)	0.041(0.015)
β_1	$\ln w_1$	0.074(0.113)	0.310(0.140)	0.085(0.111)	0.074(0.133)
β_2	$\ln w_2$	0.926(0.113)	0.690(0.140)	0.915(0.111)	0.926(0.133)
β_{11}	$\ln w_1 \cdot \ln w_1$	–0.089(0.012)	–0.076(0.015)	–0.085(0.012)	–0.096(0.014)
β_{22}	$\ln w_2 \cdot \ln w_2$	–0.040(0.003)	–0.040(0.003)	–0.029(0.003)	–0.036(0.004)
β_{12}	$\ln w_1 \cdot \ln w_2$	0.129(0.014)	0.116(0.017)	0.114(0.014)	0.132(0.017)
γ_1	$\ln y \cdot \ln w_1$	–0.005(0.003)	0.001(0.004)	0.001(0.003)	–0.001(0.004)
γ_2	$\ln y \cdot \ln w_2$	0.005(0.003)	–0.001(0.004)	0.001(0.003)	0.001(0.004)
δ_1	cmi	0.571(0.098)	0.671(0.141)	0.793(0.102)	0.966(0.159)
δ_2	los	–0.005(0.001)	–0.004(0.001)	–0.004(0.000)	–0.001(0.000)
δ_3	govt	0.029(0.029)	-0.038(0.035)	–0.008(0.029)	–0.015(0.037)
δ_4	nprof	0.029(0.028)	–0.045(0.071)	–0.149(0.071)	–0.080(0.069)
δ_5	system	–0.052(0.059)	–0.019(0.038)	–0.026(0.032)	0.001(0.040)
δ_6	church	0.053(0.033)	–0.007(0.087)	0.040(0.045)	–0.006(0.067)
δ_7	large	–0.003(0.053)	0.347(0.058)	0.288(0.042)	0.316(0.059)
z_2		–0.889(0.078)	-0.212(0.097)	-0.192(0.081)	-0.354(0.082)
n		886	664	875	657
Adj R^2 (ln cost)		0.971	0.953	0.972	0.946
Adj R^2 (ln share 1)		0.467	0.456	0.283	0.415

Standard errors in parentheses. All values in 1998 dollars.

1.6 Conclusion

Unlike previous studies, which focus on either an input-demand equation or the cost function of the firm, this paper estimates the two jointly using a system of nonlinear equations. Moreover, this paper addresses the longitudinal problem of institutions adopting contract management in different years, present in previous studies, by creating a matched control group of non-adopters with the same longitudinal distribution as the treatment group. Thus, this study was able to compare the inefficiency parameters of institutions that outsourced their management with those institutions that did not.

The results of the estimation procedure finds that labor, and not capital, is the preferred input in all U.S. hospitals regardless of managerial contract status. However, institutions that adopt contract management benefit from lower labor inefficiencies than the simulated non-contract adopters. These results suggest that while there is a propensity towards expense preference in the labor input, contract managed firms are far more efficient in the allocation of their inputs, in particular labor, than their owner controlled counterparts. That is, subletting contracts to third-party managers is a way by which owners, board of directors, or board of trustees can impose greater efficiencies and market discipline on the institutions they control.

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CHAPTER 2

ECONOMIES OF SCALE AND SCOPE, AND RELATIVE COST EFFICIENCY OF FLORIDA HOSPITALS

2.1 Introduction

The costs associated with operating a hospital in the state of Florida has been rising to historically unprecedented levels. Over the last four decades the average annualized growth rate of hospital spending has exceeded the growth rate of Florida's Gross State Product by a fairly large margin, 17.1%, see Figure 2.1. With hospitals facing ever increasing costs, many to the point of insolvency – including one of the nation's top ranked trauma centers, Jackson Memorial Hospital – questions have been raised about the future structure of the industry. State policy makers have been advocating the notion that greater efficiency may be achieved through consolidations within the industry. As a first step, in the search for cost cutting measures, a clear understanding of potential production efficiencies faced by hospitals in the state is needed.

Two different production efficiencies may be achieved by hospitals in the state, economies of scale and economies of scope. The presence of economies of scale means that there are gains to efficiency by increasing hospital size, while economies of scope means that gains to efficiency may be experienced by focusing on expanding a product line. Economies of scale exist if production costs increase proportionally less than output when there are increases to a hospital's output mix. Economies of scope exist when two or more products can be produced jointly at a lower cost than producing the products separately.

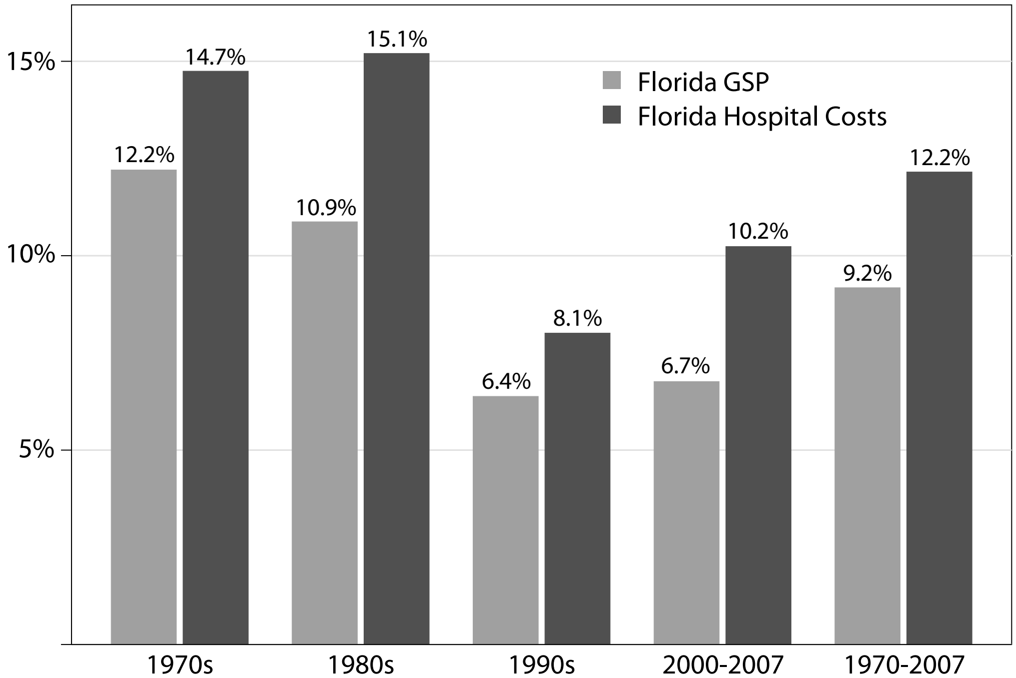
The Florida hospital industry is greatly influenced by the presence and nature of these production efficiencies. Do average costs decrease as hospitals increase their output? If so, then economies of scale are present and the industry will tend to be made up of large institutions. These large institutions can produce their output at lower average costs than smaller ones and therefore take advantage of the cost savings. Are costs for Florida hospitals less when they provide a multitude of services, or is it less costly for them to provide a few selective services? If economies of scope are present, then the industry will potentially be made up of largely diversified institutions; if not, then the industry will mostly be comprised of smaller more specialized hospitals. My study will attempt to answer these questions by providing information on economies of scale and scope, as well information on a measure of relative cost efficiencies for Florida hospitals.

This paper continues as follows. The second section discusses the specification of the multiproduct cost function along with describing the measures of economies of scale, economies of scope, and relative cost efficiency. The third section describes the data samples used in the study. The fourth, presents and reviews the empirical results. While the fifth and final section summarizes the results and concludes the paper.

2.2 Estimating Efficiency

The production structure of the Florida hospital industry can be empirically studied by estimating either a production function or a cost function. Direct estimation of the production function is the most straightforward and attractive way to proceed. However, the process of estimating the production function entails certain assumptions that are not appropriate for to the hospital industry, in particular, that hospitals are free to choose the level of output that maximizes their profits.

Figure 2.1
Annualized Growth Rates of Florida's Gross State Product (GSP) and Hospital Costs (in 2005 dollars)



Sources: Bureau of Economic Activity and American Hospital Association

Florida hospitals are required to provide emergency services to all that seek it and as the need arises. With few exceptions, they have little to no control over the number of illnesses they treat, nor the severity of such illnesses. They supply health services as it is demanded. It is, then, reasonable to assume that the output mix that Florida hospitals must contend with is not within their control and therefore exogenous. Florida hospitals also compete, in the health service market, for factors of production. This competition for inputs leads to the plausible assumption that, along with the output mix, the factor prices Florida hospital face are also exogenous. This paper, therefore, studies output efficiency via the dual of production, the cost function [1]. Unlike the

[1]Duality theory shows that for every production function there is a corresponding or dual cost function. See (Diewert, 1973) for more details.

production function, which assumes that the firm has control over how much to produce and what factor prices to pay, the cost function treats a firm's output mix and input prices as exogenous.

2.2.1 The Cost Function

In modelling hospital costs, the present study uses the Transcendental Logarithmic Cost Function (translog). The translog cost function is a second-order Taylor approximation to an arbitrary cost function that places no restrictions on substitutions between inputs and allows economies of scale to vary with output (Caves, Christensen, & Tretheway, 1980). The translog estimated in this paper has the following form:

$$\begin{aligned}\ln TC = \alpha_0 + \sum_{i=1}^{n}\alpha_i \ln Y_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_{ij}\ln Y_i \ln Y_j + \sum_{k=1}^{m}\beta_k \ln W_k \\ + \frac{1}{2}\sum_{k=1}^{m}\sum_{h=1}^{m}\beta_{kh}\ln W_k \ln W_h + \sum_{i=1}^{n}\sum_{k=1}^{m}\delta_{ik}\ln Y_i \ln W_k + \gamma X + \varepsilon, \qquad (2.1)\end{aligned}$$

where TC is total cost, Y_i is the ith output, W_k is the price of the kth factor input, and X is a vector of other variables that have been shown, in the hospital literature, to affect hospitals costs. When estimating the above cost function, the normal symmetry conditions, $\alpha_{ij} = \alpha_{ji}\ \forall\ i,j$ and $\beta_{hk} = \beta_{kh}\ \forall\ h,k$, are imposed in order to ensure continuity in output and input prices. For the translog to behave according to general economic principles, total cost must increase in proportion with increases in factor prices, when output is held fixed. That is, in order for the translog to be a well behaved cost function[2], it must be linearly homogeneous in input prices (concave in W_k), and increasing and continuous in output (Y_i) and input prices (W_k). Therefore, the following

[2]For a more detailed description of the translog cost function see (Diewert, 1973).

restrictions are imposed on equation (2.1):

$$\sum_{k=1}^{m} \beta_k = 1 \tag{2.2}$$

$$\sum_{k=1}^{m} \beta_{kh} = 0 \quad \text{for all } h \tag{2.3}$$

$$\sum_{i=1}^{n} \delta_{ik} = 0 \quad \text{for all } i. \tag{2.4}$$

By Shephard's lemma (Shephard, 1953) the share of each input in cost can be derived from the translog. The cost share of input h is derived as:

$$S_k = \frac{\partial \ln TC}{\partial \ln W_k} = \beta_k + \beta_{kk} \ln W_k + \sum_{k \neq h}^{m} \ln W_k + \sum_{i=1}^{n} \delta_{ik} \ln Y_i \tag{2.5}$$

Since the cost share equations sum to unity, one cost share must be dropped in order to avoid a singular covariance matrix. Estimating the full system, the translog cost function along with the corresponding share equations, via the iterative seemingly unrelated regression (ISUR) approach, yields much more robust estimates than just estimating the cost function alone. It also addresses any problems that may arise with degrees of freedom and small sample sizes (Berndt & Christensen, 1973).

2.2.2 Economies of Scale

For multi-output institutions, economies of scale can be subdivided into two types. The first is known as overall or ray scale economies, while the second is known as product-specific scale economies. Overall scale economies are present when a hospital's average total cost decreases as output increases while maintaining a consistent output mix. Product-specific scale economies are present when the average total cost of a specific output decreases as the production of that specific output increases.

Overall scale economies are measured by calculating the inverse of the sum of individual output cost elasticities. Following Panzar and Willig (1977), overall scale economies (OScale) can be derived as

$$\text{OScale} = \frac{TC(Y,W)}{\sum_i Y_i MC_i}. = \frac{1}{\sum_i \eta_{\text{tc},\text{y}_i}}, \tag{2.6}$$

where MC_i is the marginal cost associated with the ith output, and $\eta_{\text{tc},\text{y}_i}$ is the ith output cost elasticity. For the multi-output translog cost function described in (2.1) the overall scale measure is given by

$$\begin{aligned} \text{OScale} &= \left[\sum_{i=1}^{n} \frac{\partial \ln TC}{\partial \ln Y_i}\right]^{-1} \\ &= \left[\sum_{i=1}^{n}\left(\alpha_i + \sum_{j=1}^{n} \alpha_{ij} \ln Y_j + \sum_{k=1}^{m} \delta_{ik} \ln W_k\right)\right]^{-1}. \end{aligned} \tag{2.7}$$

The summation of the individual output cost elasticities is equivalent to the percent change in total cost that is a result of a percent change in overall output. Hospitals exhibit constant, increasing, or decreasing returns to scale when OScale is equal to, greater than, or less than one. If constant returns to scale are present, then no production efficiencies are being derived in the over-all output range. If increasing returns to scale are present, then hospitals are enjoying production efficiencies in the over-all output range. And, if decreasing returns to scale are exhibited, then over-all production efficiencies are not being realized.

The measurement of ray scale economies is ideal for understanding the efficiencies being realized by the over-all output mix, but in order to get a more detailed view of the production efficiencies of each individual output, a measurement of product-specific scale is employed. Product-specific scale economies measure how the change in a specific output, while holding the remaining output mix constant, affects cost. Product-specific scale economies exist if the average cost of a specific output decreases as the production of that output increases. Baumol, Panzar, and Willig (1982) derived a measure for product-specific scale economies for good i (PScale_i) as

$$\text{PScale}_i = \frac{IC_i(Y,W)}{Y_i MC_i} = \frac{IC_i(Y,W)/TC}{\eta_{\text{tc},\text{y}_i}}, \tag{2.8}$$

where IC_i is the incremental cost of the ith output. Incremental cost can be calculated as the difference in total costs when the firm produces a given level of output i while keeping the remaining output mix constant (Baumol et al., 1982), $IC_i = TC(Y_1, \ldots, Y_n, W) - TC(Y_1, \ldots, Y_{i-1}, 0, Y_{i+1}, \ldots, Y_n, W)$.

Measuring product-specific scale economies with equation (2.8) requires the calculation of the total cost function at zero output levels. The calculation of (2.1) at zero output levels is infeasible given the nature of hospital output, i.e., hospitals have little to no control over the output mix that is produced. However, a work around method has been proposed by Kim (1986). The problem associated with the calculation of incremental costs can be resolved by using a reference point, with the suggested reference point being ten percent of the sample mean outputs. Following (Kim, 1986), product-specific scale economies for the translog cost function, at the approximation point, can then be derived as

$$\text{PScale}_i = \frac{\exp(\alpha_0) - \exp\left(\alpha_0 + \alpha_i \ln z + 1/2\ \alpha_{ii}(\ln z)^2\right)}{\alpha_i \exp(\alpha_0)}. \tag{2.9}$$

Given that both the dependent and independent variables of the cost function are in natural logarithms, and that $\ln = 0$ is not defined, the suggested ten percent, $z = 0.1$, of the sample means is used in place of the zero output levels.

Additionally, product-specific scale economies between a set of outputs (PScale_{ij}) can be calculated, at the approximation point, as,

$$\text{PScale}_{ij} = \frac{\exp(\alpha_0) - \exp\left[\alpha_0 + \alpha_i \ln z + \alpha_j \ln z + 1/2\ \alpha_{ii}(\ln z)^2 + 1/2\ \alpha_{jj}(\ln z)^2\right]}{(\alpha_i + \alpha_j)\exp(\alpha_0)}. \tag{2.10}$$

Product-specific scale economies between sets of output measures whether or not cost savings can be had by increasing only a given set of products.

2.2.3 Economies of Scope

Just like with scale economies, there are two types of scope economies that can be calculated for multi-output institutions: overall scope economies, and product-specific scope economies. Overall scope economies arise if the total cost associated with the joint production of all the products in the output mix are less than the sum of the costs of producing each product separately. While product-specific economies of scope exist if the cost associated with the addition of a specific product to the output mix is lower than the cost of producing that product alone.

Following Panzar and Willig (1977) overall scope economies (OScope), for the multi-product firm can be calculated as

$$\text{OScope} = \frac{\sum_{i=1}^{n} TC_i(Y,W) - TC(Y,W)}{TC(Y,W)}, \tag{2.11}$$

where $TC_i(Y,W)$ is the total cost associated with the production of the specific output Y_i. If OScope is greater than zero, then hospitals are experiencing cost savings that result from the joint production of their output mix, thereby exhibiting overall scope economies.

If OScope is less than zero, then hospitals are experiencing overall diseconomies of scope and are incurring increased costs that are a result from the joint production of the output-mix.

Product-specific scope economies are present when the joint production of an output, along with the existing output mix, is less costly than independently producing the output alone. According to Kim (1986) product-specific economies of scope (PScope_i), for the translog cost function at the point of approximation, for a product Y_i is given by

$$\begin{aligned}\text{PScope}_i =& \frac{\exp\left(\alpha_0 + \sum_{j\neq i} \alpha_j \ln z + 1/2 \sum_{j\neq i} \alpha_{jj} (\ln z)^2\right)}{\exp(\alpha_0)} \\ &+ \frac{\exp\left(\alpha_0 + \alpha_i \ln z + 1/2 \alpha_{ii} (\ln z)^2\right) - \exp(\alpha_0)}{\exp(\alpha_0)}.\end{aligned} \tag{2.12}$$

A PScope_i value greater than zero indicates the existence of product-specific scope economies for the i^{th} output. Meaning that the firm is experiencing cost savings due to the joint production of the i^{th} output along with the existing output mix. If PScope_i yields a value less than zero, then the firm is exhibiting diseconomies of product-specific scope. That is, the firm is incurring higher costs by jointly producing the i^{th} product with the remaining output mix.

2.2.4 Relative Cost Efficiency

When a hospital is technically efficient it means that it is deriving the maximum output from its inputs. In order to derive a general sense of a hospital's technical efficiency, when estimating the relationship between total cost and outputs, this study estimates the translog cost function via the stochastic frontier approach (SFA). Estimation of the translog via SFA is particularly attractive as it has been shown that the method tends to explain the true structure of cost reasonably well (Worthington, 2004). Unlike estimation of the cost function via ISUR, SFA focuses on the residual deviation between a hospital's true cost and the predicted costs.

Stochastic frontier analysis separates the error term from the regression into a stochastic component and an efficiency component (Jondrow et al., 1982). So, the error term in Equation (2.1) takes the form

$$\varepsilon = v + u, \tag{2.13}$$

where v represents the stochastic component of the regression, which is assumed to be an independently and identically distributed (i.i.d.) normal variable with a mean of zero and variance σ^2; and, u is the inefficiency component, which is assumed to have a strictly non-negative i.i.d. half-normal distribution. The inefficiency component shows panel-specific effects and is modelled as a truncated-normal random variable which is multiplied by a function of time,

$$u = \gamma_t u = \{\exp\left[-\gamma(t - T)\right]\} u, \tag{2.14}$$

where γ is an unknown scalar paramater at the tth period of observation over T time periods (Battese & Coelli, 1992). Equation (2.14) is such that the inefficiency component increases, decreases, or remains constant as t increases. That is, the exponentional specification constrains, over time, the inefficiency component to either decrease at an increasing rate, increase at a decreasing rate, or remain constant when $\gamma > 0$, $\gamma < 0$, or $\gamma = 0$, respectively. So, when γ is positive hospital inefficiency can be assumed to be decreasing.

Once the coefficients of the translog are estimated, a technical inefficiency score is calculated. The inefficiency component is interpreted as the percentage difference between actual observed hospital costs and the minimum costs represented by the best-practice cost frontier.[3] The best-practices cost frontier, determined by the other hospitals in the sample, represents the minimum feasible cost given the inputs being employed in the industry.

2.3 Data

The majority of the data used in this analysis come from the American Hospital Association (AHA) Annual Survey Database and the Department of Health and Human Services (HHS) Cost Reports. The patient case-mix data comes from the Center for Medicare and Medicaid Services (CMS). While the Hospital Producer Price Index comes by way of the Bureau of Labor Statistics.

The sample is made up of an unbalanced panel of 181 short-term care hospitals from the state of Florida, for the period of 1998 through 2007, consisting of 1725 observations. The dependent variable of total cost (TC) is made up of total operating expenses, including interest and depreciation. Three main output variables were used in the analysis; inpatient admissions, emergency room visits, and outpatient visits. Inpatient admissions (Y_1) report the total number of acute and intensive care patients admitted to the hospital. Emergency room visits (Y_2) consist of the number of patients admitted through the hospital's emergency room.

[3] For more information on SFA see (Kumbhakar, Kumbhakar, & Lovell, 2003).

Table 2.1
Summary Statistics

Variable	Description	Mean	Standard deviation
Dependent			
TC	Total cost (000 dollars)	117,952	141,636
Independent			
Y_1	Inpatient admissions	97,847	72,844
Y_2	Emergency visits	39,185	42,756
Y_3	Outpatient visits	25,260	26,338
W_1	Labor costs	55,668	14,742
W_2	Capital costs	232,760	112,765
Explanatory			
DRG	DRG Case-mix index	1.40	0.238
GOV	Govt binary	0.09	0.296
$NPROF$	Non-profit binary	0.51	0.500
SYS	System binary	0.57	0.495

Values in 2005 dollars.

Outpatient visits (Y_3) report the number of same day, non-emergency, patient procedures. Input prices were not readily available in any of the data sets so, following previous studies, reasonable measures were constructed. The price of labor (W_1) was created by dividing total labor costs by the number of full-time equivalent employees. The price of capital inputs (W_2), i.e., drugs, medical supplies, materials, utilities, capital stock and the book value of land, was created by dividing the cost of capital by the total number of facility beds. All cost measures along with input prices and other monetary values are expressed in 2005 dollars.

In order to account for product heterogeneity, the CMS diagnostic related group (DRG) case-mix index was added to the cost function. The DRG case-mix measures, on a per unit basis, the severity of inpatient care, emergency room visits, and outpatient visits in such a way that can be aggregated into an index representing the overall severity of health service demanded. In addition to the DRG case-mix index, commonly used variables, which have been shown to explain variation in hospital costs, have been added to the cost function (e.g. Vita, 1990; Dor et al., 1997; Li & Rosenman, 2001). Binary variables indicating whether a hospital was a member of a multi hospital system (SYS), whether it was organized as a non-profit ($NPROF$), and whether the hospital was government operated (GOV) were added. Table 2.1 contains a summary of the variables along with descriptive statistics.

2.4 Empirical Results

The SFA results of the translog cost function were derived using the `xtfrontier` routine in STATA 11. All models converged after 21 iterations.

2.4.1 Cost Function Results

Table 2.2 presents SFA estimates of the translog cost function coefficients, by hospital size, for the state of Florida. Using the definition of hospital size provided by Preyra and Pink (2006), the sample was partitioned into three groups: (1) small hospitals consisting of institutions with fewer than 100 hospital beds; (2) medium sized hospitals consisting of hospitals that have more than 100 beds but fewer than 300; and, (3) large hospitals consisting of institutions that have 300 or more beds. With the exception of the labor cost coefficient for large hospitals, the estimated results with respect to the outputs (α_i's), input prices (β_k's), and treatment complexity mix (cmi) take on plausible values.

As expected, regardless of hospital size, the leading output contributing the most to a hospital's cost is inpatient care, followed by emergency room service, then by outpatient visits. The labor component contributes the most to overall hospital costs, for small and medium sized hospitals. Capital costs, however, is bigger than expected for large institutions, and is significantly larger than the capital cost faced by medium and small sized hospitals. In return, the labor cost component for large institutions is negative, which is not reasonable. This result may be related to the inability of flexible form cost functions, such as the translog, to accurately represent a firm's technology for outputs that are far from the point of approximation (Wales, 1977).

Flexibility is the notion that the functional form of the cost function places no restrictions on the substitution and scale elasticities of a firm's inputs; it is a local property. It is not a global property and thus flexible form cost functions may perform poorly for data points far from the mean (Caves & Christensen, 1980). That is, the translog is able to match the first and second derivatives of an arbitraty cost function at a given point, generally at the sample means. But, the translog may be a poor indicator of the unknown true cost function at distances far from the sample means.

This may very well be the case in this instance, since there is no upper bound restriction in the number of beds that make up the sample group of large hospitals. Of the 594 observations in the sample of large hospitals, 217 have capital cost, per bed, in excess of $432,000. Which is almost two standard deviations larger than the group's mean capital cost of $255,360 per bed. However, regardless of the limitations of flexible functional form cost functions, the translog cost function still provides insight into the behavior of an institution's costs. In particular, the degree of scale and scope economies exhibited by hospitals. The results reported here are local estimates, not global, meaning that they are valid for small changes in output near the point of approximation and may not hold for very large changes or deviations in output.

Table 2.2
SFA Results

Coefficient	Variable	Results		
		Small	Medium	Large
Constant	α_0	2.085(1.842)	16.69(2.012)	18.64(2.051)
$\ln Y_1$	α_1	0.490(0.139)	0.579(0.079)	0.635(0.273)
$\ln Y_2$	α_2	0.239(0.116)	0.278(0.042)	0.369(0.081)
$\ln Y_3$	α_3	0.186(0.056)	0.208(0.029)	0.249(0.113)
$\ln Y_1 \cdot \ln Y_1$	α_{11}	0.006(0.007)	0.007(0.026)	-0.013(0.026)
$\ln Y_1 \cdot \ln Y_2$	α_{12}	0.105(0.041)	0.028(0.026)	0.047(0.027)
$\ln Y_1 \cdot \ln Y_3$	α_{13}	-0.146(0.044)	-0.030(0.029)	-0.002(0.031)
$\ln Y_2 \cdot \ln Y_2$	α_{22}	0.027(0.029)	0.093(0.029)	0.127(0.028)
$\ln Y_2 \cdot \ln Y_3$	α_{23}	0.001(0.024)	0.013(0.024)	-0.159(0.029)
$\ln Y_3 \cdot \ln Y_3$	α_{33}	0.076(0.018)	0.146(0.029)	0.366(0.047)
$\ln W_1$	β_1	0.560(0.131)	0.591(0.083)	-0.182(0.091)
$\ln W_2$	β_2	0.441(0.131)	0.409(0.083)	1.182(0.091)
$\ln W_1 \cdot \ln W_1$	β_{11}	0.019(0.013)	0.020(0.007)	0.050(0.007)
$\ln W_1 \cdot \ln W_2$	β_{12}	-0.027(0.004)	-0.038(0.003)	-0.003(0.002)
$\ln W_2 \cdot \ln W_2$	β_{22}	0.008(0.013)	0.018(0.007)	-0.046(0.008)
$\ln Y_1 \cdot \ln W_1$	δ_{11}	0.015(0.005)	0.021(0.003)	0.004(0.004)
$\ln Y_1 \cdot \ln W_2$	δ_{12}	0.080(0.017)	0.212(0.022)	-0.039(0.018)
$\ln Y_2 \cdot \ln W_1$	δ_{21}	0.009(0.006)	0.001(0.004)	0.008(0.004)
$\ln Y_2 \cdot \ln W_2$	δ_{22}	-0.150(0.032)	-0.339(0.032)	0.216(0.034)
$\ln Y_3 \cdot \ln W_1$	δ_{31}	-0.018(0.006)	-0.010(0.004)	0.003(0.005)
$\ln Y_3 \cdot \ln W_2$	δ_{32}	0.064(0.033)	0.115(0.029)	-0.192(0.033)
DRG	γ_1	0.446(0.086)	0.266(0.038)	0.227(0.031)
GOV	γ_2	0.133(0.037)	0.009(0.022)	-0.034(0.017)
$NPROF$	γ_3	-0.032(0.025)	0.048(0.013)	0.111(0.014)
SYS	γ_4	-0.025(0.024)	0.008(0.012)	0.007(0.012)
N		342	805	578

Standard errors in parentheses.

2.4.2 Economies of Scale Results

The first step in determining if there are any potential gains to production efficiency for Florida hospitals is to look at economies of scale. From the stochastic frontier results of the translog cost function, overall scale economies were derived using Equation (2.7). The result are presented below in Table 2.3 along with their standard errors.[4]

Table 2.3
Scale economies*

Small	1.113 (0.014)
Medium	0.963 (0.008)
Large	0.839 (0.006)
All	0.948 (0.008)

* Mean values derived via Equation (2.7). Values greater than, equal to, or less than one indicate increasing, constant, or decreasing returns to scale.

The results show that, on average, only small sized institutions enjoy gains from overall scale economies; while, medium and large sized hospitals exhibit diseconomies of scale. It is curious to note that even though medium sized institutions exhibit disceconomies of scale, they are very close to the point of constant returns. That is to say, small hospitals enjoy overall production efficiencies, while large hospitals, and to a lesser extent, medium sized hospitals, are not enjoying efficiency gains from their overall output. As a whole, the results suggests that, for the state of Florida, as hospital size increases the gains from overall scale economies decreases.

[4]The results were derived from the predicted economies of scale function along with the data. Thus, the results are vectorized over the observations and are not scalars. The standard errors were generated by the statistical software, Stata, using the `predictnl` command which uses the delta method in deriving the test statistics. For more information see the Stata 11 Base Reference Manual.

Point estimates of product-specific scale economies for both single outputs and combinations of outputs are presented in Table 2.4. Given that the measurement of incremental cost is not feasible, as detailed in the section of the text dealing with economies of scale, only point estimates are presented. Therefore, no standard errors are reported in Table 2.4.

Table 2.4
Product-specific scale economies at point of estimation*

Y_1 – Inpatient admissions	1.397
Y_2 – Emergency visits	1.450
Y_3 – Outpatient visits	1.129
Y_1 and Y_2	1.009
Y_1 and Y_3	1.052
Y_2 and Y_3	1.082

* Point of approximation values derived via Equations (2.9) and (2.10). Values greater than one indicate that economies of scale are present.

Product-specific scale economies are present for all three outputs. With emergency room visits and inpatient admissions, 1.450 and 1.397 respectively, being larger than outpatient visits, 1.129. While hospitals as a whole exhibit product-specific scale economies, we would have expected them to have more control over the average costs associated with outpatient visits, as outpatient procedures are generally scheduled and can be planned for in advance, unlike emergency room visits and most inpatient admissions. The results suggests that hospitals have focused on achieving cost efficiencies on the outputs which contribute the most to costs but are the most stochastic. Florida hospitals can then obtain greater output efficiencies and therby greater cost savings by the expansion of emergency room visits and inpatient admissions.

Product-specific scale economies associated with the combined output groups reveals that hospitals in the state are enjoying a little more than constant returns to scale in all combinations of product sets. With the product sets that include outpatient visits providing the most gains in cost efficiencies; 1.082 for emergency room visits combined with outpatient visits, 1.052 for inpatient admissions combined with outpatient visits, and 1.009 for inpatient admissions combined with emergency room visits.

Hospitals exhibit overall diseconomies of scale while enjoying product-specific scale economies. This is because of the fact that the measurement of product-specific scale economies only takes into account the cost associated with the output being considered. So, if hospitals produced solely one ouput, say inpatient admissions, then economies of scale, of magnitude 1.397, would be present. However, hospitals are multiproduct institutions and as such produce mutliple outputs simultaneously. It is in the production of multiple outputs that Flodia hospitals, as a whole, experience overall disceonomies of scale.

2.4.3 Economies of Scope Results

Results on scope economies are presented in Table 2.5. All three partitioned groups enjoy the presence of overall scope economies. Large hospitals experience particularly pronounced economies of scope of 2.186, followed by medium-sized hospitals at 1.869. Small hospitals enjoy the least gains from expanding scope, at 1.421. The results on overall scope economies can be interpreted as the percentage difference between the cost associated with joint production and the cost associated of producing each output seperately. That is, the value of overall economies of scope of 1.421 for small hospitals means that it would cost small hospitals, on average, 142.1 percent more to produce the outputs seperately rather than jointly.

Table 2.5
Scope economies*

Small	1.421 (0.032)
Medium	1.869 (0.012)
Large	2.186 (0.063)
All	1.732 (0.033)

* Mean values derived via Equation (2.11). Values greater than zero indicate the existence of scope economies. Standard errors in parentheses.

The results reported imply that small Florida hospitals benefit the least from output diversification, while large hospitals benefit the most. The results suggest that small hospitals can benefit more, relative to larger institutions, from focusing on expanding the scale of production rather than diversifying their product mix. The opposite is true for large hospitals, they can benefit by continuing to expand and diversify the services they provide.

Table 2.6
Product-specific scope economies at point of estimation*

Y_1 – Inpatient admissions	0.302
Y_2 – Emergency visits	0.270
Y_3 – Outpatient visits	0.318

* Point of approximation values derived via Equation (2.12). Values greater than zero indicate that product specific economies of scope are present.

Point estimates of product-specific scope economies are reported in Table 2.6. All values are positive giving rise to the existence of product-specific economies of scope.

Evidently, Florida hospitals enjoy cost savings due to the joint production of each output along with the remaining output mix, rather than the production of each output separate and apart from the rest of the output mix.

2.4.4 Relative Cost Efficiency Results

The results presented in this section report an inefficiency score that is derived as the percentage difference between the actual observed hospital cost and the minimum feasible cost, or the frontier created statistically from the samples. The estimation of the translog cost function via SFA creates an inefficiency score for each observation in the samples. Table 2.7 presents the average inefficiency scores of the three partitioned Florida hospital groups, along with the average inefficiency score for all Florida hospitals. The inefficiency results indicate the existence of inefficiencies across all Florida hospitals regardless of size. The inefficiency score of 0.289, for "All", indicates that Florida hospital output is being produced at a cost inefficiency of 28.9%. That is, Florida hospitals, on average, are producing at a cost that is 28.9% higher than hospitals employing best practices.

Table 2.7
SFA inefficiency scores *

Small	0.171 (0.048)
Medium	0.308 (0.087)
Large	0.359 (0.072)
All	0.289 (0.055)

* Mean values reported with standard errors in parentheses.

From the inefficiency results we conclude that large institutions are the most inefficient, producing at a cost that is 35.9% higher than that of large hospitals employing best practices. Medium sized hospitals, on average, are operating at a cost that is 30.8% higher than their best practices, same sized, counterparts. Small hospitals are the least inefficient, operating on average at a cost that is 17.1% higher than the small hospitals operating at the minimum feasible cost frontier.

2.5 Conclusion

The assumption that efficiency gains can be readily had by consolidating smaller firms into larger institutions does not necessarily hold for the Florida hospital industry. This paper analyzed output and cost efficiencies for Florida hospitals over the period between 1998 and 2007. When comparing the output efficiency results with those of relative cost efficiency, some tentative conclusions can be drawn.

First, the empirical evidence supports the conclusion that only small sized hospitals in the state, those with fewer than 100 beds, enjoy overall economies of scale. The same evidence also suggests that medium and large hospitals exhibit diseconomies of scale. Albeit, medium sized institutions are very close to enjoying constant returns to scale. Second, the empirical evidence suggests that, regardless of size, all Florida hospitals, on average, enjoy significant overall scope economies. Larger institutions enojoy the greatest benefits from product diversification, followed by medium, and then by small, sized hospitals. Third, the empirical evidence also supports the conclusion that, on average, all Florida hospitals enjoy costs savings due to the joint production of output. Finally, small hospitals, which enjoy the highest levels of overall economies of scale, also are the institutions operating closest to the minimum cost frontier.

From a policy perspective, the lack of a cost advantage for large diversified hospitals implies that the industry appears to be in no danger of being dominated by a few large firms. Policy choices that can help the process of consolidation, especially between relatively small hospitals, may be desirable. Smaller hospitals appear to stay competitive by operating closer to the efficient frontier. These smaller hospitals can then improve output efficiency by expanding their scale of production or merging with other institutions. Even though there is a threat that smaller hospitals can and may be taken over by larger more diversified firms, the evidence suggests that there is opportunity for smaller and less diversified hospitals to operate efficiently. To conclude, the results have shown that policy should be geared towards increasing scale for institutions with fewer beds and towards facilitating multiproduct production in larger institutions.

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CHAPTER 3

EFFICIENCY OF FLORIDA HOSPITALS: A DATA ENVELOPMENT ANALYSIS APPROACH

3.1 Introduction

In spite of continued efforts to curb health spending, healthcare costs in the United States continue to rise. According to a recent publication by the National Center for Health Statistics, health expenditures totaled \$2.3 trillion and accounted for 16% of Gross Domestic Product (GDP) in 2008, compared to \$1.3 trillion and 13.6% of GDP in 2000 (National Center for Health Statistics, 2010). Furthermore, during the same period real per capita spending on hospital care rose by approximately 68%. It is believed that a large contributing factor associated with the rising cost of hospital care is the inefficiency of health care institutions (Worthington, 2004). Having a clear understanding of the causes of hospital inefficiency, along with the inputs of production, and environmental factors that lead to those inefficiencies is of central importance to the managers of healthcare establishments. It is particularly important when they are making policy and budgeting decisions that will affect their institutions.

Efficiency analysis can be an extremely helpful tool for decision makers that allows for a better understanding of the performance of the health care institutions under their control. The primary aim of this study is, therefore, to measure hospital efficiency in the state of Florida by applying a nonparametric empirical approach, known as Data Envelopment Analysis (DEA), in order to derive relative efficiency scores for each hospital. Data Envelopment Analysis allows the identification of hospitals that are inefficient relative to their peers and report by how much their inefficiencies differ. Additionally, the approach taken in this study will identify the factors of production that hospitals are over utilizing and that are causing added inefficiencies. This analysis will help managers to directly target those specific inputs when trying to improve their institution's performance. Finally, I will identify structural, managerial, and environmental factors that lead to improved efficiency results.

The present paper continues as follows. The second section discusses the two stage approach and the models used in each stage. The third section describes the data and the variables used in the study. The fourth section presents and reviews the empirical results from each stage of the analysis, with the fifth and final section summarizing the results and concluding the paper.

3.2 Methodology for Estimating Efficiency

In this paper a two-stage approach is used to analyze a hospital's overall technical efficiency and the factors that may explain variations therein. The first stage uses the Banker, Charnes, and Cooper (1984) (BCC) DEA model in order to derive a technical efficiency score, from a set of inputs and outputs, for each non-specialty hospital in the state of Florida. In addition to the individual efficiency scores, in the first stage the amount of input over utilization (inputs slacks) associated with each hospital are calculated. The second stage involves regressing the efficiency score generated in the first step on a number of structural, managerial, and environmental factors that may have an impact on the efficiency of Florida hospitals via a Tobit regression model.

3.2.1 Data Envelopment Analysis

Data Envelopment Analysis is a nonparametric method for measuring the overall technical efficiency of a decision making unit (DMU), in this case Florida hospitals. It constructs a production frontier from the data set based on the best observed practices. The DEA approach is a nonparametric technique based on linear programming. Being nonparametric makes DEA highly attractive for measuring hospital efficiency. The hospital industry is one of the very few markets where not-for-profit, for-profit, church and government owned institutions produce similar outputs simultaneously. Unlike parametric methods of estimating a one-size-fits-all production, or cost, function in order to measure efficiency, DEA constructs a linear-segmented piece-wise production frontier, from the available data, without making any assumptions about the underlying production technology. This frees the DEA results from any sort of error due to misspecification of the production technology[1].

In DEA, technical efficiency is defined as the ratio of the weighted sum of a DMU's outputs to the weighted sum of its inputs. Assuming convexity of production possibility sets, technical efficiency is then derived by solving the following mathematical programming problem for each DMU,

$$\max_{u,v} \left(\frac{\sum_{s=1}^{S} u_s y_{si}}{\sum_{m=1}^{M} v_m x_{mi}} \right) \tag{3.1}$$

[1] A full and comprehensive treatment of DEA can be found in Fare and Knox Lovell (1978); Fare, Grosskopf, and Lovell (2008); Lovell et al. (1994); Charnes (1994); Coelli, Rao, and Battese (1998); Cooper, Seiford, and Tone (2000).

subject to:

$$\frac{\sum_{s=1}^{S} u_s y_{sj}}{\sum_{m=1}^{M} v_m x_{mj}} \leq 1, \qquad j = 1, \ldots, I$$

$$u_s, v_m \geq 0$$

where y_{si} is the quantity of output s for DMU$_i$, u_s is a positive weight associated with output y_s, x_{mi} is the quantity of input x_m for DMU$_i$, and v_m is a positive weight associated with input x_m.

If we let the M inputs and S outputs for the ith DMU be represented by the column vectors $\mathbf{x}_i$ and $\mathbf{y}_i$, respectively; the formulation in (3.1) can be more succinctly written as,

$$\max_{\mathrm{u,v}} \quad \left(\frac{\mathbf{u}'\mathbf{y}_i}{\mathbf{v}'\mathbf{x}_i}\right), \tag{3.2}$$

subject to:

$$\frac{\mathbf{u}'\mathbf{y}_j}{\mathbf{v}'\mathbf{x}_j} \leq 1, \qquad j = 1, \ldots, I$$

$$\mathbf{u}, \mathbf{v} \geq 0.$$

Intuitively, the mathematical programming problem in (3.2) seeks to find the output and input weights that maximize the efficiency of the ith DMU, relative to all its peers, with the constraints that the maximum efficiency any DMU may attain is equal to one. The optimal weights are computed for each DMU and are calculated in order to maximize a DMU's weighted output-input ratio. However, a problem with the formulation in (3.2) is that there are an infinite number of solutions (Coelli et al., 1998).

If $(\mathbf{u}^*, \mathbf{v}^*)$ is a solution to the mathematical programming problem, then $(\alpha\mathbf{u}^*, \alpha\mathbf{v}^*)$, for any positive value of α, must also be a solution. In order to overcome this issue either the numerator or the denominator must be restricted to equal to one (Cooper et al., 2000). Thus, the problem becomes to either maximize the weighted outputs subject to the weighted inputs being equal to one, or to minimize the weighted inputs subject to the weighted outputs being equal to one.

According to Coelli et al. (1998) the problem of multiple solutions can be overcome by rewriting the mathematical programing problem in multiplier form, as opposed to ratio form, as follows

$$\max_{\mu,\nu} \; (\mu'\mathbf{y}_i)\,, \tag{3.3}$$

subject to:

$$\begin{aligned} &\nu'\mathbf{x}_j = 1, \\ &\mu'\mathbf{y}_j - \nu'\mathbf{x}_j \leq 0, \qquad j = 1, \ldots, I, \\ &\mu, \nu \geq 0, \end{aligned}$$

where $\mathbf{u}$ and $\mathbf{v}$ have been replaced with μ and ν in order to emphasize that the mathematical programming problem has changed. The maximization problem in (3.3), sets out to measure efficiency by maximizing the output given the level of inputs a DMU employs. However, hospitals are not free to choose the level of output they produce. Florida hospitals are required to provide emergency services to all that seek it and as the need arises. With few exceptions, they have little to no control over the number of illnesses they treat, nor the severity of such illnesses. They supply health services as it is demanded. Therefore, this study is interested in the dual of the maximization problem in (3.3). That is, we are interested in measuring efficiency by minimizing the amount of inputs a hospital employs given the level of outputs it produces. According to Coelli et al. (1998), following the duality in linear programming, (3.3) can also be written as the following minimization problem

$$\min_{\theta,\lambda} \ \theta, \tag{3.4}$$

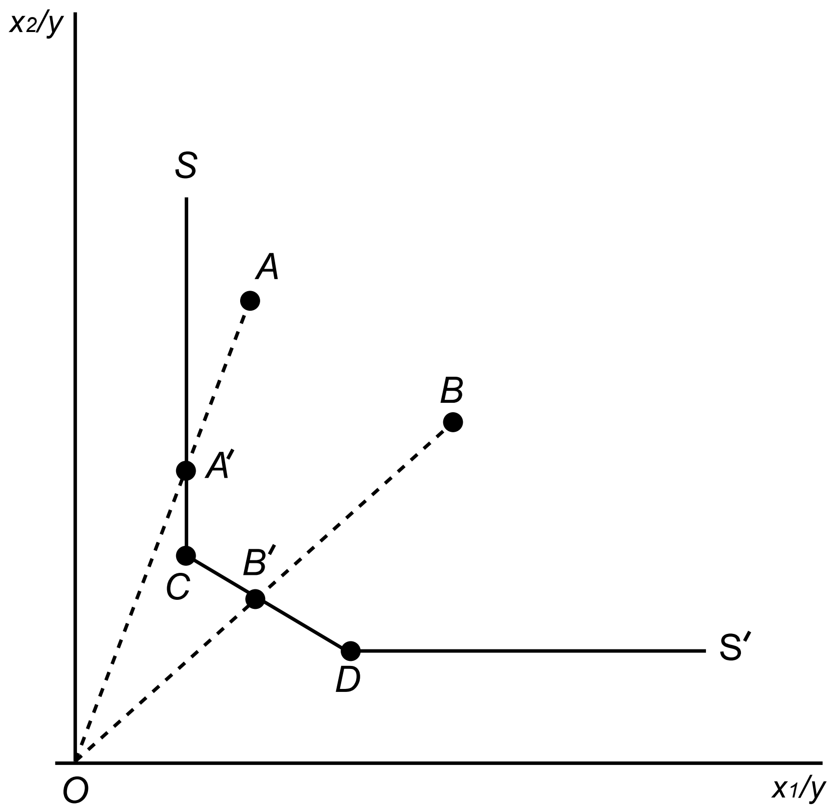
subject to:

$$\begin{aligned} &-\mathbf{y}_i + \lambda\mathbf{Y} \geq 0, \\ &-\theta\mathbf{x}_i - \mathbf{X}\lambda \geq 0, \\ &\lambda \geq 1, \end{aligned}$$

where θ is the efficiency component, λ is an a $I \times 1$ vector of weights that is associated with each specific DMU, $\mathbf{X}$ and $\mathbf{Y}$ are the input and output matrices representing the data of all the DMUs.

The linear programming model in (3.4) is known as the input-oriented technical efficiency DEA Model with variable returns to scale. The input-oriented DEA model seeks optimal values for θ and λ that will radially contract the ith DMU's input vector, $\mathbf{x}_i$, while maintaining output constant. The input-oriented model in essence measures by how much and to what extent it is possible for a DMU to reduce its inputs without affecting the level of its outputs. The value of θ is the efficiency score obtained for the ith DMU, with a value of one indicating a technically efficient point and thus a point on the frontier. The linear programming problem must be solved for each DMU in the sample in order to derive the value of θ for each hospital.

Figure 3.1
Production Possibility Set



To illustrate, suppose there are four hospitals using two inputs, x_1 and x_2, in order to produce one output y. Figure 3.1[2] shows that hospitals C and D form the piece-wise linear isoquant that is the efficient production frontier. Hospitals A and B are off the frontier and are thus inefficient. The efficiency measure can then be calculated for hospital A as OA'/OA and for hospital B as OB'/OB. A point such as A' is considered to be Farrell-Efficient (Farrell, 1957). However, whether a point such as A' is efficient is questionable because the hospital at point A' can further reduce its use of x_2, by CA', to the level employed by hospital C. A situation like A' occurs when there is the presence

[2]Figure 3.1 was adopted from Coelli et al. (1998) and Cooper et al. (2000) .

of input slacks in the input constraint of the linear programming problem found in (3.4), $-\theta \mathbf{x}_i - \mathbf{X}\lambda \neq 0$. A value greater than zero in the input slack represents the additional amount by which a DMU can decrease its input after accounting for its inefficiency, while producing the same level of output. A point such as B', which is on the frontier and exhibits zero input slack is known as being Koopmans-Efficient (Koopmans, 1951). Both the value of overall technical efficiency, θ, and the corresponding input slacks are derived and reported in this study.

3.2.2 Tobit Regression

In the second stage, a Tobit regression (Tobin, 1958) model is used in order to evaluate the affect various structural, organizational, and environmental factors may have on the overall technical efficiency of Florida hospitals. A Tobit regression model was selected since the dependent variable of the regression, overall hospital technical efficiency which reports values within the interval $(0, 1]$, is censored from above. In this instance, using an ordinary least square (OLS) regression was ruled out given that the results would have been biased and inconsistent (Amemiya, 1973). The Tobit regression is specified as follows

$$\theta_i = \beta_0 + \beta' \mathbf{Z} + \varepsilon_i \tag{3.5}$$

where θ_i is the relative overall technical efficiency score for the ith DMU, the β's are coefficient estimates for the numerous structural, organizational, and environmental factors, $\mathbf{Z}$, thought to affect a hospital's overall technical efficiency, and ε_i is a normally distributed error term.

3.3 Data

The data for this study were obtained from the American Hospital Association (AHA) Annual Survey Database, the Department of Health and Human Services (HHS) Cost Reports, and the Center for Medicare and Medicaid Services (CMS) for the year 2007. The sample consists of all short-term care, non-specialty, hospitals for the state of Florida. Focusing on a single state eliminates variation in the results from different state level regulatory and economic factors. Additionally, the study excludes long-term care, psychiatric care, and cancer centers from the sample and focuses solely on general acute short-term care hospitals. Four output variables and four input variables are used in the study, along with a range of variables that may help explain variation in hospital efficiency.

Following previous studies (Cowing and Holtmann (1983); Grannemann, Brown, and Pauly (1986); Hollingsworth and Parkin (1995)) hospital output is measured as an array of outputs. Four separate intermediate outputs are considered in this study; acute care (AC), intensive care (IC), surgeries (SU), and emergency care (EC). It must be noted that these measures of output are a second-best alternative to the conceptually ideal measure of improved health status. Unfortunately, a measurement of patient health status is unavailable in the data. We have, however, focused on in-hospital care and the most common outputs produced by hospitals. The acute care variable consists of short-term medical treatment for patients having an illness or injury, it is measured in the number of admissions. The intensive care variable is also measured in the number of admissions, and accounts for the treatment of critically ill patients.

Surgeries are counted as the number of inpatient and outpatient surgical operations performed during the period under study. Finally, the emergency care variable consists of all ambulatory outpatient visits and emergency room visits.

Inputs include the number of full-time equivalent physicians (DR), the number of full-time equivalent licensed and registered nurses along with the number of nurses' assistants (RN), the number full-time equivalent medical technicians (EM), and the number of beds (BD). The physicians variable includes all residents plus all physicians that are employed, associated, or affiliated with the hospital. The registered nurses variables includes all the licensed practical nurses, registered nurses, and nurse assistants employed by the the institution. The medical technicians variable is comprised of all radiology, laboratory, pharmacy, respiratory technicians, and other medical personnel employed at the hospital. Following previous studies (Fare, Grosskopf, Lindgren, & Roos, 1992; Linna, 1998; Maniadakis, Hollingsworth, & Thanassoulis, 1999; Blank & Valdmanis, 2010) the number of fully staffed beds is included as a proxy for the hospital's physical capital. Capital, particularly in the health care sector, is a notoriously difficult variable to collect accurately. Since the number of fully staffed beds a hospital has represents each hospital's capacity, we will follow the current literature and allow it to proxy each hospital's level of capital.

The independent variables used in the Tobit regression analysis portion of this study were chosen from previous research as factors that may possibly have an effect on hospital efficiency. A hospital's ownership structure along with other managerial and environmental factors have been closely related to a hospital's cost structure and have been linked to overall inefficiencies in the hospital literature (Valdmanis, 1990; Chien, Rohrer, Ludke, & Levitz, 1995; Wang, Ozcan, Wan, & Harrison, 1999; Chen, Hwang,

& Shao, 2005). Namely, we look at the effect ownership status has on a hospital's overall efficiency; that is, whether structured as a for-profit or not-for-profit institution (NPROF), being affiliated to a church (CHRCH), or whether being government operated (GOVT) has any effect on a hospital's overall efficiency measure. Managerial decisions may also affect a hospital's efficiency outcome. Managerial variables considered in this study include: whether a hospital is contract-managed (MNGMT); whether it is a member of a system of hospitals (SYSTM); whether it is a member of the Council of Teaching Hospitals (TEACH); and whether it is a community hospital as defined by the Hospital Association of America (CMNTY). Moreover, in order to account for output heterogeneity, variables for patient average length of stay (AVLOS) and the CMS's diagnostic related group (DRG) case-mix index (CMI) are also considered. Both the AVLOS and CMI variables serve as proxies for the complexity of care each hospital provides. The CMI measures, on a per unit basis, the severity of inpatient care, emergency room visits, and outpatient visits in such a way that can be aggregated into an index representing the overall severity of health services provided by a hospital; while, AVLOS represents the average length of bed-days or the amount of factor resources consumed by longer-term patients. Finally, we constructed a Herfindahl-Hirschman Index (HHI) to account for the level of competition in a DMU's county. Market share was computed as the ratio between a hospital's total admissions and the total hospital admissions in the county of operation. The market share for each DMU was then squared and then summed in order to create an index of competition for each county. Summary statistics, along with a brief description of each variable, are reported in Table 3.1.

Table 3.1
Summary Statistics for all Non-Specialty Florida Hospitals

Variable	Description	Mean	Standard Deviation
Outputs			
AC	Acute care admissions	139,123	173,901
IC	Intensive care admissions	1,162	1,888
SU	Total surgeries	7,495	7,519
EC	Emergency & ambulatory visits	65,191	77,296
Inputs			
DR	FTE physicians & residents	132	105
RN	FTE nurses	505	513
EM	FTE medical technicians & medical personnel	1158	1190
BD	Total number of staffed beds	306	285
Explanatory variables			
NPROF	Not-for profit hospital	0.562	0.497
CHRCH	Church operated hospital	0.057	0.238
GOVT	Government controlled	0.173	0.376
MNGMT	Contract managed hospital	0.0392	0.174
SYSTM	Member of a system of hospitals	0.773	0.419
TEACH	Teaching hospital	0.541	0.496
CMNTY	Community hospital	0.943	0.603
AVLOS	Average length of stay, in days	9.694	8.571
CMI	Case-Mix index	1.395	0.258
HHI	Herfindahl-Hirschman index	0.347	0.291
N = 194			

3.4 DEA Results

The DEA efficiency results measure each hospital's performance relative to the best practice frontier, which is constructed from the observations in the data. Therefore, all the results in this study are relative measures and not absolute. Table 3.4 in section 3.7 presents, for all non-specialty Florida hospitals, the full results of overall technical efficiency, θ, along with the corresponding input slacks, as derived from the linear programming model in (3.4). The overall technical efficiency value reports how efficient a hospital is relative to its peers or the best practice frontier. The overall technical inefficiency score indicates, in percentage terms, the amount by which each input can be proportionally reduced, while keeping the level of outputs constant, in order to move the DMU onto the production frontier. The input slacks, on the other hand, represent sources of additional inefficiency to a DMU. Input slacks in the linear programming problem in (3.4) indicate the additional amount by which inputs can be reduced after moving onto the efficient production frontier. That is, input slacks that are greater than zero represent the additional amount by which an individual input can be reduced after eliminating overall technical inefficiency. Therefore, it is important to keep in mind, when looking at the results, that a DMU is completely efficient only when θ equals to 1 and the associated input slacks are all equal to 0, i.e., the DMU is Koopman's-Efficient (Koopmans, 1951). For example, DMU 14 has an efficiency score of 0.805. This means that hospital 14 can reduce the use of all inputs by the amount of its inefficiency, $1 - \theta_{14} = 0.195$, or 19.5%. Moreover, DMU 14 has positive slacks for the inputs RN and EM. This means that not only can DMU 14 reduce the use of all it's inputs by 19.5%, but it can also reduce the number of RNs it employs by 343 and the number of EM's by 86. That is, there is input over-utilization by DMU 14, relative to it's peers, of 19.5%, plus there is over-utilization of RNs and EMs by the amount of the overall technical inefficiency plus the amount of each input slack.

Table 3.2 reports average technical efficiency and input slack results for all non-specialty Florida hospitals by Metropolitan Statistical Area (MSA).

Table 3.2
Mean Efficiency and Input Slack Results for all Non-Specialty Florida Hospitals, by MSA

MSA	θ	Input Slacks			
		BD	DR	RN	EM
Cape Coral-Fort Myers, FL	0.88(0.16)	6.29(10.27)	0.25(0.57)	0.22(0.49)	4.95(5.64)
Crestview-Fort Walton Beach-Destin, FL	0.90(0.19)	7.05(14.09)	3.81(6.86)	8.16(9.43)	8.29(16.58)
Delton-Daytona Beach-Ormond Beach, FL	0.82(0.17)	5.31(11.86)	1.24(1.71)	75.46(150.1)	40.43(56.35)
Gainesville, FL	0.92(0.12)	0.00(0.00)	5.74(9.95)	7.17(10.89)	0.00(0.00)
Jacksonville, FL	0.97(0.07)	5.35(11.02)	0.00(0.00)	24.55(48.72)	47.68(99.07)
Lakeland-Winter Haven, FL	0.90(0.15)	1.92(4.30)	0.00(0.00)	3.47(7.76)	6.57(14.68)
Miami-Fort Lauderdale-Pompano Beach, FL	0.85(0.15)	4.38(13.10)	4.43(22.44)	14.90(26.36)	28.55(79.45)
Naples-Marco Island, FL	0.98(0.03)	66.06(90.15)	0.00(0.00)	1.65(2.34)	3.45(4.89)
North Port-Bradenton-Sarasota, FL	0.86(0.19)	23.42(17.81)	0.00(0.00)	11.69(13.81)	10.69(16.61)
Ocala, FL	0.92(0.12)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)
Orlando-Kissimmee-Sanford, FL	0.87(0.13)	1.52(4.81)	0.00(0.00)	11.82(16.62)	23.88(38.62)
Palm Bay-Melbourne-Titusville, FL	0.95(0.13)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)
Palm Coast, FL	0.68(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	4.51(0.00)
Panama City-Lynn Haven-Panama City Beach, FL	0.95(0.08)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)
Pensacola-Ferry Pass-Brent, FL	0.91(0.12)	10.60(16.86)	0.00(0.00)	2.29(6.05)	0.00(0.00)
Port St. Lucie, FL	0.96(0.07)	0.00(0.00)	0.00(0.00)	0.00(0.00)	44.22(76.59)
Punta Gorda, FL	0.68(0.14)	0.00(0.00)	0.86(0.91)	23.61(30.62)	0.00(0.00)
Sebastian-Vero Beach, FL	0.71(0.21)	0.00(0.00)	0.00(0.00)	22.09(21.28)	0.00(0.00)
Tallahassee, FL	0.99(0.02)	15.17(21.46)	12.94(18.31)	13.10(18.52)	24.41(34.52)
Tampa-St. Petersburg-Clearwater, FL	0.81(0.14)	5.01(11.66)	8.49(29.21)	24.03(75.97)	6.67(14.53)
Non-MSA	0.89(0.15)	3.36(9.50)	0.09(0.26)	3.06(7.64)	11.64(38.49)

N = 194
Number of Koopmans-Efficient DMUs = 62

Standard deviations in parentheses

3.5 Tobit Regression Results

Using the overall technical efficiency score derived from DEA, θ, as a dependent variable, we use a Tobit model in order to understand the effects non-production factors may have on a DMU's overall efficiency. This second step is particularly important in order to understand which factors may affect a hospital's efficiency. For example, from Table 3.4, DMUs 79 and 94 have identical technical efficiency scores, $\theta_{79} = \theta_{94} = 0.827$. The major source of inefficiency, however, for DMU 79 comes from the over utilization of nurses, DMU 74's input slack for RN is 83.7. By comparison, DMU 94 uses all its inputs efficiently, all the input slacks associated with it are equal to zero. There are obvious factors at work, in the above example, that are not explained by DEA. Thus, the purpose of this second step is identify some of the structural, managerial, and environmental factors that can influence a hospital's overall technical efficiency.

Table 3.3 reports the results of the second stage Tobit regression. With the exception of SYSTM, CMNTY, and AVLOS all independent variables are statistically significant. The results indicate that a hospital's ownership or organizational type has a significant impact on a hospital's overall technical efficiency. Hospitals that are not-for-profit experience, on average, an overall efficiency scores that is .087 higher than for-profit hospitals. Inversely, church (CHRCH) and government (GOVT) owned hospitals are less technically efficient than hospitals that are not.

In line with the incentives literature (Baumol, 1957; Williamson, 1963; Becker, 1971), the results show that institutions whose management (MNGMT) is contracted to third-party firms are less technically efficient than those institutions managed by its own managers. The logic behind the theory is that third-party managers have a preference for employing factors of production well above the cost minimizing level. That is, third-party managers are not driven by cost-minimization and the efficiencies that are derived therefrom. The Tobit results indicate this very fact. Contract managed hospitals experience lower efficiency scores, 0.148 less, than hospitals which do not outsource their management.

Teaching hospitals often require more investment in capital and equipment for teaching purposes and often take one more complicated and severe cases for instructional purposes. The results for the TEACH coefficient reflect this fact. Teaching hospitals, on average, are less technically efficient than non-teaching hospitals, by a magnitude of 0.236. Similarly, community (CMNTY) hospitals are less technically efficient than their non-community peers.

The two variables chosen to account for product heterogeneity indicate that there are small efficiency losses from treating more severe medical cases. It should be noted that the average length of stay (AVLOS) variable, chosen as a measure of the proportion of factor resources used by inpatients and thus as a proxy for case severity turns out to be statistically insignificant. The case-mix index (CMI), which measures, on a per unit basis, the severity of inpatient care, emergency room visits, and outpatient visits serves as a proxy for overall severity of health services provided by the hospital. The results as they relate to CMI indicate that hospitals with more severe cases experience a minimal reduction, on average, in overall efficiency of 0.011.

The Herfindahl-Hirschman Index (HHI) accounts for the level of competition in a hospital's county of operation. The results, indicate that the higher the level of concentration, or the less the competition a hospital faces, the higher the gains to overall technical efficiency. That is, institutions that operate in higher concentrated counties experience, on average, higher levels of overall technical efficiency.

Table 3.3
Tobit Regression Results for Non-Specialty Florida Hospitals

Variable	Coefficient	Standard Error
Constant	0.986***	0.089
NPROF	0.087**	0.034
CHRCH	-0.109*	0.063
GOVT	-0.045**	0.016
MNGMT	-0.148**	0.057
SYSTM	0.020	0.034
TEACH	-0.236***	0.030
CMNTY	-0.005	0.043
AVLOS	0.001	0.002
CMI	-0.011***	0.003
HHI	0.112**	0.059

*p< 0.1, **p< 0.05, ***p< 0.01

3.6 Conclusion

The purpose of this study was to introduce an approach that enables the measurement of hospital efficiency by decision makers in order to evaluate the policy choices they make with respect to their institutions. I employed this approach on a sample of Florida hospitals in order to derive a technical efficiency score for each institution, and derived over utilization rates for the factors of production being employed by each hospital. I found that 112 Florida hospitals, from a sample of 194 observation, are operating away from the efficient production frontier, while 132 hospitals exhibit factor over utilization. Additionally, I regressed the relative overall efficiency score of each hospital on a number of structural, managerial, and environmental factors in order to explain variations in hospital efficiency. I found several factors that affect a hospital's efficiency conditional on its input mix, these include an institution's for-profit status, external agency control, teaching status, case-mix severity, and market competition. With additional and less aggregated data, the approach outlined in this paper can be expanded and built upon by hospital managers to derive a complete analysis of their institution's relative efficiency and the factors of production that may need specific attention.

3.7 Complete Results

Table 3.4
DEA Results for all Non-Specialty Florida Hospitals

		Input Slacks			
DMU	θ	BD	DR	RN	EM
1	1.000	23.657	0.000	1.107	5.809
2	1.000	0.000	0.000	0.000	0.000
3	0.787	0.000	0.000	0.000	13.759
4	0.969	7.791	0.000	0.000	5.182
5	0.654	0.000	1.268	0.000	0.000
6	0.626	0.000	1.185	0.000	0.000
7	1.000	0.000	0.000	0.000	0.000
8	1.000	28.181	0.000	15.709	33.164
9	0.993	0.000	14.063	16.913	0.000
10	0.681	0.000	2.732	0.000	0.000
11	0.626	0.000	3.457	0.000	0.000
12	1.000	26.529	0.000	34.740	115.947
13	1.000	0.000	0.000	0.000	0.000
14	**0.805**	**0.000**	**0.000**	**342.570**	**86.179**
15	0.982	0.000	0.000	19.703	0.000
16	1.000	0.000	0.000	0.000	0.000
17	0.780	0.000	17.234	1.805	0.000
18	1.000	0.000	0.000	0.000	0.000
19	1.000	0.000	0.000	0.000	0.000
20	0.862	0.000	0.000	79.056	333.376
21	0.960	14.475	0.000	0.000	0.000
22	1.000	14.044	0.000	151.719	76.574
23	1.000	0.000	0.000	0.000	0.000
24	1.000	0.000	0.000	0.000	0.000
25	1.000	0.000	0.000	0.000	0.000
26	1.000	0.000	0.000	0.000	0.000
27	0.795	0.000	0.000	0.000	30.754
28	1.000	35.666	0.000	63.847	131.437
29	1.000	0.000	0.000	0.000	0.000
30	1.000	0.000	0.000	0.000	0.000
31	0.855	0.000	0.000	0.000	0.000
32	0.665	0.000	0.000	0.000	0.000
33	1.000	9.610	0.000	17.351	32.833

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Table 3.4 – *continued from previous page*

DMU	θ	Input Slacks			
		BD	DR	RN	EM
34	1.000	0.000	0.000	0.000	0.000
35	1.000	19.876	0.000	18.162	92.682
36	1.000	0.000	0.000	0.000	0.000
37	1.000	0.000	0.000	0.000	0.000
38	0.700	0.000	6.068	18.782	0.000
39	0.816	0.000	0.000	66.621	0.000
40	1.000	0.000	0.000	0.000	0.000
41	0.930	0.000	0.000	0.000	0.000
42	0.865	0.000	154.352	10.323	276.688
43	0.664	0.000	0.000	76.219	0.000
44	1.000	0.000	0.000	0.000	0.000
45	1.000	5.406	0.000	9.570	97.840
46	0.930	0.000	0.000	0.000	446.988
47	0.751	24.741	0.000	0.000	0.000
48	0.691	0.000	0.000	32.361	0.000
49	1.000	0.000	0.000	0.000	0.000
50	0.756	0.000	0.000	0.000	0.000
51	0.769	0.000	0.000	0.000	0.000
52	0.863	0.000	0.000	0.000	0.000
53	0.719	0.000	0.114	0.000	0.000
54	1.000	0.000	0.000	0.000	0.000
55	0.765	26.702	0.256	0.000	0.000
56	0.582	0.000	0.009	37.609	0.000
57	1.000	0.000	0.000	0.000	0.000
58	0.807	0.000	0.000	0.000	0.000
59	0.943	0.000	6.398	26.081	151.206
60	1.000	0.000	0.000	0.000	0.000
61	0.682	6.599	0.000	9.303	0.000
62	0.833	0.000	0.000	0.000	0.000
63	0.634	0.000	47.065	0.131	0.000
64	1.000	60.360	0.000	56.639	156.688
65	0.842	0.000	0.000	0.000	97.216
66	0.895	0.000	0.000	0.000	61.436
67	0.620	0.000	6.729	0.000	0.000
68	1.000	0.000	0.000	0.000	0.000
69	0.679	0.000	0.000	6.231	0.000
70	0.821	0.000	0.000	0.000	0.000
71	1.000	1.276	0.000	1.801	34.413
72	0.747	62.983	0.000	27.002	0.000

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Table 3.4 – *continued from previous page*

DMU	θ	Input Slacks			
		BD	DR	RN	EM
73	0.823	4.013	0.000	85.279	0.000
74	0.857	0.000	0.000	0.000	0.000
75	0.333	11.670	0.000	13.852	24.216
76	0.761	0.000	0.000	0.000	16.681
77	1.000	0.000	0.000	0.000	0.000
78	0.944	0.000	4.428	90.458	0.000
79	**0.827**	**0.000**	**0.000**	**83.743**	**0.000**
80	0.819	0.000	0.000	67.785	0.000
81	1.000	0.000	0.000	0.000	0.000
82	1.000	0.000	0.000	0.000	0.000
83	0.588	0.000	0.000	21.810	0.000
84	1.000	0.000	0.000	0.000	0.000
85	1.000	0.000	0.000	0.000	0.000
86	1.000	2.314	0.000	3.306	6.909
87	0.951	129.810	0.000	0.000	0.000
88	0.544	42.047	0.000	0.000	0.000
89	0.894	39.700	0.000	32.786	0.000
90	1.000	0.000	0.000	0.000	0.000
91	0.722	6.358	0.000	0.000	0.000
92	1.000	33.900	0.000	18.188	30.185
93	1.000	18.537	0.000	19.171	33.973
94	**0.827**	**0.000**	**0.000**	**0.000**	**0.000**
95	1.000	0.000	0.000	0.000	0.000
96	0.871	0.000	0.000	16.624	0.000
97	0.704	0.000	0.000	3.904	0.000
98	0.952	0.000	0.000	0.000	71.037
99	1.000	15.195	0.000	25.037	85.376
100	1.000	0.000	0.000	0.000	0.000
101	0.727	0.000	0.000	23.614	0.000
102	1.000	0.000	0.000	0.000	0.000
103	0.746	0.000	0.000	49.055	0.000
104	1.000	0.000	0.000	0.000	0.000
105	0.720	0.000	0.000	0.000	82.427
106	1.000	0.000	0.000	0.000	0.000
107	1.000	0.000	0.000	0.000	0.000
108	1.000	0.000	0.000	0.000	0.000
109	1.000	0.000	0.000	0.000	0.000
110	0.671	0.000	0.000	0.000	0.000
111	1.000	0.000	0.000	0.000	0.000

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Table 3.4 – *continued from previous page*

		Input Slacks			
DMU	θ	BD	DR	RN	EM
112	0.681	0.000	0.000	0.000	4.507
113	0.856	0.000	0.000	0.000	0.000
114	1.000	0.000	0.000	0.000	0.000
115	1.000	0.000	0.000	0.000	0.000
116	0.927	43.128	0.000	0.000	0.000
117	1.000	0.000	0.000	0.000	0.000
118	0.769	24.200	0.000	16.019	0.000
119	0.985	0.000	0.000	0.000	0.000
120	1.000	0.000	0.000	0.000	0.000
121	1.000	0.000	0.000	0.000	0.000
122	0.704	6.896	0.000	0.000	0.000
123	0.998	0.000	0.000	0.000	132.655
124	0.875	0.000	0.000	0.000	0.000
125	1.000	0.000	0.000	0.000	0.000
126	0.525	0.000	0.773	0.000	0.000
127	0.737	0.000	0.000	58.215	0.000
128	0.783	0.000	1.806	12.625	0.000
129	0.562	0.000	0.000	21.921	0.000
130	0.866	0.000	0.000	22.255	0.000
131	0.973	0.000	25.888	0.000	0.000
132	1.000	30.343	0.000	26.195	48.812
133	0.640	5.421	0.000	0.000	0.000
134	0.787	0.000	1.356	9.300	0.000
135	1.000	31.532	0.000	106.585	51.915
136	0.651	0.000	1.273	0.000	0.000
137	0.770	0.000	0.000	95.656	0.000
138	0.984	0.000	0.000	413.008	0.000
139	0.738	0.000	0.000	0.000	0.000
140	0.998	0.000	116.822	0.000	0.000
141	0.617	0.000	0.000	0.000	0.000
142	0.758	0.000	0.000	0.000	0.000
143	0.745	0.000	0.000	0.000	35.112
144	0.699	0.000	0.000	0.000	13.931
145	0.816	3.187	0.000	0.000	0.000
146	1.000	0.000	0.000	0.000	0.000
147	0.764	0.000	0.000	8.010	6.309
148	0.749	23.719	0.000	0.000	0.000
149	0.603	0.000	0.632	0.000	0.000
150	0.768	0.000	24.151	0.000	0.000

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Table 3.4 – *continued from previous page*

DMU	θ	Input Slacks BD	DR	RN	EM
151	0.801	37.500	0.000	0.000	0.000
152	1.000	0.000	0.000	0.000	0.000
153	0.700	0.000	7.143	0.000	49.870
154	1.000	0.000	0.000	0.000	0.000
155	0.703	0.000	0.000	53.707	0.000
156	0.677	0.000	0.000	0.000	30.461
157	0.713	0.000	0.000	52.656	0.000
158	0.650	0.000	0.000	0.000	0.000
159	0.723	43.497	0.000	20.602	0.000
160	1.000	0.000	0.000	0.000	0.000
161	0.847	8.553	120.274	0.000	0.000
162	1.000	0.000	0.000	0.000	0.000
163	1.000	0.000	0.000	0.000	0.000
164	1.000	6.958	0.000	9.482	16.236
165	1.000	13.099	0.000	18.304	38.084
166	0.688	0.000	0.000	3.419	0.000
167	1.000	19.125	0.000	5.270	14.004
168	0.754	28.699	0.000	0.000	0.000
169	1.000	0.000	0.000	0.000	0.000
170	1.000	0.000	0.000	0.000	0.000
171	0.668	0.000	0.000	1.647	0.000
172	1.000	0.000	0.000	0.000	0.000
173	1.000	0.000	0.000	0.000	0.000
174	0.981	0.000	0.000	0.000	0.000
175	0.939	0.000	0.000	0.000	0.000
176	0.701	0.000	0.162	0.000	2.602
177	0.621	0.000	1.166	0.000	0.000
178	0.673	0.000	0.532	5.781	0.000
179	0.829	0.000	0.000	12.886	0.000
180	1.000	0.000	0.000	0.000	0.000
181	1.000	39.966	0.000	36.503	207.567
182	1.000	0.000	0.000	0.000	0.000
183	1.000	0.000	0.000	0.000	0.000
184	1.000	0.000	0.000	0.000	0.000
185	1.000	0.000	0.000	0.000	0.000
186	0.896	0.000	0.042	0.000	17.448
187	0.829	0.000	0.000	0.000	0.000
188	1.000	0.000	0.000	0.000	0.000
189	1.000	0.000	0.000	0.000	0.000

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Table 3.4 – *continued from previous page*

DMU	θ	Input Slacks			
		BD	DR	RN	EM
190	1.000	0.000	0.000	0.000	0.000
191	0.956	0.000	0.000	8.032	38.928
192	0.540	0.000	0.000	0.000	16.556
193	1.000	0.000	0.000	0.000	0.000
194	0.752	0.000	0.768	0.000	14.140

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