Walden University

COLLEGE OF MANAGEMENT AND TECHNOLOGY

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Jose Fernandez

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2012

Abstract

Comparison of the Technical Efficiency of Tax-Supported and Nonprofit Florida Hospitals Using Data Envelopment Analysis

by

Jose Fernandez

M.B.A., University of Miami, 1985

B.S., Florida International University, 1981

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Applied Management and Decision Sciences

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Abstract

In Florida, state budgetary constraints have resulted in political pressure to justify the taxing authority granted to tax-supported hospitals. Yet little research has examined the differences between the various sectors of the hospital industry. To address this concern, this study identified the relative differences in technical efficiency between tax-supported and nonprofit hospitals. The research questions focused on identifying the relative technical efficiencies of these 2 sectors of the hospital industry and quantifying the potential savings to be achieved if all the study hospitals operated at the efficiency frontier. Using a form of linear regression, data envelopment analysis allowed a multiple-input, multiple-output matrix that determined efficiency based on achieved performance rather than on theoretical targets. Data were collected from public sources. All the data were available from the Florida Department of Health Services. The sample included all nonprofit and tax-supported hospitals in matching health planning districts. Thirty hospitals met the inclusion criteria. Adjusting for hospital size, location, and matched comparisons, there was no significant technical efficiency difference between the two categories of study hospitals. Additionally, a potential of $320.06 million in savings could be achieved if all hospitals operated at the efficiency frontier. These findings justify the tax levying authority of tax-supported hospitals and quantify opportunities to policy makers to improve efficiency and reduce waste of public resources.

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Dedication

This dissertation is dedicated to the two most influential people in my life: my wife, Marianela and my late mother, Carmen. Without these two strong, loyal, loving women influencing every aspect of my personality, I could not have accomplished most of the successes, both professionally and personally that I have been blessed with.

My mother instilled in me confidence and a belief that I could accomplish anything that I set my heart on. She unfailingly believed in me and her encouragement and love was unconditional and persistent. I am sorry that she is not physically present to share in this accomplishment.

My wife has been a constant in my life for over 40 years, always supporting me and making sacrifices, even at her own expense, to make sure that my goals were achieved. She has been a loyal, loving, supportive constant raising my spirits when I had doubts and strongly encouraging me to pursue my goals. Her unfailing loyalty and love has been a source of strength and confidence.

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To Dr. Marcia S. Steinhauer, who has been a source of strength and inspiration beyond her official role as mentor and teacher and who became a friend during the process. She has demanded that I push beyond my level of comfort to make sure that I rose above my perceived limitations. Her honest feedback made my writing crisper and taught me to be a better researcher.

To Dr. Thomas Spencer, who served on my committee, I want to express my appreciation for his concise and insightful comments and his help with data envelopment analysis. I owe a debt to the Walden Writing Center staff, which provided a great deal of instruction with an uncanny ability to provide information at all levels of complexity. Also, the Walden Library research librarians were always available and eager to help with my requests. Both of these groups were always eager to get involved, and they actually enjoyed being involved.

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Chapter 1: Introduction to the Study

Overview

The focus of this study was the productivity performance difference between two categories of not-for-profit hospitals in Florida: those that are tax-supported via special taxing districts, and those that receive no direct tax funding. Special hospital taxing districts face increasing political pressure to justify their tax levying authority and to demonstrate that public funds are being prudently used (Office of the Governor, 2011). Equally important, the significance of efficiency measurement and performance improvement in this segment of the hospital industry is becoming urgent as health care reforms are implemented forcing these types of hospitals into direct competition with a proliferating number of multihospital, for-profit health care delivery systems (Kaplan, 2001). As the State of Florida is pressured by budget constraints into minimizing payments for the Medicaid program, it is helpless in controlling the continuing escalation in costs, mainly as a result of the demand for more services. Increases in state health care costs are unsustainable as they crowd out other needed investments such as those for education and corrections.

Florida provided an adequate study population because of the distribution of different types of hospitals. Of the 280 licensed hospitals in the state, 39% are nonprofit and 49% are for-profit. Twenty-seven hospital special taxing districts have the authority to levy taxes and collect special assessments. This diversity of hospital types provided a suitable sample for this study. Obtaining the necessary data for this study was facilitated because

Florida has required audited financial reports from all hospitals beginning in 1979, and the data were publicly available.

Tax-funded hospitals in Florida are exposed to increasing pressure to justify why they deserve to receive public monies when community nonprofit hospitals, usually located in the same service areas and providing the same services, are able to survive without this revenue source. The 2007/2008 recession exacerbated pressures in Florida to review local taxes because ad valorem tax income had decreased and government was asked to do with less income.

In the sections to follow, to the causes of the rise in health care costs are reviewed, including the rise in Medicaid expenditures, which have increasingly pressured state treasuries. The problem addressed and the research questions to be answered are detailed in context with the chosen research methodology to be used. Further, the theoretical foundation for this study and the definition of terms clarify the basis for the research. Limitations, delimitations, and the scope of the study are discussed. Finally, the significance of the study and its importance to contributing to positive social change conclude this chapter.

Background of the Study

Health care costs account for more than one sixth of the total American economy, and its rate of growth has increased as a share of the gross domestic product (GDP) for the past 50 years (National Center for Health Statistics, 2010). While the United States spends almost 16% of gross domestic product in health care services, other industrialized nations

spend substantially less and obtain similar or better outcomes. In 2006, Germany spent 10.6%, France 11.1%, and the United Kingdom 8.4% of their GDP in health care, while, in the United States, it was nearly 16%, (Figure 1). The high costs of the American health care system do not result in better health outcomes. For example, in 2009, life expectancy rates were lower, infant mortality rates were higher, and potential years of life lost were higher in the United States than for industrialized nations (OECD, 2011).

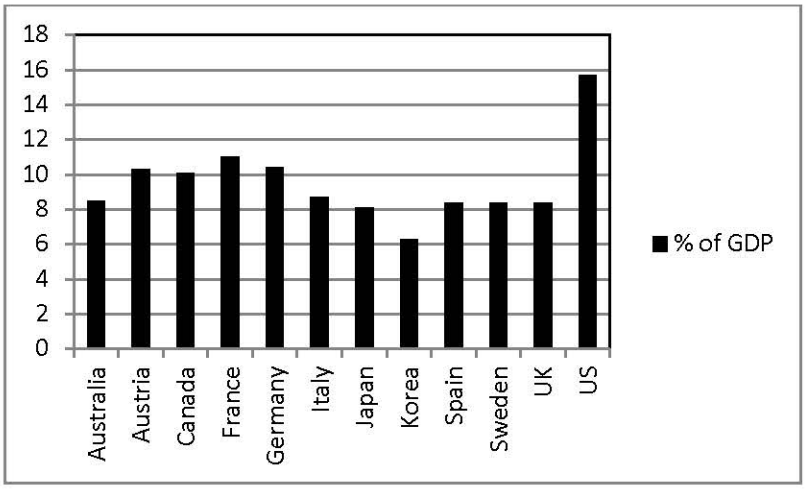

Figure 1. Percent of GDP expenditures for healthcare, select OECD countries. Data from (OECD, 2011).

Additional health care costs cannot be justified in terms of safety since a report by the Institute of Medicine (IOM, 2000) claimed that "more people die (in the United States) in a given year as a result of medical errors than from motor vehicle accidents, breast cancer, or AIDS" (p. 1). In the Commonwealth Fund's Commission on A High Performance Health System, Davis, et al. (2007) identified common factors in inefficiency and waste contributing to the high costs of health care in the United States (pp. viii-ix):

- Overuse of medical services by providing unnecessary procedures or the use of unproven technologies.
- Inappropriate care which had no demonstrable benefits.
- Barriers to access to primary and preventive health care forcing patients to seek care from higher cost specialists.
- Inadequate clinical reporting systems including the dearth of electronic medical records.
- Perverse payment systems that incentivized volume over quality; current payment systems pay for procedures performed rather than for episodes of care.
- Low ratios of primary care to specialty providers.
- Over reliance on emergency rooms for primary care.
- Lack of appropriate quality measures.
- Lack of appropriate efficiency performance measures (pp. viii-ix).

In addition to these factors, other trends contributed to the continuing growth in costs in the health care industry such as the adoption of unproven technologies, the aging of the population, and upward pressures on wages. All these factors continue to drive costs upward unless strategies are developed to mitigate their impact (Davis, et al., 2007).

The importance of reining in health care costs was highlighted by testimony from the director of the Congressional Budget Office (CBO) who testified to a committee of the U.S. Senate that "the single most important factor influencing the federal government's long term fiscal balance is the rate of growth in health care costs" (Orszag, 2008, p. 1). The CBO

director further predicted that, absent major changes in health care financing, health care costs would rise to 25% of GDP by 2025 and to 49% of GDP by 2082. Currently, the federal government pays for approximately 50% of all health care expenses and projections are that by 2019 payments will increase by $600 billion (U.S. Census Bureau, 2011, p. 99). Figure 2 illustrates the rise in health care expenditures in the United States over the past 50 years, demonstrating these accelerating trends. In order to address efficiency and effectiveness in the healthcare system, the Agency for Healthcare Research and Quality (AHRQ), a division of the U.S. Department of Health and Human Services began to promote research on efficiency measurement (Fraser, Encinosa, & Glied, 2008).

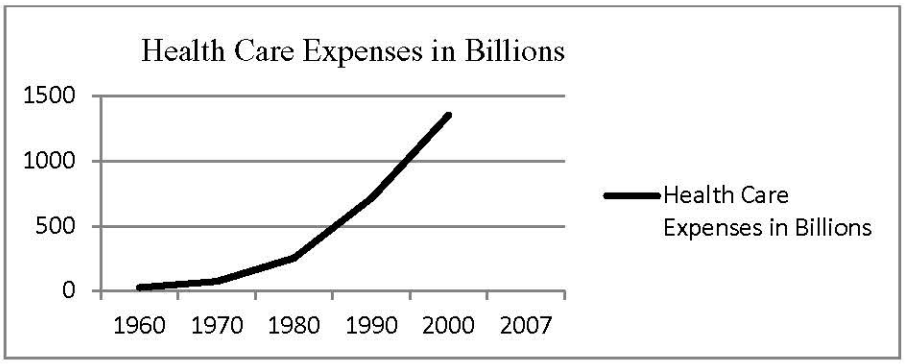

Figure 2. U.S. health care expenses 1960-2007. Data from (Centers for Disease Control, 2011).

Additionally, market pressures have been exerted by private insurers demanding that health care providers document their efficiency and demonstrate that continuous evaluation and improvement programs are being implemented (Hussey et al., 2009). Further pressures to improve efficiency have come from large employers as they have experienced

considerable and rapidly growing increases in their health insurance premiums. No consensus has been reached regarding which performance measurement systems are effective in determining achievable efficiencies as opposed to the development of theoretical productivity targets. Multiple efficiency measurement methods have been proposed discussed in Chapter 2, yet there is no acceptance of a specific method because of the complexity and heterogeneity of the hospital industry. For instance, a measure that may be effective in a for-profit hospital system may not be applicable to a government-owned and operated hospital. Present models have not produced uniform criteria for establishing performance measurement systems, Drummond (2004) asserted "The use of economic evaluation in health care is rather mixed…Decisions in health care always depend on a complex interplay of political, social and economic factors" (p. 7). Further complicating the development of performance measures for hospitals in the United States is that the mix of governance is structurally different from those of most other countries in that for-profit, nonprofit, and government-owned hospitals are commonly present in most communities. In other developed countries, for-profit hospitals are not major players and the financing of health care relies heavily on government payments. This may change in the United States with the implementation of broad based health care reform.

The Patient Protection and Affordable Care Act of 2011 expands Medicaid eligibility to individuals under age 65 with incomes up to 133% of the federal poverty level. Although the federal government is expected to assume up to 95% of the new costs (Holahan & Headen, 2010), states will be faced with a large incremental expense. In a report by the

Florida Hospital Association (2011), Medicaid expansion is projected to cost the state an additional $1.2 billion by the year 2019, when full implementation of health care reform is expected with the addition of 1.376 million new Medicaid recipients. By then, Medicaid will consume 32.8% of the total state budget. In FY 2009/2010, Medicaid consumed 27% of the state budget. The Florida Hospital Association reported that in, FY 2010/2011, there were a total of 2.9 million Medicaid beneficiaries with an estimated cost to the state of $19.8 billion (Florida Hospital Association, 2011). Additional pressures on the state budget exist because Medicaid pays for more than 50% of all newborn deliveries (Florida Hospital Association, 2011). At the other end of the demographic spectrum, although the elderly only comprise 14.23% of Medicaid beneficiaries, they consumed 21.96% of all Medicaid dollars (Florida Hospital Association, 2011). The trend line of Medicaid expenditures growth needs to be controlled to protect the state's fiscal health (see Figure 3).

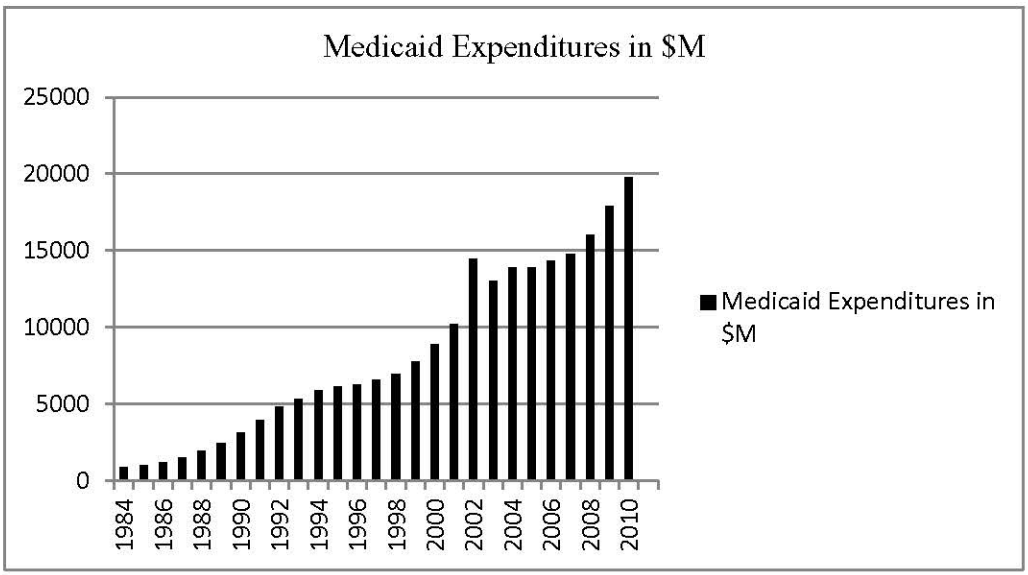

Figure 3. Florida Medicaid expenditures 1984-2010. Data from (AHCA Medicaid Services Budget Forecasting Systems Report, 2011).

In addition to the fiscal impacts on the state budget, an additional concern is the impact of the healthcare industry as a major industry in Florida. Any change negatively affecting this important economic driver has statewide impacts. The hospital industry in Florida employed approximately 843,000 people in 2007 and had total operating expenses of $31.87 billion (Florida Hospital Association, 2011, p. 3). The industry is a significant economic player contributing $1.1 billion in sales tax revenue, $863 million in property taxes paid, and paying $687 million in corporate profit taxes. For example, if Medicaid funding in Florida were to be reduced by $100 million, it would result in the loss of 2,187 jobs and reduce value added to the Florida economy by $157 million (Hodges & Rahmani, 2010). Because of the demographics in Florida, Medicaid comprised 11.6% of total hospital revenue with Medicare contributing an additional 46.4%. Even though Medicaid is

a significant source of revenue for most hospitals, this reimbursement source is not as lucrative as other payers and thus as Quinn (2008) stated "Medicaid typically pays less than hospital costs" (p. 270). Even with this reduced reimbursement, community hospitals rely on Medicaid patients since the alternative is to get patients with no revenue source. Concurrently, hospitals are faced with rising costs and decreasing revenues, contributing to reduced operating margins. The operating margin for Florida hospitals in 2007 was only 0.4% (Agency for Healthcare Care Administration, 2009) further demonstrating their precarious financial position. While Medicaid payments are low and not as desirable as other payers, many hospitals, particularly those serving inner city and poor communities, rely heavily on this income source for their survival since even low reimbursement contributes to offsetting fixed costs.

A response to mitigate the chronic underfunding by Medicaid, as well as the large numbers of uninsured patients that community hospitals care for, has been the creation of special healthcare taxing districts. They were intended to augment revenues through the power of levying local, general taxation and special assessments. These taxing districts have been used in Florida "as a means to provide capital, facilities, and services in [a] defined locality" (Studnicki, Fisher, & Kamble, 2010, p. 312). The specific mission and purpose of the taxing district is outlined in the documents creating these districts. Initially, taxing districts in Florida, which date back to 1845, were created to meet a single purpose or programmatic need (Committee on Urban and Local Affairs, 2008). One type of special taxing district is the hospital special taxing district of which there are 36 hospital/health

facility districts supporting public hospitals. These districts are not uniformly distributed; some counties have as many as four taxing districts while most counties have none. The role of these hospital taxing districts has also morphed over time from one of augmenting support for public hospitals serving indigent patients to one of providing broader operating subsidies to offset losses due to the proliferation of managed care plans (Studnicki et al., 2007) and to compensate for underpayments from Medicaid. Studnicki et al. (2007) asserted that "absent from these discussions has been any comprehensive assessment of the impact of these districts on the health outcomes of the communities in which they operate" (p. 117). In addition to the lack of data on the benefits of taxing districts in terms of health outcomes, Honore, Fos, Wang, and Moonesinghe (2011) suggested that "maintaining support for taxation policies can be greatly influenced by demonstrating a return on taxpayer investments" (p. 472). The ability of special taxing districts to demonstrate their value to the communities they serve is a central purpose of this dissertation, this issue is explored further in the purpose section.

The State of Florida legislature has made attempts to establish accountability for taxing districts by creating reporting standards to ensure oversight ("Uniform Special District Accountability Act of 1989," 1997). Reporting standards created by this act resulted in the creation of a database which is maintained by the Florida Department of Community Affairs. The required reports allow the state to perform its oversight functions and to create transparency as all data is publicly available. Although all of these reports are available online to allow citizens to compare the relative performance of their local tax district, no

mechanism for taking actions is available since the implementing statutes do not permit for recall provisions. In order to assess whether hospital taxing districts were operating consistent with the purpose for which they were initially established, Florida Governor Rick Scott issued Executive Order number 11-63 in March, 2011, creating a Commission on Review of Taxpayer Funded Hospital Districts (Office of the Governor, 2011).

This governor's commission was charged with assessing and making recommendations on the role of hospital districts to (Office of the Governor, 2011, pp. 2-3):

- Determine whether costs at taxpayer funded hospitals were higher or lower than at non-government supported hospitals.
- Determine the reason for cost differences at taxpayer funded hospital to understand the impacts due to patient mix on efficiency.
- Determine measures of outcomes based on the Centers for Medicare and Medicaid Core Measures.
- Determine the best mechanism for transitioning these hospitals to different governance models.

The governor initiated this review to determine the efficiency of tax-supported hospitals and to stimulate public debate over whether there was a justification for maintaining these hospitals' ability to continue compelling local tax support. Initially, many of these hospitals were granted tax levying authority because they were units of local governments and they provided indigent care to the medically needy. Over the past twenty years, these hospitals have been converting to nonprofit, independent status. An example is Jackson Memorial

Hospital in Miami-Dade County which was converted from a county owned and operated facility to a public health trust governed by a community volunteer board, while retaining its taxing authority. These tax-supported hospitals directly compete with community nonprofit hospitals that do not receive any local tax funds and serve the same communities.

Problem Statement

The problem that this study addressed is the relative technical efficiency differences between the two major categories of nonprofit hospitals in Florida: tax-funded and tax exempt nonprofit hospitals. Determining the extent to which these two hospital types differ in efficiency is important in deciding whether continuing the tax levying authority of taxpayer funded hospitals is justified. Understanding whether special taxing districts are using their taxing authority efficiently and, therefore, not wasting valuable resources is important because of the need to expand health care coverage to many of our citizens at a time when resources are being limited and to demonstrate the value of the taxing district. This is particularly important when the services they provide can be substituted by tax-exempt nonprofit hospitals.

Understanding whether tax-funded hospitals operate efficiently is a necessary factor in deciding whether these hospitals' tax levying authority should be continued, constrained, or eliminated. The problem faced by policymakers is that it is difficult to ascertain the relative efficiency of these hospitals because of the lack of consensus criteria. In order to assess the efficiency of these hospitals, I compared their relative efficiency to other nonprofit hospitals that do not receive a direct tax subsidy and that are located in similar

hospital service areas. The measure of efficiency derived from the Data Envelopment Analysis (DEA) model is expressed as a ratio of weighted inputs and weighted outputs. The independent variables, which serve as inputs to the DEA model, are all related to resource utilization: number of beds in service, labor costs, and, other costs. The dependent variables, which are all production measures, are used as outputs in the DEA model: total patient discharges and outpatient visits. The comparison to nonprofit hospitals was relevant because they are more closely matched in terms of mission, vision, and revenue sources than other hospital types. With the exception of direct tax revenues, they are also similar because neither type of hospital has a profit-maximizing focus; their performance is generally not measured against a bottom line (Boland & Fowler, 2000).

Nature of the Study

This study was conducted using existing data relying on financial information collected by the American Hospital Association (AHA), the Florida Agency for Healthcare Administration (AHCA), and the Centers for Medicare and Medicaid Services (CMS). Data from AHCA, which are publicly available online, provided audited financial information. AHA data provided demographic information such as the number of beds in operation, CMS data were used to improve the validity of the data from the other two sources. Since the data do not include individual patient information, and the data are publicly available, the ethical challenges of protecting confidentiality are not present in this study. These public data sources addressed all of the study's research questions.

The research objectives were to establish the relative technical efficiencies of tax-supported and nonprofit hospitals in the selected hospital service areas in the State of Florida and, then to compare the technical efficiency differences, if any, between the two hospital groups. The result of the DEA analysis was used to quantify the reductions in inputs or increases in outputs necessary to achieve the demonstrated efficiency frontier. By identifying the efficiency frontier for each hospital group and for the combined hospitals, it allowed for an assessment to be made to determine the potential savings if all hospitals operated at the most efficient level. Additionally, the placement along the efficiency frontier of all hospitals in the study group helped to determine whether tax-supported hospitals was operating efficiently enough to justify their preferred status allowing them to impose taxes and other assessments.

After conducting an extensive literature review, I was unable to find any studies comparing nonprofit and nonpublic owned, tax-supported hospitals in terms of their relative efficiency. Chapter 2 reviewed studies comparing hospital technical efficiencies using different methodologies. There was a need to determine whether the additional tax levying authority, which only special taxing district hospitals in Florida have, is being optimized in terms of efficiency in their operations. Data envelopment analysis (DEA) was utilized because it accommodates the use of multiple inputs and multiple outputs to estimate the efficiency frontier of the study hospitals. The following variables were used consistent with those used by published studies (Grosskopf, Margaritis, & Valdmanis, 2001a; Hajialiafzali,

Moss, & Mahmood, 2007; Helmig & Lapsley, 2001; Hofmarcher, Paterson, & Riedel, 2005; Magnussen, 1996):

- Input (independent variables) DEA standard terminology is to use the term inputs rather than independent variable.
- Number of beds in service—used as a surrogate for capital
- Labor costs—full time equivalents of physicians, nurses, and other
- Other costs—both variable and fixed costs to include supplies
- Output (dependent variables) DEA standard terminology is to use the term outputs rather than dependent variable.
- Total discharges—all inpatient discharges
- Outpatient visits—to include outpatient surgeries/procedures and emergency department visits

Descriptive statistics were used to summarize the characteristics of both nonprofit and tax-supported hospitals to assist in understanding the distribution of these hospitals. The DEA model generated the best practice frontier for each type of hospital. Chapter 2 presents in detail alternative efficiency measurement models and detailed the rationale for the selection of DEA for this study over alternative methods.

Purpose of the Study

The purpose of this study was to empirically examine the relative technical efficiency for each of these hospital categories to determine whether one hospital type had greater efficiency than the other. Any variation in efficiency highlighted the differences in

the relative efficiencies of these hospitals and helped to answer the public policy question of whether the tax levying capacity of hospital districts was justified based on their efficient use of resources. This study is timely because of the Florida governor's interest in addressing the continuing value of the taxing authority granted to certain hospitals. Prior hospital efficiency studies have not addressed this issue.

As health care reforms are implemented, particularly the expansive Patient Protection and Affordable Care Act of 2010, the need for greater efficiencies is magnified because of the proposed reductions in Medicare, Medicaid, and other third party reimbursements ("Patient Protection and Affordable Care Act," 2010). For this study, I used 2007 as the baseline year to establish the relative technical efficiencies of tax-funded and nonprofit hospitals. I chose this baseline year because the debates over health care reform did not materialize until 2008 thus, the performance of hospitals in 2007 did not reflect any operating adjustments to health care reform. Additionally, audited data for 2007 were complete and available. Thus, the results of this study provided an understanding of the differences in technical efficiency between these two hospital categories and established a benchmark to determine how hospitals change their operating strategies to adapt to the new environmental conditions created by health care reform. Further, I estimated the overall savings that could be realized if all hospitals operated on the efficiency frontier.

Research Questions

This study addressed the following research questions:

1. To what extent are there differences in technical efficiency between tax-supported and nonprofit hospitals serving similar hospital service areas?
2. What are the quantifiable potential savings to be achieved by all the study hospitals if they all operated at the efficiency frontier?

Research Hypotheses

Consistent with the research questions, the following hypotheses were formulated:

H_1—Tax-supported hospitals are more efficient than nonprofit hospitals. This hypothesis is tested by using DEA to calculate the relative technical efficiencies of each hospital in the sample and then determining those hospitals which lie outside the efficiency frontier. By grouping hospitals' efficiency rankings, an assessment of the significance of the differences in performance can be conducted.

H_2—There are no savings that can be generated by moving hospitals to the efficiency frontier. The efficiency differences in hospitals are quantified to assess the change in inputs and outputs necessary to move to the efficiency frontier and thus describe the savings that can be realized.

Theoretical Framework

The theoretical foundation for the study is Farrell's (1957) measurement of productive efficiency. The technical efficiency of the two hospital categories was determined using DEA which was developed by Charnes, Cooper, and Rhodes based on Farrell's work. According to Ferrier and Valdmanis (2004), DEA offers special benefits to

the study of hospital efficiency. First, there is no requirement to use price data. Second, it accommodates multiple inputs and multiple outputs. Third, it is preferable to other techniques since hospital behavior is not easily defined in terms of cost minimization or profit maximization, particularly among the study hospital in this sample. Fourth, inputs and outputs are measured in their natural units. Finally, reasonable estimates of efficiency can be produced with small samples. There are large numbers of studies using DEA assessing hospital productivity in all types of hospitals and using multiple variables confirming the value of this method. DEA is a proven method for efficiency analysis with over 40 years of use and is an accepted methodology which fit the research objectives of this study.

Definition of Terms

Allocative efficiency: This efficiency measure is used when costs and prices are known exactly (Cooper, Seidford, & Tone, 2007, p. 257).

Case mix, diagnosis related group (DRG): The case mix, DRG is a method for adjusting payments for medical care based on intensity of care delivered taking into account severity of illness (Battistella, 2010).

Center for Medicare and Medicaid Services (CMS)—Agency of the United States Department of Health and Human Services responsible for Medicare and Medicaid policy and for establishing and issuing provider payments (Battistella, 2010).

Congestion—a situation in which an increase in or more inputs causes the worsening of one or more outputs (Cooper et al., 2007, p. 353).

Data envelopment analysis—method developed by Cooper, Charnes, and Rhodes to describe their nonparametric approach to efficiency evaluation (Bowlin, Charnes, Cooper, & Sherman, 1985).

Decision making unit (DMU)—a collection of departments, divisions, or administrative units which have common inputs and outputs (Norman & Stoker, 1991, p. 15).

Discriminant analysis—linear combination of interval variables used to predict class of an observation. A technique used for classifying a set of observations into predefined classes for analysis (Wennberg, Freeman, & Culp, 1987, pp. 29-30).

Effectiveness—the attainment of predetermined medical outcomes (Ozcan, 2008, p. 4).

Efficacy—an assessment of a therapeutic intervention's ability to do more good than harm (Ozcan, 2008, p. 4).

Efficiency—Measure of optimization of resource utilization by market share, profitability, or ratio analysis (Ozcan, 2008, p. 4).

Efficiency frontier—the line describing the highest slope of input to output (Cooper et al., 2007, p. 3).

Federal hospitals—facilities owned and operated by the US government such as Indian Health Service, Department of Defense, and Department of Veteran's Affairs.

Financial Accounting Standards Board (FASB)—non-governmental body which establishes standards of financial accounting and reporting.

Fraud and abuse—investigative tools to determine the billing of services not performed (fraud) and the unnecessary provision of services (abuse).

Government Accounting Office (GAO)—independent, non-partisan agency that provides Congress with studies on how the federal government spends tax payer funds.

Indigent care—category of patients served by hospitals who have no means of payment and no health insurance including Medicaid. All care for these patients is provided free of reimbursement.

Isoquant—line which represents all possible combinations of inputs that are needed to produce the same amount of a single output (Cooper et al., 2007, p. 258).

Linear regression—a model that fits the relationship between two variables by fitting a linear equation to observed data (Wennberg et al., 1987, p. 248).

Malmquist Index—provides an evaluation of the productivity change of a DMU between two time periods (Ozcan, 2008, p. 11).

Medicaid—program under Title XIX of the Social Security Act which provides medical assistance to certain people with low income and some categories of disabled. It is jointly funded between the state governments and the federal government based on a formula which uses the relative states' per capita income to determine federal participation levels (Battistella, 2010).

Medicare—program under Title XVIII of the Social Security Act which provides medical insurance to persons aged 65 or over and certain categories of the disabled (Battistella, 2010).

Nonparametric analysis—production function is built empirically from observed inputs and outputs (Norman & Stoker, 1991, p. 12).

Nonprofit hospital—hospitals approved under section 501c(3) of the Internal Revenue code which grants them certain tax exemptions because they operate as non-profit corporations providing community benefits.

Office of Management and Budget (OMB)—office under the executive branch of the United States which implements and executes the president's budget and policies.

Organization for Economic Co-operation and Development (OECD)—international organization that promotes policies to improve economic and social well-being of people around the world (OECD, 2011).

Outpatient visits—overall measure of hospitals services which do not include an overnight stay, including emergency room visits, same day surgery, and outpatient diagnostic/therapeutic interventions.

Parametric analysis—the form of the production function is either assumed to be known or is estimated statistically (Norman & Stoker, 1991, p. 12).

Pareto-Koopmans efficiency—a DMU is considered efficient if and only if it is not possible to improve any output or input without worsening another input or output (Cooper et al., 2007, p. 45)

Productive Efficiency—describes how well an organization performs in terms of resource utilization in producing all outputs (Norman & Stoker, 1991, p. 11).

Ratio analysis—method for assessing performance by comparing similar quantities over time or across organizations to determine the relative value, used to place the results in context. This produces information on the relationship between one input and one output (Altman, 1968).

Return on investment (ROI)—a measure of the proportion between the amounts of capital invested and net operating margin from that investment.

Scale efficiency—evaluating the impact of organizational size's impact on efficiency. In the DEA model, return to scale refers to the proportional change of outputs to inputs. A constant return to scale assumes a constant rate of substitution between inputs and outputs (Ozcan, 2008, p. 54).

Special taxing district—in Florida, agencies which are granted taxation and special assessment authority under Chapter 189 of Florida Statutes to provide specific community-wide benefits such as the provision of health care services (Studnicki et al., 2007).

Stochastic frontier analysis—a parametric technique which accounts for statistical noise (Cooper et al., 2007, p. 426).

Technical efficiency—Measure by which percentage of input can be reduced proportionately without reducing output (Cooper et al., 2007, p. 11).

World Health Organization (WHO)—an agency of the United Nations with the responsibility for directing and coordinating health within the United Nations system (OECD, 2011).

Z-score—a measure of organizational viability using a composite measure of the weighted sum of key financial ratios (Altman, 1968).

Assumptions

The assumptions in this study follow: Hospitals within each category and between the two categories have homogeneous inputs and outputs; their strategic goals and behaviors were congruent in terms of not having a profit maximization orientation; and each decision-making unit (DMU) had control over the inputs used. To adopt the premise that hospitals moving towards the efficiency frontier could generate savings, they must be operationally similar. These assumptions suggest that the lesser efficient hospitals are able to improve their productivity to arrive at the efficiency frontier because they have access to the same technology and have similar patient mix, patient demographics, and intensity of illness. Additionally, the presence of a medical teaching program was not considered to be a differentiator because the costs of these programs are both an input which causes greater costs and an output by increasing productivity thereby cancelling its impact. Earlier studies have been inconclusive on the impact of teaching programs on hospital operating costs (Grosskopf et al., 2001a). Additionally, the assumption was made that all hospitals in the study had as their primary mission the provision of health care services and no other social community benefits, such as providing employment or primarily serving a medical teaching function.

Limitations

There were several limitations to this study. First, DEA cannot assess the maximum theoretical level of efficiency of an organization. DEA derived measures of efficiency are based on actual best performance of the set of hospitals in the study. Second, DEA does not allow for statistical noise; therefore, the derived statistics may lack precision. Third, the results produced a point estimate in time since only one year of data were being analyzed; changes over time will not be discovered. Fourth, the sample size is small because it was limited by the number of hospital taxing districts in Florida. Any extrapolation of results should take the sample size into account. Finally, the model assumed no impact of economies of scale on the results.

The sample size was limited by the number of tax-supported hospital districts which support full service hospitals and the presence of nonprofit hospitals in the same district. The presence of nonprofit hospitals was a necessary ingredient of the study design because it allowed for a direct comparison of the efficiencies without regard to extraneous factors. The State of Florida is segmented into 11 districts, as shown in Table 1. There were no study hospitals from Districts 1 and 5. The sample included a total of 33 tax-supported hospitals and 42 nonprofit hospitals. Further discussion on the inclusion and exclusion criteria is provided in Chapter 3.

Table 1

General Acute Care Hospitals by Geographic Regions

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1. District 2 - Panama City - Tallahassee
2. District 3 - Lake City - Gainesville - Ocala - Leesburg - Brooksville
3. District 4 - Jacksonville - Daytona
4. District 5 - Pasco - Pinellas
5. District 6 - Tampa - Lakeland - Bradenton - Sebring
6. District 7 - Greater Orlando and Brevard
7. District 8 - Sarasota - Ft. Myers - Naples
8. District 9 - West Palm Beach - Stuart - Ft. Pierce - Vero Beach
9. District 10 - Broward
10. District 11 - Miami-Dade and Monroe

Delimitations

This study was limited to the state of Florida, and the results may not apply to other states or types of hospitals. Additionally, the study's scope was restricted to the difference in technical efficiencies between tax-supported and matched nonprofit hospitals serving comparable communities. Lastly, although there were no prior studies using DEA to guide this research, there was extensive literature applying DEA to health care research.

Significance of Study

This study was designed to address an existing gap in the literature by exploring the differences in technical efficiencies between tax-supported hospitals and nonprofit hospitals. As expected health care reforms are instituted, the efficient use of resources will have greater importance since funds are expected to be decreasing while, at the same time, more persons are expected to be insured increasing demands on hospital services. The use of DEA will add to the health care management literature by providing an additional tool for

policy makers and hospital administrators to use to benchmark their hospitals. Health care administrators have relied on backward looking evaluations of performance based on ratio analysis. DEA offers a tool to identify where their organizations fall on the efficiency frontier, and it also quantifies the necessary changes required in terms of reductions in inputs or increase of outputs to achieve greater productivity.

From a management perspective, the results of this study can be used by hospital administrators as a valuable tool to assess the relative efficiency of their facility against their similarly matched competitors. Further, depending on the results, it will allow the management of tax-supported hospitals to either justify their special status allowing for taxing authority, or to develop a plan to increase their efficiency to match that of the non-profit hospitals in their market. Even though DEA does not specify the tactical changes needed to achieve greater efficiency, it does provide management with strategic data on the necessary reductions of inputs or increases in outputs necessary to improve efficiency.

Social Significance

Efficient use of healthcare resources, particularly in an era when over 47 million individuals are uninsured, and lack regular access to medical care, is of social importance. Tax-supported hospitals have the further responsibility to document that the taxing authority awarded them is not being wasted. This study contributed to positive social change by providing a process of benchmarking to assess the relative efficiency of a set of hospitals and a baseline to measure their response to the implementation of nationwide health care reform. By documenting the efficiency of these hospitals, they will be more likely to

receive community support. As comprehensive health care reform is implemented, having a baseline to compare efficiency changes over time is important in addressing the impact of reform on hospital long-term viability. Harrison asserted that DEA is an "effective tool for identifying cost savings and assist in prioritizing limited health care resources" (2004, p. 412). This is the ultimate health care policy goal, to maximize resources in order to serve a greater number of patients. The results of this study assist policy makers in developing appropriate ways to reduce potential waste of public funds. In an era of diminishing public resources, it is imperative that those organizations receiving public money are able to demonstrate that they are operating efficiently

Summary

This study assessed the relative technical efficiencies of tax-supported and nonprofit hospitals in the State of Florida. As health care reform is implemented, added demands on the healthcare system will require that hospitals operate at the most efficient achievable productivity level. This is particularly important for those hospitals receiving either direct tax support or tax benefits such as property tax exemptions. In Florida, the governor has convened a task force to evaluate whether taxpayer supported hospitals are operating efficiently. DEA provides a model for assessing productivity by comparing hospitals to the efficiency frontier achieved by peer facilities rather than against a theoretical efficiency level.

This study had two primary purposes. First, the assessment of the technical efficiency of tax-supported hospitals compared to that achieved by comparable nonprofit

hospitals to assess whether there was a significant difference in productive efficiency between the two groups. The results allow the identification of the magnitude of savings that can be potentially achieved by operating all facilities at the efficiency frontier. Second, implementing national health reform will force hospitals to operate more efficiently since more persons will be covered as hospital reimbursement will be simultaneously decreasing. For this reason, the results of this research establishes a baseline to measure productivity changes that hospitals make to adjust to this new environment.

Although DEA does not identify the specific management tactics necessary to improve efficiency, it quantifies the increases in outputs or decreases in inputs required to reach the efficiency frontier. This process provides management with an additional strategic management tool. In addition, those hospitals on the efficiency frontier will have a marketing advantage over their competitors and will be able to publicly justify their tax levying authority. Several studies have reviewed the components that need to be taken into account in determining efficiency

Chapter 2 to follow includes a detailed literature review synthesizing multiple studies that have measured hospital performance using methods other than DEA. This demonstrates the shortcomings and benefits of these approaches. A review of DEA-based hospital productivity studies follows to determine whether there was a gap in the literature. Lastly, Chapter 2 synthesizes research articles using DEA in health care research to determine the variables and methodologies used by these researchers.

Further detailed discussion on the methodology to be used is presented in Chapter 3. In the methodology section, the use of DEA as the preferred model is discussed in terms of alternative models and an explanation of why alternative methods were not chosen. In addition, the choice of DEAFrontier software as the tool for data analysis is explained. Chapter 3 follows with a review of the research methodology used in this study, including the data acquisition strategy and analysis methods. The methodology is congruent with the research questions, the data are all existing data, and three data sources assisted in triangulating the accuracy of the data.

The remaining sections of the dissertation detail the process, analyze the data, and answer the research questions. Chapter 4 covers the data analysis process using both DEA and descriptive statistics. Data are displayed in tabular and graphic form. Data analysis was performed using DEAFrontier software. Chapter 4 concludes with a synthesis of the findings to include any inconsistencies or conflicts discovered in the data analysis. The final section, Chapter 5 summarizes the data and puts the findings in context with the research questions. The implications of the findings to the management profession and to social change are highlighted and related to the current research literature. The dissertation concludes with a recommendation for further research.

Chapter 2: Literature Review

Overview

This chapter analyzes and synthesizes the relevant academic research literature on health care productivity and efficiency measurement. This literature review begins with the historical use of performance measurement systems and progresses through the different research methods currently in use. Finally, the strengths and weaknesses of the different methods are synthesized to explain the rationale for choosing DEA as the research methodology for this study. The roadmap followed to assess the literature from the initial use of key search words to the databases and specific journals searched are described to substantiate the literature review method used. Emphasis was placed on methodologies that had been used in prior research studies to assess different efficiency measures in multiple categories of healthcare organizations. There is no consensus as to which institutional factors appropriately demonstrate whether a health care organization is operating efficiently. Many methods have been used, generally focusing on financial performance, as a surrogate for institutional and industry-wide efficiency. Recent literature has emphasized linear regression based models applying broader variables rather than relying exclusively on financial ratios.

While several performance measurement methods are explored, emphasis was placed on the development of measures based on a single linear regression based model—data envelopment analysis (DEA). DEA has been applied in numerous studies to assess the efficiency of hospitals in the United States and internationally, it has also been used in many

forms of health care settings including nursing homes and home health care agencies. Although DEA was originally developed to determine the efficiency of public organizations, it has been extensively used to study a variety of organizational models both in the private and public health care sectors. Multiple studies have been conducted to determine whether there is any variation in performance among different hospital ownership and governance categories. The results of these studies have not provided clear direction, Shen, Eggleston, Lau, and Schmid (2007) concluded that "despite a large empirical literature on hospital ownership and performance, there remains a disconnect between theory and evidence" (p. 43).

The purpose of this literature review was to explore the application of various methods to explore the efficiency of for profit, nonprofit, and public organizations. The use of DEA is highlighted since it is the method which is receiving the most attention in recent studies. Foundational theory is included to understand the development and extension of the DEA model from its original inception by Farrell (1957) to its initial application to health care organizations (Nunnamaker, 1983) and its subsequent expansion internationally and across all sectors of the healthcare industry including at the hospital department level. After reviewing and synthesizing the literature on DEA, specifically the foundational literature on this method, emphasis was placed on the application of DEA to the health care field. The procedure used to ensure completeness of the literature review was a "funnel search" (Boell & Ccez-Kecmanovic, 2010, p. 139), where the initial search strategy is gradually narrowed to achieve the desired level of precision and completeness.

This literature review also informed the understanding of key DEA variables applied by many researchers. The initial search was guided by the seminal articles in DEA: Farrell's (1957) "The Measurement of Productive Efficiency," which established the measurement of efficiency using multiple inputs; Charnes, Cooper, and Rhodes (1978), the first article proposing a method based on Farrell's work which they named DEA laying the groundwork for practical applications; and finally, Nunnamaker's "Measuring Routine Nursing Service Efficiency: A Comparison of Cost per Patient Day and Data Envelopment Analysis Models" (1983), the first published application of DEA to the health care field. By 2005, 27 years after Charnes, Cooper, and Rhode's (1978), over 1,500 articles, dissertations, and working papers had been published using DEA as their primary research method (Phillips, 2005).

Databases and Resources

The search strategy focused on peer reviewed academic journals published over the past five years with the inclusion of older articles that were of historic or seminal importance. Initial searches were conducted on the Walden Library by accessing the following databases: Academic Search Complete; National Library of Medicine at the National Institutes of Health; Expanded Academic ASAP; Business Source Complete; Science Direct; and, Proquest. In addition to these databases, I conducted in-depth reviews of journals that had published extensively in this field, such as *The Journal of Social Change; Health Affairs; Health Services Research;* and the *European Journal of Operations Research.*

In addition to the above databases and journals, I searched a number of government databases because the United States Federal government, as the largest single payer for health care, collects massive amounts of data. It also supports and conducts primary research. The main governmental databases used were the Agency for Healthcare Research and Quality, the lead federal agency tasked with the mission of improving the "quality, safety, efficiency, and effectiveness of health care for all Americans" (AHRQ, 2011); the Centers for Medicare and Medicaid Services; the Institutes of Medicine; United States Bureau of Census; the Health Resources and Services Administration; and the Congressional Budget Office. For a Florida specific focus, Florida TaxWatch and The Florida Department of Health Services' Agency for Healthcare Administration provided important supplemental research data. Additionally, two international organizations provided valuable data, the Organization for Economic Co-operation and Development (OECD) and the World Health Organization (WHO).

Many professional organizations also collect and disseminate data and conduct primary health services research. These organizations may slant their research to satisfy the needs of their specific constituencies; nevertheless, they provide useful data. The primary non-governmental organizations used in my research were: The American Hospital Association (AHA); Florida Hospital Association (FHA); National Association of Public Hospitals (NAPH); Financial Accounting Standards Board (FASB); Healthcare Financial Management Association (HFMA); and, American College of Healthcare Executives (ACHE). Three independent organizations also provided important research data: The Inter-

University Consortium for Political and Social Research (ICPSR); Dartmouth Atlas of Health Care; and the RAND Corporation.

Because medical care is such an important and ubiquitous service, it draws numerous advocacy groups. The research from advocacy organizations included The Robert Wood Johnson Foundation and the Kaiser Family Foundation which predominantly produces health care research. Some of their potential bias may be mitigated by comparing studies to determine if results vary based on the organization sponsoring the research. The field of health care advocacy is rapidly expanding including a large number of professional organizations representing patient and consumer groups. One prominent university has developed a health care advocacy certificate program describing the career path as "not only a respected livelihood, but a bright career" (University of Miami, 2011).

Search Strategy

After identifying potential literature sources, I began the literature search using key words. As articles were found, the keywords identified by the editors of the articles, suggested search thesauruses, and cited texts in the individual article bibliographies were used to expand the search strategy. In addition to the citations used by authors, the ability of some databases to track forward citations was also incorporated into the literature search. Lastly, Boolean logic was used to combine search terms to limit or amplify the search results. Initially, broad search terms were used and then narrowed to more specific terms to ensure broad coverage. All search terms were recorded including inclusion and exclusion criteria and the dates that databases were searched.

The initial search strategy began by using *"efficiency," "performance measurement",* and "*DEA"* as the primary keywords. The literature review was limited by using Boolean logic to narrow the search to hospitals and health care organizations. The next step in the literature review was to search for *hospital/medical efficiency* and *performance measures* to cull any articles that explored the concept of performance measures regardless of the specific techniques used. Using this process allowed for an understanding of any methodologies, other than DEA, used to develop performance measures. A further narrowing of the search strategy included using terms to limit results to hospitals by ownership categories. The final keyword count exceeded 50 terms to both limit and expand the literature search to ensure an exhaustive and complete inclusion of relevant literature. After the initial search strategy was completed, additional reference mining was accomplished by studying the reference lists of retrieved articles. These additional sources provided relevant publications that expanded the initial literature results. The library search continued throughout the dissertation process to update the literature review with the most recent research.

Health Care Performance Assessment

Performance measurement in healthcare systems, especially in hospital settings, is not a new phenomenon. Smith (2005) stated that, as early as 1860, "Florence Nightingale pioneered the systematic collection, analysis and dissemination of comparative hospital outcomes data in order to understand and improve performance" (p. 218). Health care in the 19th and early 20th centuries was akin to comfort care, since the technology of medicine

was simple and caregivers lacked understanding of the disease process. Patients did not pay for services, and providers of medical services were not personally remunerated, thus removing the financial accountability inherent in developing performance measurement protocols (Starr, 1982). Medical services were organized as a charitable activity provided by religious organizations and was thus devoid of the pressures normally exerted on economic activities, Starr (1982) noted,

> The reconstruction of the hospital [in the twentieth century] involved its redefinition as an institution of medical science rather than of social welfare, its reorganization on the lines of a business rather than a charity, and its reorientation to professionals and their patients rather than to patrons and the poor. (pp. 147-148)

Delivery of health care services has evolved over the past centuries because of the increasing complexity, broader business orientation and more intrusive involvement in people's lives. With the advent of third party payment systems, commercial health insurance, and government sponsored medical plans beginning in the middle 1930s, greater attention began to be focused on the efficiency of medical providers. Because of the explosive growth of medical services, and therefore costs, emphasis was placed on this "crisis of money" (Starr, 1982, p. 381) to develop standards focused exclusively on reducing rising costs. For many years, little attention was paid to the effectiveness of care delivered, since the dominant philosophy was that health care providers always acted selflessly in the best interests of the patient. Before the health care system could address efficacy, though, an understanding of the gains that efficiency improvement could generate was necessary

(Fraser et al., 2008). Several efficiency measures have been developed with varying degrees of acceptance.

Development of Efficiency Measures

Many factors militate against the development of efficiency measures for health care organizations because of the heterogeneity of the industry. There is also a lack of understanding of what causes variations in medical services. For example, the Dartmouth Atlas has compiled Medicare utilization data by hospital service areas (HSA) for over 20 years to determine regional variations in resource utilization. An HSA is a collection of zip codes that helps to define the local market for hospital care. The Dartmouth Atlas has reported substantial cost variability across regions, variations which are not justified based on regional cost of living criteria (Bach, 2010). The real reasons for the variability have been conjectured but have not been empirically demonstrated.

An additional factor in the complexity of measuring hospital efficiency is the variability in hospital size and governance structures, according to the United States Department of Health and Human Services (2005). Of the 6,012 licensed American hospitals, approximately half are under 100 beds in size, roughly one fourth are between 100-199 beds, another fourth are between 200-499 beds, and a small number (326) are over 500 beds. Also, because of the variety of hospital governance structures and hospital ownership models, uniform efficiency improvement programs have been difficult to implement.

Hospitals vary in ownership between: public hospitals owned and operated by municipalities and states; hospitals owned and operated by the federal government, both for active and retired military; for-profit, corporately owned hospitals responsible for producing a return on investment for their investors; and non-profit hospitals including religious and secular community-based ownership. Given the broad range of missions in terms of income sources, profit orientation, and service mission, emphasis on performance is viewed differently by each of these organizations (Micheli & Kennerley, 2005). Finally, developing performance measures is further complicated because of the lack of understanding of the impacts of economies of scale on efficiency.

As the health care insurance industry became more ubiquitous, and government's involvement in both the provision and financing of medical care grew, greater emphasis was placed on the efficacy of the services delivered. At the same time, demand for services increased, this was referred to by Wennberg (1987) as "provider induced demand" (p.1187). Additional pressure was exerted on health care providers by the proliferation of medical malpractice litigation. Although the number of malpractice cases has remained stable over the past 10 years, the average payment amounts rose 52% (Chandra, Nundy, & Seabury, 2005). A solution to reduce medical malpractice litigation growth would be to standardize medical care, but, while the development of effectiveness standards could be used to defend against spurious litigation, the same standards could also be used to establish what became known as "community standards of care" (Zipursky, 2007). These standards of care forced providers to practice medicine more uniformly, removing the art of medical practice and

adding a source for justifying litigation since any deviation from what was considered to be the standard practice of medicine could be used as a basis for litigation. Medical malpractice litigation influences led to the practice of defensive medicine, whereby procedures are performed purely to build a record to defend against litigation, even if the procedures performed may not be medically indicated (Mello, Chandra, Gawande, & Studdert, 2010; Studdert et al., 2005). The proliferation of new technologies also contributed to the escalation of medical procedures both because of their inherent value and as a hedge against medical malpractice litigation (Battistella, 2010).

Medical technology has dramatically advanced over the past 50 years and the rate of growth of new technology continues rising. Technological advances have positively contributed to the faster diagnosing and curing of many diseases that were intractable a generation ago. For instance, the ability of modern imaging equipment to map the internal structures of the human body in a noninvasive fashion has sped up the diagnosis of complicated disease mechanisms. This technology comes at a steep price though, both in costs and expectations (Folland & Hofler, 2001). Imaging techniques provide the medical practitioner with invaluable information, but these same techniques can be used to show real or perceived inadequacies in the medical care rendered. Medical practitioners use the latest technology not only to diagnose patients properly, but also as a shield against potential litigation to demonstrate that all efforts were expended to treat a particular patient. These pressures to provide the latest medical care precipitated an environment where providers felt they must have access to the newest technology. The main cost driver in this area is not

only that the newest technology is generally the costliest technology, but also that new technology does not necessarily displace old technology, the resultant effect is that more tests than necessary are conducted (Fisher, Bynum, & Skinner, 2009). There are also additional hidden costs to all this proliferation of technology since doing more is not without the potential for harm to the patient (IOM, 2000). Finally, as technology proliferates and becomes more ubiquitous, the expectations of patients are also heightened to sometimes unrealistic levels. These drivers of medical costs are present in an environment where the United States is facing major demographic changes which naturally force greater use of the health care system.

The population of the United States is growing older across all demographic groups while, at the same time, there are signs of chronic health concerns such as the growth of obesity and some chronic diseases which contribute to the continued escalation of healthcare costs (Breyer, Costa-Font, & Felder, 2010). The aging of the population has political implications since the elderly vote at a greater rate than the young and thus garner the political clout to demand more services while reducing their contributions to pay for such services (File & Crissey, 2008). Younger generations are also increasingly using more medical services, Martini, Garrett, Lindquist, and Isham (2007) reported that "the baby boom generation is increasing its use of medical services at higher rates than older generations" (p. 214), further increasing pressure to demand and develop adequate performance measurement systems to protect resources and ensure adequate availability of services.

As expectations and demands on the healthcare system grow, the escalation of demands for services becomes a self-fulfilling feedback loop leading to the provision of more services and to greater expectation that access to the latest services should be available to all, regardless of ability to pay. Health care is increasingly being perceived as a right of all citizens, and although, in the United States, access to emergency services has been available to all, there is a growing realization that a more rational approach to financing and delivering of medical care is necessary. A necessary component of universal access and financing of healthcare is government involvement. While the merits of this approach are beyond the scope of this study, the fact is that the federal government currently pays for half of all medical services delivered (U.S. Census Bureau, 2011). As health care financing reforms such as the Patient Protection and Affordable Care Act ("Patient Protection and Affordable Care Act," 2010) are implemented, which involves the government to a greater degree in financing medical care, the pressures to develop performance standards will increase. Providers are likely to be faced with the need to do more with less requiring that limited resources be used as efficiently as possible.

Complicating the development of efficiency measures is the political rhetoric that savings can be gained by simply eliminating fraud and abuse. Fraud is estimated to consume approximately 3% of total health care expenditures; for fiscal years 2006/2008, the Office of Inspector General in the U.S. Department of Health and Human Services reported investigative receivables of $2 billion per year (Levinson, 2010) due to fraudulent billing for services. Fraud is an easily determined component since it hinges on investigative methods,

a service is either performed or not, if not performed and it is billed for, then fraud is present. A more difficult component of waste is when unnecessary or duplicative services are performed; this is the abuse component (Levinson, 2010). While objective standards exist to determine what medical services should be performed, the rigid application of these standards may impact the art of medicine reducing practitioner's flexibility in providing services. In the absence of hold harmless provisions to mitigate medical malpractice litigation, medical care providers will be slow to accept restrictions on their practice. Rhetoric notwithstanding, the total elimination of fraud and abuse is impossible, while gains are possible, the savings may not significantly exceed the additional policing costs (Levinson, 2010). Computer technology, such as electronic medical records (Kazley & Ozcan, 2009), offer important potential advances in this area but, the area for greatest cost and productivity improvements is through better organizational performance.

Financial Measurement Systems

Historically, measurement of healthcare organizational performance efficiency was based on ratio analyses such as cost per patient day or number of payroll hours per unit of service. These measures provided a crude approximation of efficiency because the output of these measures yielded a ratio that did not have any anchoring to reflect whether the results were achievable over time. Essentially, ratio analysis served the function of providing a baseline to measure changes over time (Pronovost, Miller, & Wachter, 2007). Improving ratios were considered positive and degrading ratios were cause for alarm. The one major flaw in ratio analysis was that ratios could be improved by withholding services as well as

through greater efficiency, and the final number gave no indication of the quality of the interventions taken to improve efficiency. Many methods to identify inefficient hospitals failed to uncover the reasons for their inefficiency or to generate strategies for improvement (Fraser et al., 2008; Gandjour, Kleinschmit, Littmann, & Lauterbach, 2002). Thus, financial improvements could be achieved through sacrificing quality by reducing essential services at the expense of patient outcomes. Financial indicators based on established ratios have been touted as an appropriate tool for benchmarking hospital performance (Schuhmann, 2008) although they have not been demonstrated to be effective as a strategic management tool. Exacerbating the difficulty in the development of measures of efficiency is the complexity of the health care delivery system.

Health care is considered a complex adaptive system (CAS) which, due to its complexity and interrelatedness is difficult to change. A necessary change to improve services which may be successfully implemented in one area may generate negative consequences downstream, and more importantly, may have unknown or immeasurable consequences (Begun, Zimmerman, & Dooley, 2003). Begun et al. (2003) described a complex organization as one "with multiple, diverse, interconnected elements…accompanied by feedback effects, nonlinearity, and the unpredictability of the emergence of new entities" (p. 252).

Performance Measurement Methodologies

Historically, the measurement of hospital performance was dominated by techniques which monitored financial health using traditional accounting standards. Using ratio

analysis, Jha, Orav, Dobson, Book and Epstein (2009) developed a relative cost index using average Medicare cost per case for their set of study hospitals. Even after adjusting for case mix, they found no correlation between lower costs and the quality of care delivered overall, yet they concluded that "low-cost hospitals typically had slightly worse quality for common medical outcomes" (p. 905). This finding is in contrast to Bach (2010) who discussed the conclusions reached by the Dartmouth Atlas of Health Care which found that regional variations in costs do not correlate with improved health outcomes (Bach, 2010). The lack of these methods to produce adequate results in measuring hospital efficiency was raised by a report issued by Krumholz et al. (2008) in behalf of the American Heart Association's Interdisciplinary Council on Quality of Care and Outcomes Research that discussed the problems of attempting to define efficiency in the absence of the results produced. They admitted that there is no "matched consensus regarding the essential attributes of measures of efficiency in the allocation of health care resources" (p. 1518) that should be included. They argued that perhaps the discussion should be focused on healthcare value as opposed to efficiency because of the difficulty in measuring outcomes because of the large variation among patients and hospitals.

In attempting to measure efficiency, it is necessary to identify the policy goals which are being implemented, whether the goal is to reduce costs, to improve outcomes, or ideally both improving efficiency and effectiveness. These goals may not be congruent since any reduction in costs may result in fewer services being provided which may lead to lower quality of care and thus poorer outcomes. Safety net hospitals have been reported to have

lower levels of quality of care (Werner, Goldman, & Dudley, 2008). Attempts at collecting data for performance measurement in these facilities may be difficult because they lack resources since they typically operate on very low margins. A policy consideration then becomes whether an attempt to implement performance measurement systems based on effectiveness is cost effective across all types of hospitals.

Goldman, Henderson, Dohan, Talavera, and Dudley (2007) raised an additional concern that hospitals serving the indigent may be pressured by public perceptions of transparency and accountability into participating in performance measurement programs, which are perceived as being of limited benefit, at the expense of serving their patients who have limited resources. This view contradicted recent findings by (Alexander, Young, Weiner, & Hearld, 2008) who reported "weak or lax governance on the part of some of these [non-profit hospitals] organizations" (p. 200), and Stone and Strower (2007), who suggested that "public governance concerns accountability for performance" (p. 423). An additional benefit of performance monitoring systems is the early detection of financial distress, particularly in non-profit hospitals that are heavily dependent on Medicaid and Medicare patients because they are more at risk due to their lower bond ratings and lower overall profitability (Kim, 2010) compared to for-profit hospitals.

Any system of performance measurement must be equally adept at addressing costs as well as quality concerns to eliminate incentives that skew results towards greater efficiency at the expense of quality and appropriateness of medical care rendered (Lagoe & Noetscher, 2000). In the for-profit sector, the balanced scorecard (BSC) has been used

extensively to provide strategic direction at the board of director's level since it measures both financial and non-financial performance (Griffith & Alexander, 2002). The BSC has not received widespread acceptance in the non-profit sector because these organizations are not "profit maximizing" (Micheli & Kennerley, 2005). Safety net hospitals are caught in the vise of competitive and financial pressures requiring greater efficiencies because their "ability to maintain viability may depend on the same strategies being used in the private sector" (Cunningham, Bazzoli, & Katz, 2008, p. 381). Gandjour et al. (2002) posited that the proliferation of computerized medical records would reduce the obstacles to develop integrated financial and non-financial performance measurement systems across all hospital categories. Even though the implementation of performance measurement systems has been touted as a valid policy goal, "there has been limited evidence that hospitals that perform better on process measures also have better quality for the average patient" (Werner & Bradlow, 2006); thus, no consensus appears as to what constitutes a valid performance measurement system.

The quality and effectiveness of care debate is not settled even though data show that hospital errors may cause up to 7,000 deaths annually and medication errors may increase hospital costs by as much as $4,700 per admission (IOM, 2000). Hospital performance efficiency programs lack measures to account for the quality of care delivered (Binder & Rudolph, 2009) and, consequently, fail to link the tradeoff between effectiveness and efficiency. This absence of understanding of the potential conflicts between quality and efficiency has led to the use of subjective financial measures such as return on assets and

various operating indicator ratios as valid measures of performance. These financial indicators have been reported in the literature to be "the best indicators of healthcare organization performance" (McCracken, McIlwain, & Fottler, 2001, p. 211). In September 2004, the American Academy of Family Physicians (AAFP), the American College of Physicians (ACP), America's Health Insurance Plans (AHIP), and the Agency for Healthcare Research and Quality (AHRQ), created the AQA alliance (named to resemble the Hospital Quality Alliance) to determine the best methods to improve performance measurement systems for ambulatory care. Their performance indicators measures included cost and value of care which aimed to create a combination metric of quality and cost of care (AQA Alliance, 2006). The AQA is developing medical condition-specific performance measures which may yield results in the future. To date, the most effective hospital performance measurement tools do not address the obvious main source of inefficiency—performing an unnecessary or unneeded service (Binder & Rudolph, 2009).

Review of Performance Evaluation Methods

Healthcare economists have used many methods for performance measurement in an attempt to elicit strategic management information on the efficiency of their operations. Decision makers, responding to the pressures of the new "hyper-turbulence" (McCracken et al., 2001, p. 211) secondary to the reinforcing conflicts of increasing competition at the same time as third party reimbursements were being decreased have relied heavily on financial performance ratios such as operating margin, debt ratios, and cash flow to debt ratio. These financial performance measures have been used as strategic management tools

since they monitor the viability of the organization. The most common of these financial performance tools is ratio analysis.

Ratio Analysis

The most often used ratio analysis methodology is Altman's *z* scores which is used by auditors to assess financial distress. This discriminate analysis technique, originally used as a predictor of a firm's on going ability, is also being used as a management performance tool (Calandro, 2007). This financial performance method was created as a response to the "attacks on the relevance of ratio analysis" (Altman, 1968, p. 589) because it is "essentially univariate in nature and emphasis was placed on individual signals of impending problems…susceptible to faulty interpretation and is potentially confusing" (p. 591). Altman (1968) proposed the *z* score to simultaneously analyze variable profiles rather than the sequential analysis provided by ratio analysis. Altman described the general *z* score model as follows:

$z = .012\ X_1 + .014X_2 + .033\ X_3 + .006X_4 = .999X_5$

Where X_1 = Working capital/Total assets

X_2 = Retained earnings/Total assets

X_3 = Earnings before interest and taxes/Total assets

X_4 = Market value equity/Book value of total debt

X_5 = Sales total/Total assets

Z = Overall index

While the z-score has been demonstrated to be a useful tool for auditors to determine an organization's going concern assumptions, it "does not appear by itself, to be an operational tool" (Davis, 2010, p. 241). Using simple ratio analyses or *z* scores facilitates inter-hospital performance comparisons, but the problem is that the information gleaned reflects average performance, as opposed to the best practice among comparison hospitals. Additionally, ratio-based measures apply single inputs/outputs; regression-based approaches such as frontier analysis methods are able to bypass the single input/output limitation.

Frontier Analysis Methods

Frontier analysis is a set of regression based approaches that produce a best practice frontier to compare organizations in terms of actual data driven performance rather that from a theoretical basis or by averaging data. The importance of these approaches is that the results produced allow for benchmarking which "seeks to evaluate the efficiency of an organization *relative* [sic] to other organizations in the same industry" (Worthington, 2004, p. 137). These measures allow hospital management to use the results for multiple purposes such as for efficiency performance tracking, budget allocation, and for developing strategies for efficiency improvement. Two major frontier analytic approaches have been used. The first is a regression based model called stochastic frontier analysis (SFA). The second is based on linear programming; it is called data envelopment analysis (DEA). Both of these models have the same objective, to "uncover the nature of the relationship between service provision and expenditure, and to evaluate the performance of individual hospitals" (Lovell,

2006, p. 8). Each method has its own strengths and weaknesses making them both valuable for efficiency measurement research.

Stochastic Frontier Analysis

Stochastic frontier analysis is composed of two parts, statistical noise (randomness) and inefficiency. The randomness component accounts for all uncontrollable factors in the organization plus any measurement and misspecification errors. Efficiency is variously defined as either the consumption of the least amount of resources per unit of output or conversely the maximizing of output per unit of input (Lovell, 2006). The main value of SFA techniques, according to Folland and Hofler (2001), is that it is of "practical use when applied to the task of comparing group means" (p. 13). The value of SFA over other frontier analytic methods is in cost oriented studies which require input price data (Rosko & Mutter, 2008) and when certain assumptions are made which would negate the value of DEA. The appropriate assumptions can be made using a translog cost equation; using a truncated normal distribution; including quality measures; and, applying one-stage estimation of the "impact of correlate variables on inefficiency" (Rosko & Mutter, 2008, p. 162). When doing so, SFA is "powerful for categorizing hospitals into high and low performers in … relative efficiency" (p. 162).

Although SFA has not been as commonly used as DEA (Hollingsworth, 2003), many research studies have successfully used this technique in measuring hospital efficiency. Ludwig, Groot, and Van Merode (2009) studied the make or buy decision in Dutch hospitals in terms of asset specificity and the efficiency of the hospitals based on transaction cost

theory by evaluating outsourcing of pharmacy and laboratory services. They concluded that, "in general the make-or-buy-decision does not have much effect on the efficiency of the hospital" (p. 67). The inclusion of quality indicators to understand their impact on efficiency had been studied by Mutter, Rosko, and Wong (2008), they concluded that quality had little impact on inefficiency. Conversely, Gao et al. (2011) found that there was a correlation between quality of inpatient care and efficiency among Veteran's Administration hospitals.

SFA, a parametric approach, also referred to as an econometric approach, in contrast to the other approach, which is known as the mathematical programming approach constructs a non-parametric piece-wise linear convex frontier, this is the DEA model. In SFA, sampling errors are treated as statistical noise. DEA, on the other hand, attributes variations caused by errors as inefficiency (Rosko & Mutter, 2008) thus, yielding a lower efficiency rating for the selected unit of analysis. DEA is also less susceptible to specification errors due to the omission of significant variables, "DEA makes fewer assumptions than SFA about how inputs are related to outputs" (Agency for Healthcare Research and Quality, 2008, p. 4). The strengths of DEA over SFA follow: "there are few parametric health care applications" (Hollingsworth, Dawson, & Maniadakis, 1999, p. 163); it "can provide a comprehensive picture of the operation at the hospital level" (Huerta, Thompson, & Ford, 2011, p. 2); it "may be more useful in smaller-scale studies designed to judge specific efficiency improving interventions in hospital markets" (Chirikos & Sear, 2000, p. 1406); and, "the Pareto efficiency criterion has the advantage of regarding each

separate input and output as being equal in value thus allowing hospitals to be rated along their best dimensions" (Jacobs, 2001, p. 113). This compilation of strengths makes DEA a valuable research methodology.

Data Envelopment Analysis (DEA)

Data envelopment analysis was developed by Charnes, Cooper, and Rhodes (CCR) (Charnes et al., 1978) based on Farrell's (1957) work on measurement of productive efficiency. In that work, Farrrell proposed a model "to compare performances with the best actually achieved" (p.255) instead of average or theoretical performance. The CCR paper described a process for evaluating not-for-profit agencies based on their decision making ability. They chose the term decision making units (DMU) to describe the units of analysis to differentiate them from for-profit units, which they referred to as "firms and industries." Nunamaker (1983) published the first article applying DEA to the healthcare field when he measured the routine nursing service efficiency of Wisconsin hospitals comparing them to Medicare's efficiency criteria. Sherman, in 1984, published the first article applying DEA to hospitals (Sherman, 1984) and further expanding in another article "to a class of for-profit managerial audits in addition to the non-profit and public sector audits" (Sherman, 1984, p. 35).

The hospital industry is currently being subjected to pressures which require improving efficiency to meet societal expectations in an environment of declining reimbursement. Increasing interest in efficiency measurement was best described by Farrell (1957):

> The problem of measuring the productive efficiency of an industry is important to both the economic theorist and the economic policy maker. If the theoretical arguments as to the relative efficiency of different economic systems are to be subjected to empirical testing, it is essential to be able to make some actual measurements of efficiency…. It is important to know how far a given industry can be expected to increase its output by simply increasing its efficiency, without absorbing further resources. (p. 11)

Farrell's vision was to combine multiple inputs into a single efficiency measure; the CCR model's contribution was to amplify this vision by developing procedures to assess the relative efficiency of weighted multiple inputs with the addition of multiple outputs. In addition, DEA can be used as a stand-alone method or it can be used to enhance other methods such as ratio analysis (Chen & McGinnis, 2007; Feroz, Kim, & Raab, 2003), aggregated ratio analysis (Wu & Liang, 2005), and analysis with stochastic data (Ruggiero, 2004).

DEA produces an efficiency model which determines a single performance measure developed from a set of input and output variables with all variables considered: homogeneous, independent of other DMU's variables, and without consideration to the variables' internal structure (Castelli, Pesenti, & Ukovich, 2010). Each DMU is compared to the total set of evaluation units with a linear combination of the sample (Andersen & Petersen, 1993). DEA assigns an efficiency score of less than unity to inefficient units, therefore, a score less than one means that a linear combination of other DMUs in the

sample can produce the same output level by using fewer levels of inputs or higher output with the same or lower inputs.

DEA-Based Health Care Research

The first published use of DEA in health care research was Nunnamaker's (1983) where he compared the Medicare efficiency measure against a DEA determined efficiency rating. Medicare's efficiency rating was a single measure based on cost per diem, Nunnamaker, on the other hand, used a single input and multiple outputs. He used total inpatient routine costs for an input variable along with three outputs broken down by type of patient day of service. His findings were "quite striking" (p. 194), the average cost savings of inefficient units were significantly greater when using DEA results compared to the Medicare efficiency criteria. He concluded that DEA was a model "which deserve[d] further empirical studies in health care settings" (p. 202). Since this study's publication, DEA has been used in multiple international and American health care efficiency studies. O'Neill, Rauner, Heidenberger, and Kraus (2008) provided a taxonomy of DEA-based hospital efficiency studies. They found that during their study period, 1984-2004, there had been a large increase in the use of DEA to determine the efficiency of international hospitals during the second decade, 1994/2004. From 1984, when Sherman published the first study to determine the productive efficiency of American teaching hospitals, through 1990 all DEA studies were done in the U.S. By 1998/2000, there were more DEA studies internationally than domestically (O'Neill et al., 2008).

Some international studies attempted to study the nexus between efficiency and quality, Laine et al. (2005) showed that efficiency differences between DMUs in Finnish long term care facilities might be explained in terms of quality. They concluded that "efficiency was associated with certain … quality dimensions" (p. 266). Prior (2006) used DEA to evaluate the quality and efficiency of Spanish hospitals to develop an evaluation oriented effectiveness tool. Using total quality management approaches, he concluded that "improvements in quality lead to improvements in productivity" (p. 283). Similarly, Salinas-Jimenez and Smith (1996) applied a comparable process to the provision of primary health care services in the United Kingdom's National Health Service. Some international studies have focused on specific characteristics or types of hospitals, such as evaluating ownership categories, funding characteristics, and operational features like teaching and non-teaching status.

One factor in hospital efficiency analysis is the potential benefit of mergers among hospitals in a community. To test the actual benefits experienced by hospital mergers, Kjekhsus and Hagen (2007) measured pre- and postmerger efficiency scores for 53 Scandinavian hospitals over a period of 9 years. They were expecting increases in efficiency due to the reduction of duplication of services and overhead. Instead they found that there were none of the intended effects, there were no increases of efficiency which could be attributed to mergers in Scandinavian hospitals which are all publically financed. To study the effect of ownership on efficiency, Chang, Cheng, and Das (2004) used DEA to determine whether there was a relationship between hospital ownership and operating

efficiency. They found that, public hospitals were generally less efficient than private hospitals. In direct contrast, Helmig and Lapsley (2001) found that public and welfare hospitals in Germany were more efficient than private hospitals. This dichotomy might be explained by work on governance (Bozec, Dia, & Bozec, 2010), which concluded that the quality of the corporate governance of a firm may be a better indicator of overall performance than ownership status.

International research has also expanded the original DEA model beyond pure efficiency measures. Application of some measures to account for case mix in hospitals have been used to adjust for the potential differences in efficiency which may be due solely to the complexity of the patients being treated (Filippini & Farsi, 2004). Filippini and Farsi found that adjusting by diagnosis related groups (DRG—a measure of complexity of case mix) had insignificant impacts on Swiss hospitals. Vitikainen, Street, and Linna (2009) found the opposite results in their study of Finnish hospitals. These studies have to be carefully analyzed since country specific DRG systems vary, so it is difficult to interpret whether the different findings are a result of adjusting for case mix or due to the country specific DRG methodology used. Magnussen (1996) attempted to find whether the choice of output based on complexity affected efficiency rankings in Norway "The distribution of efficiency is found to be unaffected by changes in the specification of hospital output" (p. 21). Other factors not related to case mix such as outcome measures have also been researched using DEA.

A different application of DEA was used to determine the relative efficiencies of OECD countries by using life expectancy and infant survival rates as outputs and wealth and country-specific educational level as input environmental variables (Afonso & Aubyn, 2006). This study expanded the utility of DEA by using nontraditional measures of productivity. Additional applications of DEA have evaluated changes over time to determine the effects of systemic changes to the healthcare system (McCallion, Glass, Jackson, Kerr, & McKillop, 2000). International research has also been conducted to evaluate the efficiency of public health centers in less developed countries such as Kenya (Kirigia, Emrouznejad, Sambo, Munguti, & Liambila, 2004) and Ghana (Akazili, Adjuik, Jehu-Appiah, & Zere, 2008; Osei et al., 2005) where a disproportionate amount of resources, as a proportion of GDP, are spent on health care services in comparison to more developed countries. Some hospital efficiency research found significant inefficiencies in Botswana over an extended period of time (Tlotlego, Nonvignon, Sambo, Asbu, & Kirigia, 2010), these varied uses of DEA have validated its significance.

An increasing number of studies have been performed to measure the relative technical efficiencies of public hospitals. For example, data on public hospitals from Mongolia (Munkhsaikhan, Tsai, & Chang, 2011), Jordan (Najadat & Alsmadi, 2011), Thailand (Valdmanis, Kumanarayake, & Lertiendumrong, 2004), and Iran (Hajialiafzali et al., 2007) have been compiled using DEA. Because of the increasing financial pressures on European Union publicly funded hospitals, many studies have been produced demonstrating the value of DEA. These studies from the United Kingdom (Jacobs, 2001), Spain (Caballer-

Tarazona, Moya-Clemente, Vivas-Consuelo, & Barrachina-Martinez, 2010), Greece (Boutsioli, 2010), Ireland (Gannon, 2005), Germany (Vera & Kuntz, 2007), Holland (Blank & Valdmanis, 2010), and Austria (Hofmarcher et al., 2005) have relied on DEA to develop measures of efficiency in healthcare organizations. Most of the studies in Europe, Asia, and Africa explored the efficiency of publicly owned healthcare facilities since public ownership of hospitals is the norm. In the United States only about 26% of hospitals are publicly financed. In the following section published hospital efficiency studies in the United States placed greater emphasis on structural issues.

The American hospital system is different from most other industrialized countries because of the relatively small number of government owned hospitals and the large number of investor owned and privately operated hospitals. The Henry J. Kaiser Family Foundation (2009) reported that 21.8% of hospitals were state or local government owned, 58.27% non-profit, and 37.04% for profit. Ten years earlier, the number of for-profit hospitals was smaller with only 15% being investor owned (O'Neill et al., 2008). Most publicly owned hospitals rely heavily on public funding for their survival although some non-profit hospitals also receive direct government tax funding via the formation of taxing districts. To avoid confusion, the taxonomy of hospitals that were used in this study differentiated between taxpayer supported hospitals, non-profit hospitals that are self-supporting, and private for profit hospitals that are investor owned. An additional distinction, which I did not address, is Federal hospitals which include Veteran's Administration, Public Health Service Hospitals, Department of Defense Hospitals, and Indian Health Services facilities.

The literature review which follows analyzed DEA hospital technical efficiency studies by examining the approaches used including the output and input variables included in the model. Most published studies evaluated technical efficiency at the hospital level while not addressing the health status of individual patients (Hollingsworth, 2003). Hollingsworth examined 188 published studies and reported that common inputs used measured staff costs and capital expenditures while outputs were based on physical activity such as patient days. These studies have validated aggregate measures of labor productivity as useful in quantifying labor efficiency (Ozcan, Yeh, McCollum, & Begun, 1996). This is relevant since the health care industry is heavily dependent on labor, employing about 12% of the total work force in the United States (Bureau of Labor Statistics, 2011). Before exploring structural issues of hospital efficiency, understanding the inclusion of quality factors and their influence on efficiency is necessary.

The lack of composite quality measures consensus has contributed to DEA studies not incorporating quality indicators in their studies (Nayar & Ozcan, 2008). In other health care applications, Laine et al. (2005) used SFA to study the effect of quality in long term care facilities and found no "systemic association between technical efficiency and clinical quality of care" (p.259). Nayar and Ozcan (2008) found no prior studies incorporating quality measures into DEA models, in their study, which included multiple measures of quality, they concluded that "quality outcomes were not being compromised by the efficient hospitals" (p. 197). Contradictory results were found by Huerta, Ford, Peterson, and Brigham (2008) who used measures of quality to develop a value matrix to study this effect

on hospitals by ownership and found that governance type affected efficiency more than quality. Valdmanis, Rosko, and Mutter (2008) concluded that cost containment and quality improvement are mutually consistent objectives" (p. 1830), the consensus being that quality could be left out of the DEA model and still attain valid performance measures.

Market structure also can have an impact on hospital efficiency. There has been a proliferation of market oriented moves such as mergers with multi-hospital systems in an attempt to mitigate environmental competitive factors. The first study to evaluate market factors was Bates, Murkherjee, and Santerre (2006), who evaluated the impact of HMO penetration on hospital efficiency. The authors concluded that higher market penetration by HMOs or health insurance companies increased hospital efficiency. As a response to the market influences of HMOs and health insurance companies, hospitals reacted by merging, thereby increasing their market clout. The results have been increasing efficiencies primarily due to scale efficiencies (Harris, Ozgen, & Ozcan, 2000) and increased profitability. A study comparing pre-merger, post-merger, and hospitals which did not merge Ferrier and Valdmanis (2004) confirmed the findings by Harris et al. (2000) finding scale efficiencies. Besides the macro analyzes of hospital efficiency described above, micro analysis of hospital productivity studying a single department have also been published (Schumock, Shields, Walton, & Barnum, 2009).

Further studies have evaluated specific details pertaining to the external environment such as a study to determine how uncompensated care affects hospital services and thus efficiency (Ferrier, Rosko, & Valdmanis, 2006). Another study evaluated the impacts of

hospital access capacity on emergency preparedness (Valdmanis, Bernet, & Moises, 2010) where they developed a model to determine statewide hospital capacity to deal with catastrophic emergencies. Kazley and Ozcan (2009) used a DEA model to determine whether the implementation of electronic medical records was accompanied by an increase in efficiency. DEA was also used in a study of critical access hospitals, which are a special designation of hospitals serving rural medically underserved areas, to determine the efficiency of these facilities. These hospitals receive higher reimbursement and thus having the ability to demonstrate that these funds are used efficiently has considerable policy implications. In their study, Harrison, Ogniewski, and Hoelscher (2009) found that critical access hospitals had demonstrated an increase in efficiency since implementation of augmented reimbursement. Butler and Li (2005) found similar results with the addition of evaluating the impacts of scale efficiency.

Multiple efficiency studies have explored the effects of hospital organizational structure and ownership status. One attribute of hospital performance is the presence of a medical teaching program. An early study of the relative performance of teaching hospitals compared to non-teaching hospitals assumed that both had a primary mission to provide health care services rather than a teaching mission (Grosskopf et al., 2001a). They concluded that only 10% of teaching hospitals had better performance than non-teaching hospitals. The comparison may not be valid since teaching hospitals in their sample were substantially larger than the non-teaching counterparts. Grosskopf, Margaritis, and Valdmanis (2001b) determined that teaching hospitals have higher costs than non-teaching

hospitals. Practically, this study provided decision makers the ability to determine appropriate levels of medical residents to maximize efficiency.

Lastly, the ownership or governance control of hospitals is a major source of efficiency studies to determine whether the different ownership structures impact efficiency because of their different organizational goals. Public and non-profit hospitals are differentiated by their profit maximizing focus (Boland & Fowler, 2000), and the emphasis is on the bottom line which is a valuable performance measure. The relative efficiency of these hospitals is inconclusive, Huerta et al. (2008) found that "publicly run and non-profit hospitals are, on average, more efficient than privately run hospitals" (p. 346), on the other hand, Grosskopf et al. (2004) posited that "the results suggest that private hospitals use fewer inputs to produce outputs" (p. 522). In a study of Florida hospitals, Lee, Yang, and Choi (2009) also concluded that non-profit hospitals were more efficient than for profit hospitals. White and Ozcan (1996) determined that religious hospitals were more efficient than secular non-profit hospitals while Harrison and Sexton (2006) found increasing efficiency in religious hospitals over a four year period. Evaluating the efficiency of Federal hospitals, Harrison, Coppola, and Wakefield (2004) demonstrated a potential for $2B in savings through more efficient management. Studying Veteran's Administration medical facilities, Harrison and Ogniewski (2005) found that they had increased their efficiency, yet there was a potential for $5.9M savings per hospital by reducing inefficiency. Several DEA models have evolved over time, the one that this study used was the original model developed by Cooper, Charnes, and Rhodes (CCR).

CCR DEA Model

The original Farrell (1957) efficiency model defined the overall efficiency (OE) of an organization in terms of two multiplicative components, allocative efficiency (AE) and technical efficiency (TE); OE = AE X TE (Grosskopf, 1986). Following Farrell's lead discounting the value of price efficiency being "a measure with rather limited usefulness" (p. 258), the CCR model evaluates efficiency only in terms of technical efficiency. Technically efficient operating methods refer to the use of labor, capital, and facilities to produce the best results among a given sample of DMUs. The model does not concern itself with effectiveness since the assumption was made that "this has been decided in the choice of inputs (resources) to be used and outputs (benefits) to be achieved…[and] the ways in which the inputs and outputs are to be measured" (Charnes & Cooper, 1985, p. 71). Pareto-Koopman's optimality represents efficiency and efficiency is "determined relative to prior theoretical knowledge" (p.72). Full efficiency is attained when none of the inputs or outputs can be improved without worsening some or all of the other inputs or outputs; this is called the efficiency frontier.

The efficiency frontier besides demonstrating the relative performance of each DMU also shows the relative efficiency of each unit and thus indicates which combination of input and output changes would yield maximum efficiency. This frontier is defined by using a linear programming formulation of DEA which, according the Cooper, Seiford, and Zhu (2004), "floats a piecewise linear surface to rest on top of the observations" (p. 3). In order to move inefficient DMUs towards the efficiency frontier, two approaches are possible:

input reductions with fixed outputs are made, or fixed inputs with output increases. An additional factor in the DEA model is the impact of economies of scale.

The original CCR model has allowed for the decomposition of technical efficiency into multiple factors such as the effect of the scale of operations on the results. The three models are: constant return to scales (CRS) where the size of the organization is not considered to have any impact on efficiency since increasing inputs results into a proportionate increase in outputs; increasing returns to scale (IRS), as inputs are increased outputs are also increased but at a greater rate than the input increase ; and, decreasing returns to scale (DRS) whereas inputs are increased, outputs increase but at a lesser rate than the inputs increase (Bhat, Verma, & Reuben, 2001).

Strengths of DEA

- Can handle multiple inputs and outputs.
- Efficiency is compared to actual achieved performance.
- Comparisons are made to peers.
- Does not require assumption of the functional form of inputs or outputs.
- Inputs and outputs can have different units.
- All relevant factors included in a single model.

Limitations of DEA

- Results are sample specific.
- Measurement errors can cause significant problems.

- Because it is nonparametric, large problems can be computationally intensive.
- Good at estimating performance relative to peers, not to a theoretical level.

The CCR model is well suited for this study because it has been successfully used in many healthcare efficiency studies and it is a validated method. For the purpose of this research, DEA is the only method that meets the following criteria:

- Efficiency measures are relative to actual achieved performance by comparable units.
- Measures are developed based on multiple inputs and outputs;
- DEA allows the measurement of efficiency on non-frontier units.
- DEA identifies benchmarks against which inefficient units can be compared.
- Efficient hospitals can be identified.
- The functional form of the production function is not pre-specified.

None of the other methods such as ratio analysis and ordinary linear regression methods meets the above criteria; ratio analysis is backwards looking and relies on theoretical standards for efficiency, linear regression does not accommodate multiple inputs and multiple outputs, and it also measures central tendencies rather than actual performance. Data analysis was conducted by DEAFrontier software which uses the Microsoft Excel Solver.

Summary

Data envelopment analysis provides a useful model for researchers to assess the efficiency of many organizations. Although originally developed as a tool for public organizations, the model has been extended to both profit oriented and charitable organizations. This literature review focused on research studies that have used DEA to assess the technical efficiency of varied health care organizations ranging from pharmacies to nursing homes and hospitals. Since the initial use of DEA in health care by Nunnamaker in 1983, based on Charnes, Cooper, and Rhodes's (CCR) DEA formulation, different theoretical models have been used to study various practical factors in the health care sector to assess relative performance. Based on their original DEA model, with many modifications, more than 4,000 research articles and books have been published (Chilingerian, 2010).

The original DEA model, known as the CCR model, provided a methodology for assessing the relative efficiency of decision making units by comparing them to an efficiency frontier based on those DMUs exhibiting actual best practices. Thus, DMUs are compared to actual performance rather than a theoretical measure which may or may not be achievable. DEA is a linear programming technique that envelops the variables with a nonparametric frontier based on actual best practices achieved among comparable DMUs. The efficiency frontier provides benchmarks against which inefficient units can be compared to allow management to develop strategies for performance improvement. Decision making

units on the efficiency frontier that have a score of < 1 are considered inefficient. The DEA model provides a useful alternative to prior methods of performance measurement.

The most commonly used method for performance measurement in the health care industry in the past was ratio analysis. Financial performance, auditing standards, and management operating indicators based on ratios such as payroll cost per patient day, labor hours per procedure, and other ratios provide adequate tracking information to assess performance. In the absence of standards against which to compare the ratios, it is difficult to assess the relative performance against peer organizations. Additionally, ratios are single measures. DEA addresses both of these concerns since the efficiency frontier is based on peer groups demonstrating actual performance via a measure that includes multiple inputs and multiple outputs generating a single relative performance score. Because of the complexity of healthcare delivery and the high stakes at risk, both financially and socially, a measure of hospital efficiency such as the one produced by DEA is a valuable research and management tool.

DEA based research in all sectors of the healthcare industry and throughout the world have provided a basis for addressing the research questions of my dissertation. There are many models of DEA based on the original CCR model that have been used to evaluate the efficiency of hospitals by ownership, religious affiliation, and teaching versus non-teaching status, and for evaluating individual hospital departments. The gap that exists in the published literature is a comparison of the relative technical efficiency of tax-supported hospitals and their nonprofit counterparts. This research study was designed to directly

address this gap in the literature and determine the relative technical efficiency of tax-supported and nonprofit Florida hospitals.

Chapter 3: Research Methodology

Overview

This chapter presents the proposed methodology to determine the relative technical efficiencies between tax-supported and nonprofit Florida hospitals. The reasons for choosing DEA as the quantitative methodology used in the study is described along with the rationale for the selection of the proposed research design and the criteria for selecting the independent and dependent variables. To ensure a valid sample the exclusion and inclusion parameters for the selection of study hospitals from the total population of Florida hospitals are detailed. Finally, the data analysis process is explained along with the justification for the use of commercially available software to process the data.

Upcoming health care reforms will require that healthcare providers operate at their maximum potential efficiency to maximize resources as reimbursement is constrained. Political and community pressures to operate efficiently may be greater on those hospitals which have been granted taxing and special assessment authority. In the State of Florida, these hospitals have lower operating margins while, at the same time, facing demands for greater accountability for the use of funds (Chen, Bazzoli, & Hsieh, 2009). Thus, the importance of having a process for determining their efficiency is a social imperative to ensure that limited community resources are efficiently used. Prior studies have documented the hospital characteristics that influence efficiency (White & Ozcan, 1996). The need for documenting efficiency based on ownership category is not new; White (1996)

studied the relative technical efficiencies of church-owned hospitals, and Grosskopf (2001) examined the impact of medical teaching programs on efficiency using DEA.

Data envelopment analysis was the preferred methodology for this research because of its fit in answering the research questions and hypotheses. It also overcomes the limitations found in alternative methods such as ratio analysis, regression analysis, and stochastic frontier analysis. The logic of using the CCR model is justified based on its broad application in prior health care research and the use of accepted variables which have been validated. Data envelopment analysis was well suited for this study because of its characteristics: DEA measures inputs and outputs in their natural units; it does not require price data; it uses multiple inputs and multiple outputs; it produces reasonable efficiency estimates using small samples; and it is amenable to input or output matrices (Ferrier & Valdmanis, 2004). Further, DEA produces a single comprehensive measure of performance for each DMU yielding a convenient metric to use for comparisons. By comparing the relative performance scores of all DMUs, a ranking of relative efficiency can be developed to determine whether tax-supported hospitals or nonprofit hospitals have greater technical efficiency. The computed efficiency value serves to inform the necessary strategies for those hospitals outside the efficiency frontier to move towards greater efficiency by reducing inputs, increasing outputs, or combinations of both.

After reviewing the study's methodology, the chapter concludes with a description of the protections to be taken to protect human participants. Since this study only used existing, publicly available data at the hospital level, no patient information was available

directly and the there was no possibility of identifying individual patients. Additionally, a discussion is presented to address the dissemination plan for the results of this study. Appendices provide additional information on the proposed process for dissemination of the findings of this study.

Data Envelopment Analysis

Data envelopment analysis was developed by Charnes, Cooper, and Rhodes (1978) based on linear programming techniques to assess the efficiency of homogenous decision making units (DMU) using a matrix of multiple inputs and multiple outputs. This method ranks DMUs relative to their actual performance rather than to a theoretical value, as Farrell (1957) stated "it is far better to compare performances with the best actually achieved than with some unattainable level" (p. 255). Using CCR's nonparametric model, the best practice frontier is constructed using selected inputs and outputs creating a piecewise linear function (see Figure 4). Those DMUs identified as Points a, c, e, and g in Figure 4 are on the efficiency frontier and are, therefore, technically efficient when compared to the other DMUs. Hospitals outside the efficiency frontier, Points d, b, and f, in this example, are less efficient with f being the least efficient because it lies furthest from the isoquant. The technical measure of efficiency derived in this manner determines the amount by which inputs should be decreased while holding outputs constant or the necessary increase in outputs to achieve while keeping the same inputs constant to arrive at the demonstrated technical efficiency frontier.

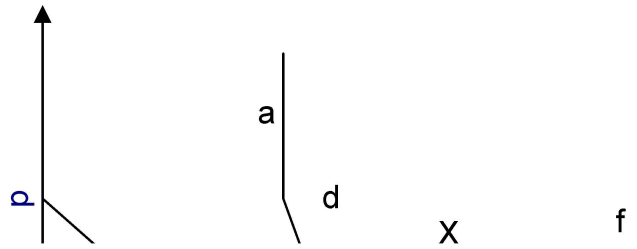

Figure 4. Efficiency frontier

The piecewise, linear frontier passing through Points a, c, e, and g is an approximation of the true efficiency function. The line p, p describes the prices charged by all DMUs. The two axes represent inputs consumed per unit of outputs produced. The different types of efficiencies are calculated as:

Overall efficiency = OZ/OX

Technical efficiency = OS/OX

Allocative efficiency = OZ/OS

This is the basic approach for developing the DEA technical efficiency frontier. Price data are omitted in further analyses because the goal is to assess technical efficiency, which does not include price data. Prices can be excluded because hospitals have little flexibility in setting prices particularly in Medicaid and Medicare, where reimbursement is contractually fixed.

The measure of technical efficiency for any DMU is a function of the maximum ratio of weighted inputs to weighted outputs "subject to the condition that the similar ratios for every DMU be less than or equal to unity" (Charnes et al., 1978, p. 430). DMUs that lie on the efficiency frontier have a score of one, those that are not as efficient will have values of less than one but greater than zero; the higher the score, the greater the relative efficiency. A value of one indicates maximum efficiency, whereas, for example, a value of 0.75 indicates 75% relative efficiency. When given a set of inputs and outputs, DEA produces a single comprehensive measure of performance against which other DMUs may be ranked. This ranking may be utilized to identify best in class performance for a comparison set of hospitals based on actual, achieved performance.

Although the CCR model does not provide tactical direction as to how to improve performance, it does inform the changes in inputs, outputs, or combinations of both that would move the DMU towards the efficiency frontier. Consider points **b, d,** and **f** which lie outside the efficiency frontier in Figure 5. It is also evident from this example that hospital f has the greatest challenge in moving towards the efficiency frontier because it lies furthest from the isoquant. DEA's methodology is oriented to the frontier, not central tendencies

like many other performance assessment models. DMUs are considered technically efficient even when they have radically different profiles such as points **a**, **c**, **e**, **g** in this example.

Figure 5. Input versus output orientation. The arrows indicate the possible direction of changes necessary to improve overall efficiency. As illustrated by the arrows at d, the choices are to reduce inputs, increase outputs, or a combination of both to move towards the efficiency frontier.

The CCR DEA method uses a ratio of outputs to inputs to measure the relative efficiency of DMUs relative to all the DMUs in the analysis. The model reduces the multiple inputs and multiple outputs to a single virtual input and virtual output combination. The formal mathematical notation for this model is (Charnes & Cooper, 1985, p. 63):

$$\max h_0 = \sum_{r=1}^{s} u_r y_{r0} / \sum_{i=1}^{m} v_i x_{i0}$$

Subject to:

$$\sum_{r=1}^{s} u_r y_{rj} / \sum_{i=1}^{m} v_i x_{ij} \leq 1;\ j = 1, \ldots, n,$$
$$v_r, v_i \geq 0; r = 1, \ldots, s;\ i = 1, \ldots, m$$

The weights of the outputs and inputs are designated by u_r and v_i respectively, which are determined entirely from the input and output data from all DMUs in the peer group. The weights used are those that maximize the focal DMU's efficiency scores. All inputs and all outputs are assumed to be greater than zero. The fractional program described above is converted to a linear programming formulation. Because the emphasis in this research was on the results achieved with DEA rather than its mathematical formulation, and commercially available software was used to do the data processing, no further mathematical exposition will be provided.

Smith (1996) identified three potential areas for misspecification in the DEA model and how they may impact the results. First, omission of a salient variable may result in a reduction of estimated efficiency. This misspecification is mitigated by using variables which have been used in published studies and consequently have been validated by prior researchers. The second potential misspecification is the inclusion of an extraneous variable. Smith found that this misspecification had no impact on the solution, and "the efficiency estimate is unaltered" (p. 241). The third misspecification is selecting incorrect returns to scale assumptions. The constant returns to scale (CRS) assumption was the most appropriate for this study because the analysis did not attempt to determine the impact of

scale on efficiency and the sole focus was on productivity. A variable returns to scale assumption would result in an increased estimated efficiency, CRS is a more conservative model and the original CCR model also had the constant returns to scale assumption (Cooper et al., 2007).

Research Design and Approach

This research was conducted using an input-oriented, constant return to scales (CRS) CCR model that computes the technical efficiency of each DMU. A CRS model assumes that an increase in inputs will result in a linear, proportionate increase in outputs. The CRS assumption also incorporates scale efficiency into the measure of pure technical efficiency (Harris et al., 2000). CRS produces results that are more robust than a variable returns to scale (VRS) model since all DMUs found efficient under VRS are always efficient under CRS, but not vice versa (Sikka, Luke, & Ozcan, 2009). The other complementary component of the CCR model is whether to use an input or an output orientation.

An input oriented model, the one chosen for this study, assumes that the organization has control over its inputs and that outputs are not directly controlled by management. In health care studies, most researchers have used an input oriented model because hospital management does not have control over the outputs such as discharges, patient days, or number of outpatient surgeries performed (Harris et al., 2000; Kazley & Ozcan, 2009; Sikka et al., 2009). These outputs are either too complex to be directly influenced by management, such as length of stay which depends on the patient's health status and response to treatment, or are beyond the control of the hospital, such as scheduling surgeries, which is

the exclusive purview of the medical staff. It is thus assumed that efficiency analysis should focus on inputs where there is greater opportunity to reduce excess resource utilization by exerting direct influence or control. Minimizing inputs is also considered to be the most appropriate strategy utilized in non-profit hospitals (Bates et al., 2006; Butler & Li, 2005). Social and political pressures on hospitals also demand that they produce more services for the same or reduced costs (Cunningham et al., 2008). Finally, from a technical perspective, Bhat, Verma, and Reuben (2001) asserted that "if an organization is technically inefficient from an input-oriented perspective, then it will also be technically inefficient from and output-oriented perspective" (p. 319).

Variables

The input variables chosen for this model are all related to hospital operating costs, the output variables are functions of production such as the number of outpatient procedures performed and total patient discharges. The independent variables, referred to as inputs in the DEA model, are limited to cost data because the premise of this study is to evaluate resource utilization efficiency because it can be directly controlled by hospital management. Input variables are generally measures of staff and capital employed whereas output variables, the dependent variables, are measures of physical activity. Inputs are indicators whose variation cause changes in outputs and thus are indicators of how efficiently resources are being utilized. Wagner and Shimshak (2007) asserted that "the challenge of DEA is to find a 'parsimonious' model, using as many inputs and output variables as needed but as few as possible" (p. 58). Part of the challenge in determining the appropriate inputs is

that any resource that is consumed to produce a result can be considered to be a valid input. The inputs and outputs proposed for this study have been empirically tested by other researchers (Butler & Li, 2005; Harrison & Ogniewski, 2005; Sikka et al., 2009). Three input variables and two output variables were used in my DEA analysis, a summary is provided in Table 2.

Table 2

DEA Variables

Variable	Description
Outputs	
Total adjusted discharges	Medicare case mix adjusted inpatient discharges
Outpatient visits	Total ER, same day surgery, OP diagnostics
Inputs	
Beds in service	Total inpatient beds available
Payroll	Total payroll for all categories
Other expenses	Variable and fixed costs

Input Variables

The three input variables are: (a) number of beds in service, (b) labor costs, and (c) other operating costs. These categories provide a clear and concise metric and are used consistent with their availability in standard cost reports produced for both Medicare and the State of Florida's Agency for Healthcare Administration's standardized hospital reporting requirements. The data are readily available from audited cost reports thus mitigating the need to assess the validity of the data. These three input variables are either a direct measure of costs or, as in the case of beds in service, a surrogate for capital expenses.

Hospital beds in service—the number of beds in service functions as an accepted proxy for capital (Wagner & Shimshak, 2007; White & Ozcan, 1996) particularly when the study focuses on a limited time frame since other measures of capital would not be appropriate over such a short period of time. Capital investments in the hospital industry are large and implemented over time, looking at only the capital expenditure for the study period would over or understate the true impact of capital on efficiency. Although this measure is not directly controllable by management over a short period of time, a surrogate measure of capital helps to ensure that this important variable is included in the analysis.

Labor costs. This input uses the total payroll for the hospital, including physicians, nurses, and all ancillary personnel. The assumption in this study is that the relative mix of labor utilized is similar among all the hospitals. This assumption needs to be further analyzed if the results show that it is a significant factor in the relative inefficiency of some hospitals. Labor cost is considered to be one of the most controllable factors in generating performance improvements, and it is the most significant single expense category for most hospitals (Harrison et al., 2004).

Other costs. This category captures all other costs including variable and fixed operational costs, such as supplies and other overhead expenses.

Output Variables

Output variables are the results of production which in hospitals are not under the direct control of management (Bates et al., 2006). There are many significant, yet not included outputs, such as community benefits, charity care, and medical teaching programs.

There are no standardized data available for these measures since there is no uniform reporting requirement for these factors and are thus not included in this analysis. The variables included in my study are consistent with prior research (Nayar & Ozcan, 2008; Ozcan, 2008). Two output variables are included in my analysis.

Total adjusted discharges. Total inpatient discharges serves as a comprehensive proxy for the number of patients treated by the hospital. This is an accepted measure of hospital inpatient productivity (Harrison et al., 2004). Inpatient discharges were adjusted using the Medicare case mix index for the study year to account for the intensity of care provided by the different study hospitals.

Outpatient visits. This is a composite measure of same day surgery cases, outpatient diagnostic procedures, and emergency room visits which may or may not result in an inpatient admission.

The total number of input and output variables is recommended to be no more than one-third the number of DMUs selected (Cooper et al., 2007, p. 284).

Population

All Florida hospitals comprise the total population. They were initially segmented on the basis of their ownership category, including only hospitals that are categorized as non-profits in the initial sample. Second, only acute care hospitals were selected because the number of specialty hospitals was small and thus limited the validity of results, also the distinct production processes of specialty hospitals is not comparable to the rest of the sample (Chen, Hwang, & Shao, 2005). Third, only hospitals with special taxing district

authority were used for the tax-supported cohort. These hospitals have the authority to collect tax monies for a specific benefit to

- subsidize health care costs,
- improve access to medical care, and
- meet other public objectives such as funding indigent care.

The importance of determining the efficiency of these hospitals is emphasized by Honore, Fos, Wang, and Moonesinghe (2011), who stated "maintaining support for taxation policies can be greatly influenced by demonstrating a return on taxpayer investments" (p. 2).

These hospitals also provide non-monetary benefits to their communities as demonstrated by Studnicki et al. (2007), who showed that taxpayer supported hospitals were associated with better community health outcomes, and Studnicki, Fisher, and Kamble's (2010) findings of a reduction of health disparities among racial groups in taxpayer supported hospitals. Although both of these findings are important, the emphasis of this study was on economic efficiency only. The hospitals thus identified as collecting local taxes to augment hospital revenues were matched with nonprofit hospitals not receiving this subsidy and their relative efficiencies are then determined. Fourth, to avoid geographic differences, the set of hospitals for each group were selected from matched counties. All sample hospitals have submitted complete, audited financial reports to the State of Florida and have also submitted Medicare audited cost reports, therefore, valid data is publicly available.

Sample

The sample selection criteria were governed by the need to avoid confounding effects of hospital size, geographic differences, and intensity of services. The selected hospitals are similar in structure, and they use similar inputs to produce the same homogeneous outputs. Florida has four different types of health related taxing districts: health care/indigent care taxing districts *(n* = 34); hospital/health facility taxing districts *(n* = 36); children's health services districts *(n* = 9); and, emergency medical services districts (n=6). Of Florida's 67 counties, only 16 counties did not report having some form of health related taxing district (Committee on Urban and Local Affairs, 2008). Eleven counties had multiple districts *(n* = 34) with two counties having six districts each. Of the total 34 hospital taxing districts, there are three which are specialty psychiatric hospitals and six small hospitals each under 70 beds located in rural counties; these nine hospitals were excluded from my sample. These facilities were excluded because psychiatric hospitals provide unique specialty services and there are no comparable hospitals in the non-profit sector. Rural hospitals were also excluded because they provide limited services and are generally the sole providers of medical care in their respective counties.

The sample size was limited by the number of tax-supported hospital districts which support full service hospitals and the presence of nonprofit hospitals in the same districts. The presence of non-profit hospitals was a necessary ingredient of the study design because it allowed for a direct comparison of the efficiencies without regard to extraneous factors such as location. In DEA studies, the minimum sample size (DMUs) is three times the sum

of inputs and outputs (Bowlin et al., 1985; Charnes, Cooper, Lewin, Morey, & Rousseau, 1985; Wagner & Shimshak, 2007). In this study there were a total of seven inputs and outputs; therefore, the minimum number of DMUs needed was 21. This study included a total of 37 DMUs. The State of Florida is segmented into eleven health planning districts (see Figure 6). There were no study hospitals from districts 1, 2, 3, 4, 5, and 8.

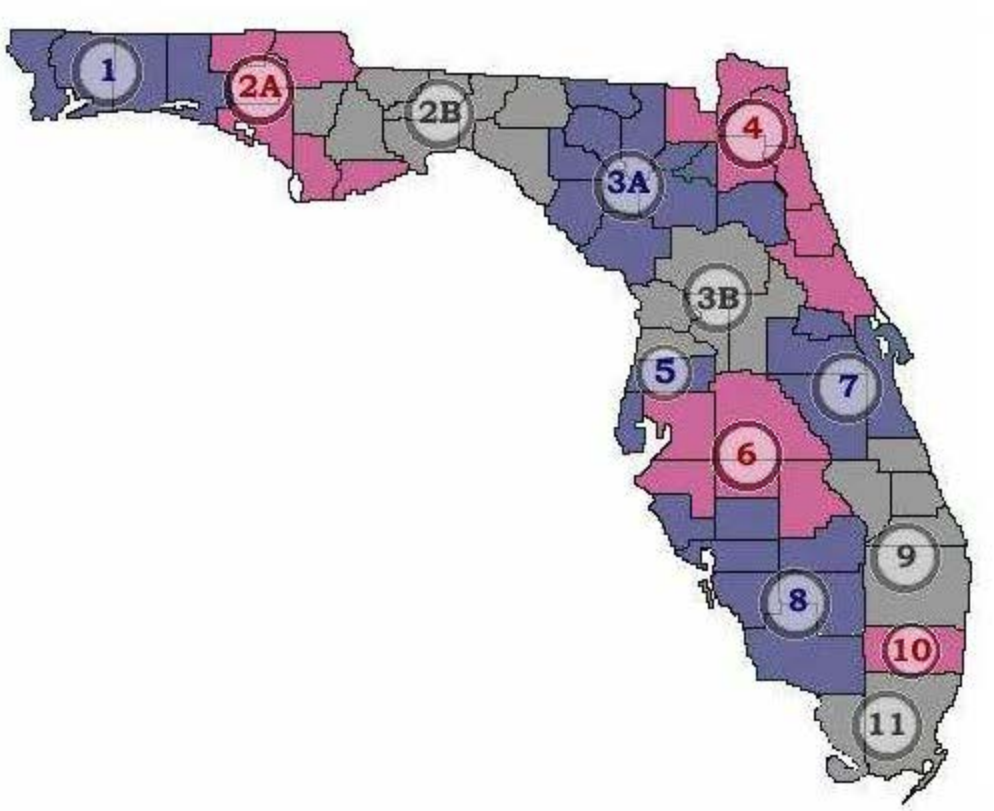

Figure 6. Florida Health Care Planning Districts. From Florida Department of Health Services, 2012.

The sample included a total of 17 tax-supported hospitals and 20 nonprofit hospitals. The sample hospitals were selected by eliminating specialty hospitals, psychiatric hospitals, children's hospitals, and hospitals under 100 beds in size. The small sample size was

empirically acceptable because "DEA models may be more useful in smaller-scale studies designed to judge specific efficiency-improving interventions" (Chirikos & Sear, 2000, p. 12). Inclusion criteria required that the two sets of hospitals included facilities located in the same counties to eliminate potential differences in performance based on geographic distribution (see Tables 2 and 3).

Table 3

Non-profit Hospitals in Study Sample

ID	Hospital Name	County
A	Baptist Hospital of Miami	Miami-Dade
B	Cape Canaveral Hospital	Brevard
C	Doctor's Hospital	Miami-Dade
D	Florida Hospital DeLand	Volusia
E	Florida Hospital	Orange
F	Florida Hospital Fish Memorial	Volusia
G	Florida Hospital Memorial	Volusia
H	Holmes Regional Medical Center	Brevard
I	Holy Cross Hospital	Broward
J	Homestead Hospital	Miami-Dade
K	Metropolitan Hospital of Miami	Miami-Dade
L	Mount Sinai Medical Center	Miami-Dade
M	Orlando Regional Health Care	Orange
N	South Miami Hospital	Miami-Dade
O	University of Miami Hospital	Miami-Dade
P	Mercy Hospital	Miami-Dade

Table 4

Taxpayer Supported Hospitals in Study Sample

Hospital Name	County	Beds in Service
Bert Fish Med Center	Volusia	112
Broward Gen Med Center	Broward	716
Broward Coral Springs	Broward	200
Broward Imperial Point	Broward	204
Broward North Broward	Broward	409
Halifax Health Medical	Volusia	654
Health Central Acute Care	Orange	171
Jackson Memorial Hospital	Miami-Dade	1259
Jackson North Med Center	Miami-Dade	382
Jackson South Comm Hospital	Miami-Dade	199
Memorial Hospital Miramar	Broward	178
Memorial Hospital Pembroke	Broward	301
Memorial Hospital West	Broward	304
Memorial Regional Hospital	Broward	713
Memorial Reg. Hosp. South	Broward	280
Parrish Medical Center	Brevard	210

Data Collection

All the data to be used in this study is available from existing, publicly available sources and was accessed directly from the Florida Department of Health Services. The use of secondary data has several limitations, according to Frankfort-Nachmias and Nachmias (2008): (a) data may be collected for purposes remote from the investigator's needs, (b) access may be restricted, and (c) information about how the data were collected may restrict its utility. All of these inherent limitations that may be present in secondary data research are addressed in this study and therefore do not have any impact on the content validity of the data.

Florida statutes require every licensed hospital to provide financial data in a uniform format. Florida Statutes Section 408.061 requires that hospitals file financial reports within 120 days of the end of their fiscal year ("Health Care Administration," 2011). All submitted data have to be audited by a Florida licensed Certified Public Accountant using generally accepted auditing and accounting standards including the auditor's opinion. After reports are submitted, the Agency for Health Care Administration conducts a review to determine that the information is complete, conforming, and validated (Agency for Health Care Administration, 2011).

The specific data that was analyzed in this research was obtained from the Florida Agency for Health Care Administration which is required by Florida Statute 408.063 to publish and distribute information based on collected data. This research used the hospital financial data published in the 2007 Hospital Financial Data Book (Agency for Healthcare Care Administration, 2009). Florida hospitals have an additional 18 months after submitting their audited financial information to correct any errors, using 2007 data allowed adequate time to correct any errors and thus improve the validity of the data. The data are available in paper form and were transcribed to an Excel spreadsheet to assist with data analysis. All the raw data is included in Appendix A.

Data Validity

Data validity in secondary research is concerned with ensuring that the variables used represent what they actually are intended to measure. The limitations and challenges of using secondary data can usually be addressed by adhering to some basic principles.

Mogalakwe (2006) outlined the basic safeguards that should be undertaken when using secondary data sources:

- Authenticity. The most fundamental principle is authenticity; the researcher has an obligation to ensure that the documents used are reliable and from a dependable origin. To assess authenticity, the researcher must be aware of obvious errors and internal inconsistencies. In addition, if there are multiple versions of the document, a process for reconciling differences must be established. And finally, the authorship of the document must be ascertained;
- Credibility. The document must be free from obvious errors or distortions. The original author's credibility and accuracy are critical to the usefulness of the document. In cases where the document expresses a point of view, this should be clearly stated and vetted to ensure that the document serves the research purpose;
- Representativeness. The document must present evidence which is consistent with the type of data for its kind; and,
- Meaning. The data must be clear and comprehensible. The ultimate meaning of the document is analyzing behind the face value of the document to discern its actual meaning.

The use of audited, uniformly defined and reported data was used in this study mitigating all the above concerns.

All of these safeguards were present in the data used in this study. To ensure uniformity of the data, hospitals have to conform to the Florida Hospital Uniform Reporting

System (FHURS). This system requires that hospitals comply with three requirements. First, the form of data reporting has to comply with the manual provided by FHURS. Second, all data are reported functionally regardless of reimbursement source to ensure that data across hospitals can be accurately compared. And, finally, a standard output measurement system is applied to types of activity rather than to responsibility (Studdert et al., 2005, p. I-1). An additional protection to ensure the validity of the data is that the Chief Executive Officer and the Chief Financial Officer have to attest to the propriety of the data submitted.

Data Analysis

Data analysis initially entailed performing descriptive statistics on hospital demographic data. Specific data used for the input and output variables in the DEA model were available directly from the available data with no further manipulation of the data necessary. Data analysis was aided by the use of a commercial DEA software package which uses Excel Solver as the processing engine. This software, DEAFrontier was developed by J. Zhu, Ph.D., who is a prolific DEA author with over 6% of all DEA publications and is among the top 12 DEA authors (File & Crissey, 2008). DEAFrontier has been used by various researchers (Lee, Chun, & Lee, 2008; Neves & Lourenco, 2009)

Protection of Human Participants

This study was conducted using publicly available aggregated hospital-level financial information. There was no patient level data that were disclosed and there is no opportunity to reconstruct the data in a way that would expose patient identity. All the data

are available pursuant to Florida Statutes 408.063 which requires the public dissemination by the Agency for Health Care Administration. All of the financial and other collected data have to be published and distributed to any interested party.

This research study is specifically exempt from The Common Rule, Title 45 Code of Federal Regulations for the protection of human subjects,

> Research activities in which the only involvement of human subjects will be in one or more of the following categories are exempt from this policy: … (4) Research involving the collection or study of existing data, documents, records…if these sources are publicly available or if the information is recorded by the investigator in such a manner that subjects cannot be identified directly or through identifiers linked to the subjects. (Emanuel, Crouch, Arras, Moreno, & Grady, 2003, p. 40)

Therefore, this study does not require that any action be taken to protect human subjects.

Dissemination of Findings

After completion of this research and the approval of this dissertation, I will disseminate the research methodology and findings to advance knowledge in the healthcare policy and hospital administration field. I will follow the recommendations of the National Center for the Dissemination of Disability Research which assert the need for the following characteristics of an effective dissemination plan:

- Oriented to the needs of the users.
- Uses multiple dissemination strategies.
- Includes effective quality controls to ensure accuracy and relevance.

- Provide complete information.
- Provides for linkages to technical assistance to assist with implementation of findings (National Center for the Dissemination of Disability and Research, 2009).

When the research is completed and findings determined, a dissemination plan will be developed consistent with the above characteristics.

After dissertation approval, I intend to develop a complete dissemination plan to include: defining who the appropriate end users are; identifying potential dissemination partners; developing a dissemination communication strategy; developing an evaluation tool to determine the effectiveness of the dissemination plan; and identifying the appropriate roll out strategies. Some of the main end users will be tax-supported hospitals in Florida, the Governor's Commission on Review of Taxpayer Funded Hospital Districts, and health care policy makers. A preliminary worksheet of potential dissemination venues is attached as Appendix B.

Summary

This chapter outlined the advantages of selecting DEA as the methodology for this study based on its ubiquity in healthcare studies by multiple researchers in varied healthcare settings. The specific DEA model used is based on the original CCR model using an input orientation and constant returns to scale. The results of this study allows for the identification of the placement of the selected hospitals on the efficiency frontier based on their technical efficiency. The technical efficiency ranking was based on the actual

performance achieved by the most efficient hospitals in the sample and therefore provides rankings based on actual achieved performance as opposed to other methods that base their rankings on theoretical performance.

The technical efficiency measures thus obtained provides those hospitals lying outside the efficiency frontier tactical direction as to the necessary reductions in inputs needed to move to the efficiency frontier as determined by the comparison to their peers. The two groups of hospitals in the analysis are tax-supported and nonprofit hospitals in the State of Florida serving the same hospital service areas. The CCR DEA model incorporates total adjusted discharges and number of outpatient visits as outputs, and beds in service, payroll, and other expenses as inputs. Data analysis was facilitated by the use of a commercial software package, DEAFrontier.

Because all the data used in the study is publicly available, and no patient-specific information was used, the potential for violating patient confidentiality is averted. Therefore this research did require steps to protect patient confidentiality. Application to Walden University's Institutional Review Board was submitted and obtained. IRB approval was obtained on June 04, 2012, approval number 06-04-12-0189982, expiring on June 3, 2013. Upon completion of this research, dissemination of findings will be undertaken based on the attached dissemination plan.

Chapter 4: Results

Overview

The purpose of this study was to determine the relative technical efficiency between tax-supported and nonprofit hospitals in Florida using data envelopment analysis. In this chapter, I present the research which was conducted to determine the answers to the two research questions:

1. To what extent are there differences in technical efficiency between Florida tax-supported and non-profit hospitals serving similar service areas?
2. What are the quantifiable potential savings to be achieved by all the study hospitals if they all operated at the efficiency frontier?

Both of the research questions were answered by evaluating the technical efficiencies of the comparison hospitals using a defined set of variables which were common among the matched set of hospitals. The constant returns to scale input oriented DEA model computes a virtual input to virtual output ratio for each DMU which describes where on the efficiency frontier each hospital is situated. Thus, the relative efficiencies of all the study hospitals can be determined. This same virtual efficiency number, which is ≥ 1.0, and the resultant slack analysis allows for a determination of the potential available savings. This analysis addressed the research hypotheses:

H_1—Tax-supported hospitals are more efficient than nonprofit hospitals.

H_2—There are no savings that can be generated by moving all hospitals to the efficiency frontier.

All of the research data were obtained from the Florida Department of Health's Agency for Health Care Administration. The data were extracted from a publically available document, the 2007 Hospital Financial Data Book. The data were first analyzed in terms of its descriptive and demographic characteristics and then analyzed with the use of DEAFrontier software. The results of the DEA analysis are then reported.

In the sections to follow, the data collection process and the measures taken to ensure validity are discussed. All the data were available from publically available sources and the source of the data is explained in detail. The sampling process and the decisions for the specific sample used in this study are described. After detailing the data collection and sampling methodology, the use of software for data analysis in the context of the DEA model chosen is demonstrated. Finally, the results of the DEA analysis are presented.

Data Collection

Data for this study were obtained from publicly available State of Florida official government sources. The primary data source was the 2007 Hospital Financial Data Book (Agency for Healthcare Care Administration, 2009) which is required to be made public pursuant to Florida Statutes Section 408.061. The data book collected data on 281 hospital campuses with a total of 61,895 licensed beds. All the data used in this study are publicly available and therefore there was no requirement to have data use agreements. Data uniformity was maintained by requiring, under Florida Administrative Code 59E-5.102, that all reporting hospitals adhere to the Florida Uniform Reporting System Manual (Agency for Health Care Administration, 2005). All reports were required to be filed within 120 days of

a hospital's fiscal year end and reports were filed electronically using a common Excel based program. The data filing also included audited financial statements and Medicare cost reports.

The validity of the data was ensured by a statutorily mandated process. After receiving the filings, the ACHA completed a review of the data within 90 days to ensure data conformity to the FHURS and to verify the data's accuracy and reasonableness. The ACHA further analyzed the data for compliance with agency rules and statutes and that it reconciled with the hospital's audit, Medicare cost report, and the state's independently collected data. To further protect the integrity of the data, the hospital's chief executive officer and chief financial officer certified that the submitted reports were true and accurate. There were some inherent strengths and weaknesses to this data gathering process:

On the positive side all data were based on audited financial reports, with an audit opinion; the reports were highly detailed using a consistent set of definitions and reporting criteria; and, the data was timely since it had to be submitted within 120 days of the hospital's fiscal year end. An additional protection for data validity was that the hospital had an additional one year to submit corrections to their financial data. All of these requirements operated in concert to ensure valid, accurate data. A concern with the data was that, when making inter-hospital comparisons, reported data may have had different hospital fiscal year ending periods. The requirement for financial data reporting for a specific calendar year was that the data submitted must be for a twelve month period ending during the calendar year regardless of fiscal year. Additionally, some data was consolidated

between multiple units and reported as a single entity, thus obviating analysis of some individual hospitals that are part of multi-hospital systems.

Data Collection Process

Data for this study were obtained from the 2007 Hospital Financial Data Book (Agency for Healthcare Care Administration, 2009). The selection of fiscal year 2007 was based on two criteria:

- 2007 was the last year with completed, audited financial information prior to the enactment of the Patient Protection and Affordable Care Act. Debates centering on health care reform were a part of the 2008 presidential election with subsequent debates prior to the passing of health reform in 2010. Thus, using 2007 data allowed for the computation of efficiency data before any potential adjustments to the upcoming health reforms could have been implemented.
- 2007 data were analyzed and were subjected to all the statutory review requirements, therefore the data was presumed to be valid and accurate.

The data for the study hospitals were extracted from the data book and transcribed to an Excel spreadsheet for analysis using DEAFrontier software.

Data Sample

The initial culling process for selecting the study's hospitals was to exclude all children's, psychiatric, federally-owned, state-owned, and any other specialty hospital not providing acute care hospital services. This decision was based on the inability to have representative comparison hospitals among the two primary categories of hospitals in the

study: nonprofit and tax-supported hospitals. The next elimination criterion was to exclude all remaining hospitals under 100 beds in size. These hospitals were usually rural facilities which were the sole community provider and did not provide full services. All the remaining hospitals, with the exclusion of for-profit facilities were considered for the study.

In order to make valid comparisons among the two categories of hospitals, a matching of non-profit with taxpayer supported hospitals in the same health care planning district was conducted. The final tally of hospitals included in the study contained 16 non-profit hospitals and 14 taxpayer supported hospitals. Due to state reporting requirements, 20 non-profit hospitals were included although the financials were consolidated for four of these facilities into their parent institutions, see Table 5.

Table 5

Study Hospitals

Taxpayer supported hospitals	Non-profit hospitals
Bert Fish Medical Center	Baptist Hospital Miami
Broward General Medical Center	Cape Canaveral Hospital
Broward Coral Springs	Doctor's Hospital
Broward Imperial Point	Florida Hospital DeLand
Broward North Broward	Florida Hospital [1]
Halifax Medical Center	Florida Hospital Fish Memorial
Health Central Acute Care	Florida Hospital Memorial
Jackson Memorial Hospital [1]	Holmes Regional Medical Center
Lee Memorial Hospital	Holy Cross Hospital
Memorial Hospital Miramar	Homestead Hospital
Memorial Hospital Pembroke	Metropolitan Hospital Miami
Memorial Hospital West	Mount Sinai Medical Center
Memorial Regional Hospital [2]	Orlando Regional Medical Center [2]
Parrish Medical Center	South Miami Hospital
	University of Miami Hospital
	Mercy Hospital
1 Consolidated with Jackson South and Jackson North	1 Consolidated with East Orlando, Orlando, and Winter Park Hospitals
2 Consolidated with Memorial Regional South	2 Consolidated with Dr. P. Phillips Hospital

A descriptive statistical summary of the variables is provided in Tables 6 and 7. The mean number of licensed beds was 500.6 for tax-supported hospitals and 552.9 for nonprofit hospitals. The total number of hospital beds included in the study was 15,848, representing 55.8% from nonprofit hospitals and 44.2% from tax-supported hospitals. See Appendix A for raw data.

Table 6

Descriptive Statistics of Nonprofit Hospital Variables (n=16)

	Beds	*Total Labor Costs*	*Other Costs*	*Total Discharges*	*Outpatient Visits*
Mean	552.9	150.29	217.86	24336.25	52032.94
Range	1844	649.1	755.09	106979	136093
Minimum	139	18.1	28.61	1581	10710
Maximum	1983	667.21	783.69	108560	146803
Sum	8847	2404.66	3485.91	389380	832527

Table 7

Descriptive Statistics of Tax-supported Hospital Variables (n=14)

	Beds	*Total Labor Costs*	*Other Costs*	*Total Discharges*	*Outpatient Visits*
Mean	500.6	131.4	169.18	19721	57362
Range	1728	622.6	725.47	106979	118425
Minimum	112	30.4	41.1	1581	19034
Maximum	1840	653.04	766.58	70373	137459
Sum	8511	2229.37	2876.08	335258	975162

Data Analysis

The data were analyzed using DEAFrontier, a commercially available DEA software package based on the Excel Solver. A constant returns to scale, input oriented model was employed because the study's hospitals were selected with a consideration towards the potential impact of scale efficiencies on the results. Hospitals with fewer than 100 beds were excluded for this reason. The mean hospital size of tax-supported hospitals in this

study was 500 licensed beds representing 8847, and 552 licensed beds for nonprofit hospitals with a total of 8511 licensed beds.

Another consideration in DEA modeling was the orientation used, whether an input, output, or both input/output orientation. In this study, the assumption was made that hospitals only had direct control over inputs since outputs were dependent on the medical staff which was not directly controlled by hospital management. White and Ozcan (1996) asserted that "it is more appropriate to direct the discussion to inputs, where planners, policymakers, and managers of resources have more control over reducing excess resource consumption" (p. 304). Therefore, the model used was a CRS, input oriented approach.

Results

The results of the data analysis performed with DEAFrontier software are detailed in Table 8. Eight hospitals were identified as technically efficient; four were taxpayer supported and four were nonprofit hospitals.

Table 8

Summary of Technical Efficiency Results

Technical Efficiency λ	Taxpayer Supported Hospitals *n*=14	Non-profit Hospitals *n*=16	Combined Hospitals *N*=30
High	1.0 (*n*=4)	1.0 (*n*=4)	1.0 (*n*=8)
Low	0.5480	0.800	0.292
Mean	0.8356	0.800	0.7957

After analyzing the two inputs and three outputs in the DEA model, the results were that overall 26.7% of the study hospitals were technically efficient. When analyzed by

governance categories, 28.6% of the tax-supported hospitals were technically efficient when compared to their peer grouping. They had a mean technical efficiency score of 0.8356. Nonprofit hospitals had 25% of the hospitals in the technically efficient category with a mean score of 0.800. The two hospital group's mean technical efficiency scores (λ) were similar with a difference of only 0.0356 in their scores. The distribution of efficiency scores are displayed in Figure 7 actual scores by hospital are presented in Appendix C.

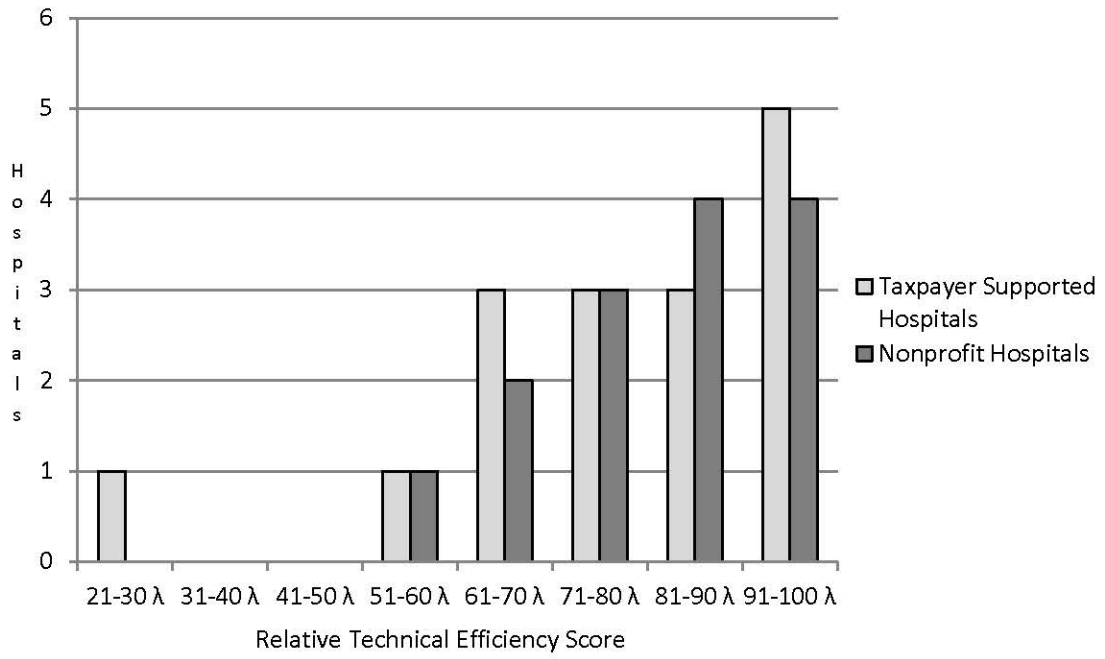

Figure 7. Distribution of technical efficiency scores.

After combining the two hospital groups to assess their relative technical efficiency, the mean score dropped to 0.7957. Only 8 out of 30 hospitals had a score of 1.0. The lowest score remained at 0.292. It was not significant that out of the eight technically

efficient hospitals, four were nonprofit hospitals and four were tax-supported hospitals. Tax-supported hospitals comprised 46% of the sample and they represented 25% of the technically efficient hospitals. While nonprofit hospitals comprised 55.5% of the hospitals they represented 28.6% of the technically efficient facilities, the results are summarized in Table 9.

Table 9

Relative Technical Efficiencies—Combined Hospitals

Technical Efficiency λ	Combined Hospitals *N*=30
High	1.0 (*n*=8)
Low	0..292
Mean	0.7957
% Nonprofit Hospitals	56 (25 λ1.0)
% Tax-supported Hospitals	44 (28.6% λ1.0)

The results of the DEA analysis demonstrated an overall small technical efficiency difference between tax-supported and nonprofit hospitals in this sample. The mean number of efficient tax-supported hospitals was 28.6% while nonprofit hospitals were, on average, 25% efficient.

Research Questions

Using DEAFrontier software, the research questions were satisfactorily addressed:

1. To what extent were there differences in technical efficiency between Florida tax-supported and nonprofit hospitals serving similar service areas?

Neither hospital category was more efficient than the other when analyzing them as a combined peer group. The number of efficient hospitals was nearly similar among both groups, see Table 10. The mean efficiency scores were nearly similar. The largest difference among the study hospitals was the lowest efficiency nonprofit hospital had a score or 0.292 where the lowest scoring taxpayer supported hospital had a score of 0.548.

Table 10

Efficiency Scores

DMU Name	Efficiency	DMU Name	Efficiency
a	0.950462226	A	0.738196611
b	0.739476098	B	0.793521162
c	1	C	0.648961475
d	0.897123895	D	1
e	0.858428871	E	0.907928305
f	0.738176101	F	1
g	1	G	0.890391144
h	0.548012963	H	1
i	0.869819601	I	0.678549942
j	1	J	1
k	0.743983099	K	1
l	1	L	0.542825194
m	0.650648412	M	0.93218414
n	0.702598308	N	0.660451422
		O	0.292048262
		P	0.76073473

2. What were the quantifiable potential savings to be achieved by all the study hospitals if they all operated at the efficiency frontier?

Slack analysis demonstrated the input reductions necessary to achieve full efficiency by the study hospitals. Table 11 summarizes these results addressing the input variables.

Table 11

Input Slack Analysis

Input	Value	Number of Facilities *
Beds in Service	348	5
Labor Costs	18.4M	5
Other Costs	301.66M	9

Note: * Number of hospitals reporting slacks per variable

Some hospitals did not have enough slack to achieve efficiency through input reductions only and they also require output increases to achieve full efficiency, these facilities are identified as having output slacks in Table 12. Overall, there is a potential for $320.06 million in savings among those hospitals with input slacks. Since the model used in this study is an input oriented model, the identification of output slacks is ignored. Nevertheless, the potential for an average of $12.8 million savings per hospital not located on the efficiency frontier was significant.

Table 12

Slack Analysis

	DMU Name	Input Slacks (I) Beds in Service	(I)Total Labor Costs ($M)	(I)Other Costs ($M)	Output Slacks (O)Total Discharges	(O) Outpatient visits
1	a	0	0	3.82	882	0
2	b	0	0	0	0	10796
3	c	0	0	0	0	0
4	d	21	0	0	0	0
5	e	0	0	0	0	3717
6	f	0	0	0	0	55042
7	g	0	0	0	0	0
8	h	0	0	0	0	129024
9	i	0	0	0	0	111888
10	j	0	0	0	0	0
11	k	104	2.37	0	0	1126
12	l	0	0	0	0	0
13	m	0	2.99	0	0	58427
14	n	0	0	0	0	0
15	A	0	0	66.70	0	55434
16	B	0	5.22	0	0	0
17	C	0	0	24.14	0	3309
18	D	0	0	0	0	0
19	E	0	0	0.00	0	273081
20	F	0	0	0.00	0	0
21	G	32	1.53	0.00	0	16777
22	H	0	0	32.31	0	87531
23	I	92	6.29	0	0	37981
24	J	0	0	0	0	0
25	K	0	0	0	0	0
26	L	0	0	26.44	0	4066
27	M	0	0	56.57	0	188390
28	N	0	0	41.11	0	17979
29	O	99	0	22.02	1970	0
30	P	0	0	6.33	0	44157

Research Hypotheses

The two research hypotheses were addressed by the study:

- H_1—tax-supported hospitals were more efficient than nonprofit hospitals.

There were no significant differences in overall technical efficiency based on hospital category.

- H_2—there were no savings that could be generated by moving all hospitals to the efficiency frontier.

DEA analysis demonstrated significant savings were potentially available if all the study hospitals operated at the efficiency frontier. The total potential savings was $302.06 million.

DEA by its very nature is not amenable to classical hypothesis testing allowing for rejecting or adopting the hypothesis based on *p* test values.

Summary

This study utilized the DEA, input-oriented constant returns to scale model to assess the potential differences between taxpayer supported and nonprofit hospitals in matched health planning districts in Florida. There were a total of 14 tax-supported hospitals and 16 nonprofit hospitals in the study. All the data used in the study were publicly available and were verified by the State of Florida's Department of Health Services. DEAFrontier software was used to analyze the data.

Evaluation of the technical efficiency of the study hospitals did not reveal a significant difference between tax-supported and nonprofit hospitals. DEA efficiency

results were nearly similar in terms of the number of facilities at the efficiency frontier. Tax-supported hospitals represented 28.6% of the efficient hospitals and nonprofit hospitals were 31.25%. The DEA model's slack analysis computed a significant potential savings of $320.06 million if all the study hospitals were operating at the efficiency frontier.

Chapter 5: Discussion, Conclusions, and Recommendations

Overview

The purpose of this study was to determine the relative technical efficiencies between a matched set of Florida tax-supported hospitals and their nonprofit counterparts. There were two primary impetuses for this study. First, pending health care reforms subsequent to the passage of the Patient Protection and Affordable Care Act will put additional pressures on hospitals to demonstrate their efficiency as it is fully implemented beginning in 2014. Tax-supported hospitals have justified their preferred status, allowing them to levy taxes, based on their provision of indigent services. In Florida, the governor appointed a commission to assess whether these hospitals were operating efficiently and thereby using public funds effectively. Second, after a thorough literature review, there was no available research discovered examining the relative efficiencies between these two hospital governance categories.

This study was conducted to assess the relative technical efficiencies between these two categories of hospitals using Data Envelopment Analysis (DEA). DEA was extensively used to assess technical efficiency in many sectors of the health care industry (O'Neill, Rauner, Heidenberger & Kraus, 2008). The variables used in the study were validated in multiple studies (Grosskopf, Margaritis, & Valdmanis, 2001; Hajialiafzali, Moss, & Mahmood, 2007; Helmig & Lapsley, 2001; Hofmarcher, Paterson, & Riedel, 2005; Magnussen, 1996). Further, the availability of software to provide the computational tools

facilitated the research. DEAFrontier was used in many studies and received wide acceptance.

After selecting a sample, matched geographically and accounting for economies of scale, a sample of 30 hospitals was used in the study. Fourteen of the study hospitals were tax-supported and the remaining 16 were nonprofit hospitals. All the hospitals were full service facilities and were matched by health planning districts. The analysis did not demonstrate a significant difference in technical efficiency between the two hospital categories. The only significant finding was that the lowest performing nonprofit hospital was substantially less efficient than the lowest performing tax-supported hospital. Slack analysis demonstrated a potential savings of $320.06 million if all the study hospitals operated at the efficiency frontier.

In the sections that follow I describe the findings in the context of previously published research. The values of using DEA as a research methodology for assessing the relative efficiencies of hospitals based on governance structure are demonstrated. Limitations of the study are addressed along with recommendations for further research. Finally, implications for social change and the implications for the practice of hospital management are discussed.

Interpretation of the Findings

Peer reviewed literature researching international health care facilities demonstrated the value of DEA as a tool for efficiency assessment in public hospitals. In the United States, studies using DEA have evaluated the impacts of mergers, the influence of HMO

penetration, and the efficiency differences between different types of hospitals. I was unable to find any studies evaluating the relative technical efficiencies between the two categories of hospitals in this study. The theoretical foundation for this study was based on Farrell's measurement of technical efficiency (Farrell, 1957). Based on Farrell's germinal work, Charnes, Cooper, and, Rhodes developed data envelopment analysis as a tool to measure productive efficiency (Charnes, Cooper& Rhodes, 1978). Ferrier and Valdmanis (2004) stressed the benefits of DEA in measuring hospital efficiency. Over the past 40 years, DEA proved to be an effective method for assessing hospital efficiency.

The results of the DEA analysis demonstrated no difference in technical efficiency between the two categories of hospitals. Slack analysis demonstrated a potential savings of $302.6 million if all the study hospitals operated at the efficiency frontier. The findings did not reveal any results that conflict with published literature. Although I found no studies evaluating these two categories of hospitals, studies evaluating the efficiency of other categories of hospitals were inconclusive.

Limitations of the Study

The primary limitation of this study was based on the nature of DEA. DEA computed technical efficiency based on actual best performance of the study hospitals. Therefore, no results could be applied to facilities that are not included in the computation. DEA did not generate a theoretical efficiency measure. Both the sample size and the geographic site provided two additional limitations. Because of the study design, where nonprofit hospitals were matched geographically with similar tax-supported hospitals, the

sample size was limited to 30 facilities which met the study criteria. The study was limited to the state of Florida.

Generalizability of results was not recommended outside of Florida. The sample size limited generalizing results to larger samples. The results were valid for this sample because the data were available from a reliable, constant formatted source, and audited by Medicare, the hospital's auditors, and the state's Agency for Health Care Administration. Further, the state required hospitals to provide amended reports if errors were discovered. The data set used for the study met all of the above criteria. The study was limited to technical efficiency and price information was omitted because technical efficiency analysis excludes prices. Analyzing efficiency with price data is known as allocative efficiency "when information on prices and costs are known exactly" (Cooper, Seiford, & Tone, 2007, p. 257). In order to use prices, they must be common among all DMUs, this is not the case in hospitals because prices are individually adjusted based on negotiated rates and state rate setting mechanisms.

Implications for Future Applications

DEA might be used as a competitive analysis tool to determine the relative technical efficiency of a facility versus its competitors. Hospital management could use DEA to rate the relative efficiency of their hospital versus their local competitors. This might be a useful tool to determine how far off the efficiency frontier they lie based on actual performance in their specific market. Additionally, demonstrating actual performance benchmarked against competitors may serve as a useful motivational tool.

The slack analysis also provides direction as to potential strategies to improve efficiency. Although, not used as a modeling tool in any of the published research included in Chapter 2, a study using DEA as a modeling tool might provide an additional tool for hospital managers in making strategic decisions. For example, slack analysis of outputs may direct whether an increase of outpatient versus inpatient services would be the most efficient tactic. This use of DEA may provide a useful competitive advantage.

Implications for Social Change

This study provided two positive contributions to social change:

1. Tax-supported hospitals can use findings from DEA in this study to justify their taxing authority by demonstrating funds are being efficiently utilized. Objective findings will obviate anecdotal arguments these hospitals are not as efficient as other hospital categories.

2. An effective way to reduce waste of valuable public resources is via slack analysis which provides direction for strategies to improve efficiency. As health care reforms are implemented, additional pressures to provide more services with limited resources will increase.

Thus, tax-supported hospitals might be able to justify their tax levying authority. Additionally, the results of technical efficiency analysis might serve as a useful marketing tool to justify increased funding to provide specific services such as preventive services and indigent care. Finally, the DEA model can be used as a management tool to ensure community support by demonstrating efficient use of resources.

Implications for Future Research

A contribution of this study is in filling a gap in the DEA research literature, which is an established hospital efficiency methodology, to extend its use to the relative efficiencies of hospitals with different governance categories. The use of DEA in benchmarking hospital efficiency based on actual performance will assist hospital management by providing an additional tool which can be used to assess where the hospital lies on the efficiency frontier. The slack analysis also provides tactical direction to improve efficiency.

Additional research in these specific governance categories of hospitals is necessary to validate this methodology as a competitive analysis tool. Extending the sample to additional geographic areas and segregating by hospital size may provide additional data to determine the applicability of DEA across health care planning districts. Lastly, the application of DEA as a management tool to monitor hospital performance should be explored.

Recommendations

This study demonstrated the value of DEA in establishing the relative efficiencies among different categories of hospitals. The variables used, called input and output variables in DEA, were extensively used in prior hospital efficiency studies and they yielded valuable results. Additional research, using these same variables and hospital governance categories in other states is advised to add to the validity of this method of assessing hospital relative efficiency. Evaluating smaller and larger data samples may validate the rule of

thumb in DEA that the sample size should be at least three times the number of inputs and outputs.

Conclusion

One of the reasons for choosing this research topic was the timeliness of the subject because Florida Governor Rick Scott had established a commission to review taxpayer-funded hospital districts. The commission was charged with, among several other factors, the cost of care and effectiveness of these hospitals, which have tax levying authority. At the same time, two additional environmental factors motivated this study. First, the recession placed additional pressures on taxing authorities to justify their level of taxation. Additionally, pending health care reforms will place greater demands on the health care system requiring more efficient delivery of services.

The Florida governor's commission did not address these issues but focused on governance structure in their recommendations. Their own finding was that "total operating expenses in public hospitals being 11 to 12 percent higher" (Commission on Review of Taxpayer Funded Hospital Districts, 2012, p. 15). This analysis is not dispositive, however, since the comparison was between public hospitals compared to all hospitals. The DEA analysis provided in my study compared two hospital categories controlling for scale, geography, and service mix. The results are useful to health policy makers, hospital managers, and health insurance providers because decisions can be based on an objective, proven methodology.

The results of this study demonstrated that there was no significant technical efficiency difference between tax-funded and a matched group of nonprofit hospitals. This finding is important for several reasons.

- It can serve to justify the tax levying capability of tax-supported hospitals.
- It demonstrated that DEA may be a useful tool to assess technical efficiency differences by policy makers and rate setting organizations.
- It demonstrated the value of DEA as a competitive analysis tool to permit hospital management to assess the relative efficiency of their organizations compared to their competitors.
- It demonstrated the potential for significant savings by moving all hospitals to the efficiency frontier.
- Finally, the study contributes to the DEA analysis literature.

Additional research is required to validate these findings in other states to determine their generalizability for public policy purposes. The variables used in this study have been validated by numerous researchers and therefore appear to be a reasonable basis for additional studies. DEA as a methodology for competitive analysis might be expanded to determine its value as a tactical tool.

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Appendix A: Raw Data

All the following data were extracted from the 2007 Florida Hospital Financial Data publication produced by the Florida Department of Health Services' Agency for Health Care Administration. The data was compiled on January 24, 2009 and made publicly available pursuant to Florida Statute. All the data are based on hospital-specific audited financial reports.

Hospital ID	(I) Beds in Service	(I)Total Labor Costs ($M)	(I)Other Costs ($M)		(O)Total Discharges	(O) Outpatient Visits
a	112	30.39	53.29		4,951.0	31,165.0
b	716	158.99	214.86		27,640.0	92,613.0
c	200	50.06	68.91		11,876.0	46,231.0
d	204	35.96	46.46		7,419.0	28,747.0
e	409	76.98	100.48		15,274.0	50,097.0
f	654	178.02	226.83		29,560.0	66,852.0
g	171	49.19	54.76		10,559.0	51,869.0
h	1840	653.04	766.58		70,373.0	137,354.0
i	709	175.80	208.80		33,803.0	36,923.0
j	178	36.46	41.10		6,860.0	44,443.0
k	301	49.44	51.49		7,387.0	35,161.0
l	304	121.82	134.24		22,602.0	83,495.0
m	993	290.78	318.57		39,936.0	137,459.0
n	210	56.43	70.57		8,606.0	41,295.0
A	680	205.42	403.47		32,522.0	93,128.0
B	150	52.18	53.12		6,844.0	33,036.0
C	281	45.28	104.58		7,843.0	18,501.0
D	156	35.81	50.52		8,648.0	46,361.0
E	1983	667.21	783.69		108,560.0	146,803.0
F	139	41.34	64.01		9,000.0	41,543.0
G	277	70.24	76.09		11,855.0	41,458.0
H	514	180.62	266.18		33,517.0	49,970.0
I	571	132.33	136.18		16,522.0	43,180.0
J	142	44.69	79.04		8,502.0	45,284.0
K	146	18.10	28.61		5,295.0	10,710.0
L	955	135.12	255.51		20,447.0	45,258.0
M	1343	510.30	665.72		81,413.0	125,837.0
N	467	113.62	220.15		17,680.0	49,704.0
O	560	50.34	146.43		1,581.0	19,034.0
P	483	102.06	152.60		19,151.0	22,720.0

Appendix B: Dissemination Plan Worksheet

Please use this form to plan for dissemination of your study, including journal publications, book publications, professional conference presentations, and local/work-related presentations.

Name	Jose Fernandez
Title of Study	Comparison of the technical efficiency of tax-supported and non-profit Florida hospitals using data envelopment analysis
Date	

Journals

Journal Title	Journal of Healthcare Management
Website	www.ache.org/publications
Submission Requirements	Manuscript text, abstract, and endnotes: Submit one document in a standard word-processing format (such as MS Word) that includes your 100-word abstract (not required for Narrative Matters submissions), the main text of the manuscript, and the endnotes; all text should be double-spaced and prepared in 12-point Courier New font or its equivalent. All pages should be numbered. This file MUST NOT include a cover page or any other pages that identify the authors of the manuscript. It must also not include any running headers or footers that identify the authors. All of the material in this file will be counted in your document word count. Do not include exhibits or supplemental material as part of this file.
Submission Deadlines	Journal is a monthly, no deadlines stated. When a special edition dedicated to one topic is produced, the deadlines are published in advance.
Planned Submission Date	November, 2012

Journal Title	Health Affairs
Website	www.healthaffairs.org
Submission Requirements	Report the number of words in the manuscript. The count that you report must include the abstract, main text, and endnotes, but not exhibits or supplemental materials. NOTE: most Health Affairs papers are between 2,500 and 5,000 words; our

	maximum length is 5,000 words (that total includes abstract, main text, and references/endnotes). The sources of funding for the paper (this information will be included with the paper if it is published, so please word it just as you would like it to appear). Whether any authors have conflicts of interest related to the submission (this information may be included with the paper if it is published, so please word it just as you would like it to appear). Whether there are acknowledgments, disclaimers, or disclosures (this information will be included with the paper if it is published, so please word it just as you would like it to appear).
Submission Deadlines	N/A, monthly journal. At times editors invite authors to submit articles
Planned Submission Date	September, 2012

Journal Title	Healthcare Financial Management
Website	www.hfma.org/hfm
Submission Requirements	Manuscript preparation. Please prepare an electronic manuscript according to the recommendations of The Associated Press Stylebook. The first page of the manuscript should include the working title of the article, as well as the author's full name, degrees, institutional affiliation, address, telephone number, and e-mail address. Multiple contributors should designate a corresponding author. Paragraphs should be kept short and single spaced, with a line of space between each paragraph. Please state your ideas simply and try to avoid wordy or overly complex sentences. An informal tone is always appreciated by our busy readers. Subheads are encouraged. It is not unusual for an 800-1,200 word article to have 2-3 subheads in addition to the main head (i.e., the title). The best subheads are short (never more than a phrase, and never a complete sentence).
Submission Deadlines	N/A
Planned Submission Date	September, 2012

Professional Conferences

Conference/ Event Title	National Council of State Human Service Administrators
Website	www.apwa.org
Requirements	Abstract submitted in advance for approval, invitation offered to present at annual conference.
Deadlines	December, 201
Planned Presentation Date	March, 2013

Conference/ Event Title	American Hospital Association Annual Conference
Website	www.aha.org
Requirements	By invitation only
Deadlines	March, 2013
Planned Presentation Date	June, 2013

Conference/Event Title	
Website	
Requirements	
Deadlines	
Planned Presentation Date	

Presentations to Local/Work Related Groups, Such As Boards

Venue	Florida Hospital Association
Website	http://www.fha.org/education/index_html
Requirements	N/A
Deadlines	By invitation
Planned Presentation Date	Annual meeting, TBA (October, 2012)

Venue	Florida Chamber of Commerce—Leadership Florida
Website	www.Leadershipflorida.org
Requirements	Membership in good standing
Deadlines	Three months before regional meetings
Planned Presentation Date	July, 2012

Venue	Walden Poster Presentation
Website	WWW.//Waldenu.edu
Requirements	Per Poster Presentation Guidelines
Deadlines	TBD
Planned Presentation Date	Summer-Winter residency

Books

Publisher	Health Administration Press
Website	www.ache.org/hap
Submission Requirements	N/A
Submission Deadlines	N/A
Planned Submission Date	Prospectus to be submitted second quarter, 2013

Publisher	
Website	
Submission requirements	
Submission Deadlines	
Planned Submission Date	

Publisher	
Website	
Submission Requirements	
Submission Deadlines	
Planned Submission Date	

Appendix C: Efficiency Scores of Study Hospitals

DMU No.	DMU Name	Efficiency
1	a	0.903914372
2	b	0.721849631
3	c	1
4	d	0.852973578
5	e	0.806071257
6	f	0.738176101
7	g	1
8	h	0.547725601
9	i	0.853532202
10	j	1
11	k	0.743983099
12	l	1
13	m	0.650648412
14	n	0.681397141
15	A	0.73370135
16	B	0.728299499
17	C	0.648163473
18	D	1
19	E	0.807238764
20	F	1
21	G	0.807942912
22	H	0.934661755
23	I	0.629144322
24	J	1
25	K	1
26	L	0.542482151
27	M	0.83706028
28	N	0.651599214
29	O	0.292048262
30	P	0.758921609

Jose Fernandez

Curriculum Vitae

EDUCATION

Walden University, Minneapolis, MN—Doctoral Candidate 2009-2012

University of Miami, Coral Gables, Florida MBA—1985

Florida International University, Miami, Florida—1981 BS in Industrial Technology

Miami Dade Community College, Miami, Florida AS 1975 Respiratory Therapy Technology

Miami Dade Community College, Miami Florida AA 1973

PROFESSIONAL EXPERIENCE

1994-1995	Interim President Molina Medical Centers, Long Beach, CA
Dec 1993--Present	President, Integrated Health Strategies, Inc.
1992-1993	Deputy Director, California Department of Health Services
1990-1992	Chief Executive Officer, Natividad Medical Center, Salinas, CA
1990-1993	Chief Executive Officer, Southeastern Medical Center, North Miami Beach, FL
1987-1989	Adjunct Professor, Andreas School of Business, Barry University, Miami Shores, FL
1986-1987	Chief Operating Officer, Southeastern Medical Center, North Miami Beach, FL

1986-1989	Adjunct Assistant Professor, Department of Family Medicine, Southeastern University of the Health Sciences, North Miami Beach, FL
1984-1986	Chief Executive Officer Coral Reef Hospital, Miami, FL
1983-1984	Assistant Administrator, Coral Reef Hospital, Miami, FL
1981-1983	Owner, Medical Instrumentation Brokers, Miami, FL
1978-1981	Director—Cardiopulmonary Services, Coral Reef Hospital, Miami, FL
1970-1978	Technical Director—Respiratory Therapy, Mount Sinai Medical Center, Miami Beach, FL. Started as Respiratory Therapy Trainee and was progressively promoted, culminating in the Director position in 1975.

RELATED PROFESSIONAL POSITIONS:

2011-Present	Florida Supreme Court Certified Mediator
1995-Present	Managing Director, privately held conglomerate
1991-1993	Advisor to National Governor's Association in care of Vulnerable Populations, appointed to advise White House on Health Care reform initiatives
1987-1989	Instructor, Barry University School of Business, Miami, FL
1986	Legal Expert Consultant, Medical Quality Foundation
1985-1986	Assistant Clinical Professor, Southeastern College of Osteopathic Medicine, North Miami Beach, FL
1980-1981	Consultant, Hospital Affiliates Management Corporation, Nashville, TN
1980-1981	President Asociasion de Latino Americano Paramedicos
1978-1980	Instructor, Respiratory Therapy Institute, Miami, FL

1976-1979 Clinical Instructor of Respiratory Therapy—Miami Dade Community College

PROFESSIONAL CREDENTIALS

1974 Certified Respiratory Therapy Technician
Physician's Assistant-SP2
1974 Registered Emergency Medical Technician—Florida license #5707
1976 Registered Respiratory Therapist #4039
CPR-ALS Instructor
Clinical Laboratory Technician—Florida #15515
1980 Certified Cardiopulmonary Technician
1981 Clinical Laboratory Supervisor #0009330 (Chemistry Special)
1981 Registered Cardiopulmonary Technician—35153

PROFESSIONAL AFFILIATIONS:

- Fellow American College of Healthcare Executives (Retired)
- Miami's for Me—Committee of 100
- Board of Director's Salinas Valley Salvation Army
- Leadership Florida
- Parent Resource Center Board of Directors
- Coconut Grove Arts Association Board of Directors
- Zoological Society of South Florida Board of Trustees
- Dade Marine Institute Board of Director
- Recipient—AMI Outstanding Achievement Award
- California Association of Public Hospitals—Board of Directors
- Asociacion de Paramedicos Pulmonares—President
- Registered Emergency Medical Technician, Florida
- Registered Respiratory Therapist
- Registered Cardiopulmonary Technologist
- Clinical Laboratory Technologist
- Physician's Assistant—SP-2

PUBLICATIONS:

Clinical Assessment of the Patient with Respiratory Distress, Respiratory Therapy, Vol. 8, No. 5, pp. 21-24

Simulated Mandatory Ventilation Placebo Therapy with a Ventilator, Chest 72:5, November, 1978.

Cultural and Linguistic Standards, Medicaid Managed Care: A Guide for States, National Academy for State Health Policy, November, 1995.

Expanding Medi-Cal Managed Care, California Department of Health Services, 1993.

PERSONAL ACHIEVEMENTS:

Successfully completed RRT self-examination, 1977,1978, 1979, and 1980
Instrument Rated Private Pilot
Extra Class Amateur Radio License
Captain—United States Air Force Auxiliary (Retired)
Civil Air Patrol Florida Wing Emergency Services Director-2005
Alumni—Boy Scouts of America

MEMBERSHIPS:

- Academy of Management
- Project Management Institute
- American Public Health Association
- American Radio Relay League—Life Member
- American Thoracic Society—Elected 1977
- Good Sam's Club—Life Member
- National Rifle Association—Life Member
- Aircraft Owners and Pilots Association
- Experimental Aircraft Association
- Warbirds of America
- Tucson Amateur Packet Radio
- SE VHF Society
- Daytona Beach Amateur Radio Association—Life Member
- American Radio Club International RP
- Cessna Pilot's Association
- Cessna Owner's Organization
- American College of Health Care Executives
- National Association of Medicaid Directors
- AMSAT
- ARCI-QRP
- National Academy for State Health Care Policy

- Society of Biomedical Equipment Technicians
- National Academy for the Advancement of Science