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BENCHMARKING COMMUNITY HEALTH CENTERS' EFFICIENCY:
MULTIVARIATE ANALYSIS

by

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ABSTRACT

Community Health Centers (CHCs), designed to provide accessible and affordable health care services to low-income families, were first funded by the Federal Government as part of the War on Poverty in the mid-1960s.

Improving healthcare organizational performance efficiency is paramount. It is an especially pressing need for CHCs' because they carry a disproportionate burden of caring for the uninsured within limited budgets. Prior studies suffer from conceptual and methodological limitations. A longitudinal multivariate analysis of factors influencing the performance of CHCs is needed.

The purpose of this study is to benchmark CHC performance in terms of technical and cost efficiency, and examine factors that affect its variation. A theoretically grounded non-experimental study design is used, with five waves of panel data from 493 CHCs for the years 2000 through 2004.

This study found that data mining and predictor tree analysis of factors influencing the variation in CHCs' technical and cost efficiency yielded inconsistent results. A declining trend in technical efficiency scores over the five-year study period was observed. Based on growth curve modeling, the three factors that influenced technical efficiency at the initial period of the study are: the percentages of Medicare, Medicaid, and Hispanic population being served by the CHCs. The five factors that positively influenced the variation in cost efficiency at the initial period were: the initial score of technical efficiency, the percentage of Hispanic patient population, staffing mix (ratio of providers to total staff), pay mix (ratio of federal grant dollars to total revenue), and percentage of Medicare-eligible. The initial cost-efficiency score and the initial

technical efficiency score are negatively associated with the growth trend of technical efficiency. The initial level of technical efficiency is not statistically significantly associated with the growth trend of cost efficiency. The two factors influencing the growth trend of cost efficiency are the growth trend of technical efficiency (with a positive influence) and the initial level of cost efficiency (with a negative influence). Analysis of the effects of contextual and organizational-structural variables on the technical efficiency and cost efficiency of community health centers found that the explanatory power of the predictors is much greater for cost efficiency than for technical efficiency. The study lends support to contingency theory and confirms the independent and additive influences of contextual and organizational predictors on efficiency. Irrespective of the efficiency measures, contextual factors have much more influence on CHCs' efficiency than design (organizational structural) factors do. The three study hypotheses supported by multivariate analysis are: technical efficiency is associated with contextual factors and organizational factors; cost efficiency is associated with contextual factors and organizational factors; and technical efficiency positively affects cost efficiency.

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LIST OF ACRONYMS/ABBREVIATIONS

AE	Allocative Efficiency
AGOF	Adjusted Goodness of Fit
ARF	Area Resource File
BPHC	Bureau of Primary Health Care
CHC	Community Health Center
CDP	Context-Design-Performance
CE	Cost Efficiency
CEO	Chief Executive Officer
CFI	Comparative Fit Index
C/MHC	Community Health Centers and Migrant Health Centers
DEA	Data Envelopment Analysis
DHHS	Department of Health and Human Services
DMU	Decision Making Unit
DTREG	Data Tree Regression
FTE	Full Time Employee
GAO	General Accounting Office
GOF	Goodness of Fit
HEDIS	Health Plan Employer Data and Information Set
HHS	Health and Human Services
HRSA	Health Resources and Services Administration
ISDI	Integrated Services Development Initiative
LP	Linear Programming
NCQA	National Committee on Quality Assurance
NP	Nurse Practitioner
OEO	Office of Economic Opportunity
PA	Physician Assistant
RMSEA	Root Mean Square Error Approximate
TE	Technical Efficiency
TEE	Total Economic Efficiency
UDS	Uniform Data Sets

CHAPTER ONE: INTRODUCTION

Background

The growth of the Community Health Center (CHC) program has been whipsawed by the changes in presidential administrations. The health center program began in the mid-1960s as part of the Johnson administration's War on Poverty and has evolved from a simple, two-neighborhood health center demonstration project into a complex system with over 3000 clinic sites comprising of community and migrant health centers, primary care programs for public housing residents, and programs of health care for the homeless (Okada & Wan, 1980; Okada & Wan, 1979). The CHC program has provided a unique model of health care that includes traditional primary care services as well as preventive and enabling (support) services. The value of more accessible and less expensive primary care is well established (Politzer et al., 2003). Since inception, CHCs have proved to be effective in overcoming barriers to health care among the uninsured. The uninsured patients served by health centers have been shown to be less likely to postpone seeking care and more likely to receive counseling on health issues than are their counterparts who seek care in other health care settings (Mathematica Policy Research, 1999).

Throughout its 40-year history, the health center program has focused on certain key goals and features: to reduce disparities in health care, to involve the community in providing services and management through community participation on health center boards, and to provide universal access to high-quality health care. As of 2001, CHCs had provided preventive and primary care to one-fifth of the nation's underserved (Politzer et al., 2003).

Community Health Centers (CHCs) were first funded by the Federal government as part of the War on Poverty in the mid-1960s. By early 1970s, about 100 neighborhood health centers

had been established under the office of economic opportunity (OEO) to provide accessible, affordable personal health care to low-income families. The Public Health Service began funding neighborhood health centers in 1969. When OEO was phased out in the early 1970s, the centers supported under its authority were transferred to the Public Health Service. Currently, the CHC federal grant program is authorized under section 330 of the Health Centers Consolidation Act of 1996, and is managed by the Bureau of Primary Health Care (BPHC). Community health centers and migrant health centers (C/MHCs) currently serve approximately 15 million people throughout the U.S. The Bush administration in 2002 authorized an expansion initiative to serve 16 million people by the year 2006, and 20 million in the near future (National Association of Community Health Centers, 2004). Since 2001, 600 new or expanded CHCs have been added. The FY 2005 budget request for a 13.5 percent increase in C/MHC funding represented a funding increase of \$219 million. Along with expansion of existing centers and addition of new sites, many centers have integrated.

CHC Mission, Activities and Appropriation

CHCs provide family-oriented, primary and preventive health care for medically underserved people living in rural and urban communities. CHCs exist in areas where economic, geographic, or cultural barriers limit access to primary health care for a substantial portion of the population.

CHCs provide the following services:

- Primary and preventive health care, outreach, and dental care.

- Ancillary services: laboratory, X-ray, environmental health, pharmacy, health education, transportation, translation, and prenatal services.
- Coordination of referral and other services such as specialty care, welfare, WIC, Medicaid, mental health and substance abuse treatment.
- Economic development: CHCs catalyze economic development, generate jobs, and ensure the presence of health professionals and facilities in underserved areas. In fiscal year (FY) 2000, CHC investment generated over \$3 billion in revenues for impoverished communities across the country.
- Grant support for a system of integrated services delivery to improve the quality and reduce the cost of health care for underserved, uninsured people.

In fiscal year (FY) 1996, The Health Resources and Services Administration (HRSA) consolidated the community and migrant health center appropriation to include the homeless and public housing programs as well. Table 1 shows the funding for CHCs (approximately 85 percent of the consolidated appropriations).

Table 1: CHC Funding

Fiscal Year (FY)	FY 1997	FY 1998	FY 1999	FY 2000	FY 2001	FY 2002
Funding	\$802.0 million	\$825.0 million	\$925.0 million	\$1.018 billion	\$1.17 billion	\$1.3 billion

Study Problems

Research Needs

The literature identifies a number of research needs. More information is needed about the characteristics of CHCs with higher proportion of uninsured, and about how that affects their financial operation (Rosenbaum et al., 2000). The relationship between financial and service inefficiencies and/or administrative factors should be explored, to help determine the appropriate grant support for the centers most in need. A valid evaluation of CHC efficiency, using longitudinal data also is needed. Organizational analysis of CHC efficiency would identify the match between organizational structure (design) characteristics and context or environmental characteristics that would maximize CHC efficiency. CHC CEOs must respond quickly and appropriately to market changes, rising costs and threats to revenue streams; this study can guide the efforts by CHC CEOs to maintain and improve CHC financial performance.

Data Set Needs

GAO (2000) reported that HRSA had recognized the significance of monitoring CHC performance, and added that HRSA “. . . could improve its monitoring processes and oversight tools, especially its data collection efforts” (GAO, 2000, p. 35). By compiling, organizing, and analyzing data, this study identifies the limitations in the data that are essential to fully assess CHC performance. The study is expected to help refine the data collection instruments such as the Uniform Data Set (UDS), and the data collection processes.

Purpose of the Study and Research Questions

Study Purposes

Performance connotes a constellation of several constructs, including effectiveness and efficiency. This study is circumscribed to the examination of efficiency. The value of conducting a thorough investigation of CHC efficiency has been highlighted by a recent GAO report (2000) that urged the development of assessment tools and analytical methods to establish best practice benchmarks. A national study of CHCs' efficiency is needed. A longitudinal analysis of a panel of CHCs will identify trajectories of efficiency indicators and the factors influencing the variation in CHC efficiency. By increasing scientific knowledge regarding CHC efficiency, this study aspires to guide efficiency improvement. Establishing the best CHC exemplars in efficiency, irrespective of time points, assessing the patterns and trends of indicators of CHC technical and cost efficiency and identifying their predictors will have immediate practical and policy applications for CHC managers and policy makers. Finally, the success of the CHC expansion initiated by the Bush administration rests on being able to identify the favorable organizational characteristics and mechanisms that can improve CHC efficiency. In particular, scientifically cogent answer to the momentous question of whether a change in CHC technical efficiency effects a positive change in cost efficiency over multiple time points would furnish the evidence needed.

Research Questions

The research questions arising from these study purposes are:

1. What are the profiles of highly efficient CHCs, irrespective of time points?

2. Are there any patterns and trends of technical and cost efficiency observed among CHCs over a period of five years?
 - a. What are the patterns and trends of technical efficiency for CHCs?
 - b. What are the patterns and trends of cost efficiency for CHCs?
3. What are the predictors of technical and cost efficiency observed among CHCs over a period of five years?
 - a. What are the predictors of technical efficiency among CHCs?
 - b. What are the predictors of cost efficiency among CHCs?
4. Does a change in a CHC's technical efficiency positively affect a change in cost efficiency?

Hypotheses

Three research hypotheses associated with the research questions are as follows:

- H₁. CHCs' technical efficiency is associated with contextual factors such as the percentage distribution of Medicare, Medicaid, and Hispanic populations in the service areas and with organizational factors such as staff mix (ratio of providers to total staff) and federal funding (paymix = ratio of federal grant dollars to total revenue).
- H₂. CHCs' cost efficiency is associated with contextual factors such as the percentage distribution of Medicare, Medicaid, and Hispanic populations in the service areas and organizational factors such as staff mix and federal funding.
- H₃. A change in CHCs' technical efficiency positively affects a change in CHCs' cost efficiency.

Conceptual Framework

Context-Design-Performance Framework

Figure 1 illustrates the conceptual model used in this study, a context-design-performance (CDP) framework that allows for observation and measurement of interrelationships among a health center environment (context), organizational structure (design), and performance. CDP is derived from the contingency theory articulated by Lawrence and Lorsch (1967) and Jay Galbraith (1973) to portray a natural, open system of organization. Its main tenet is that “there is no optimal organizational response and no two responses are equal” (Wan 1995). Contingency theory affords insufficient attention, however, to the interplay between the contextual and organizational factors that influence organizational performance. This weakness in the conventional contingency theory can be ameliorated by considering both independent and the additive influences of contextual and organizational structural (design) factors in model specification. Furthermore, a longitudinal, panel design can ascertain the causal influences of contextual and organizational factors on CHC performance.

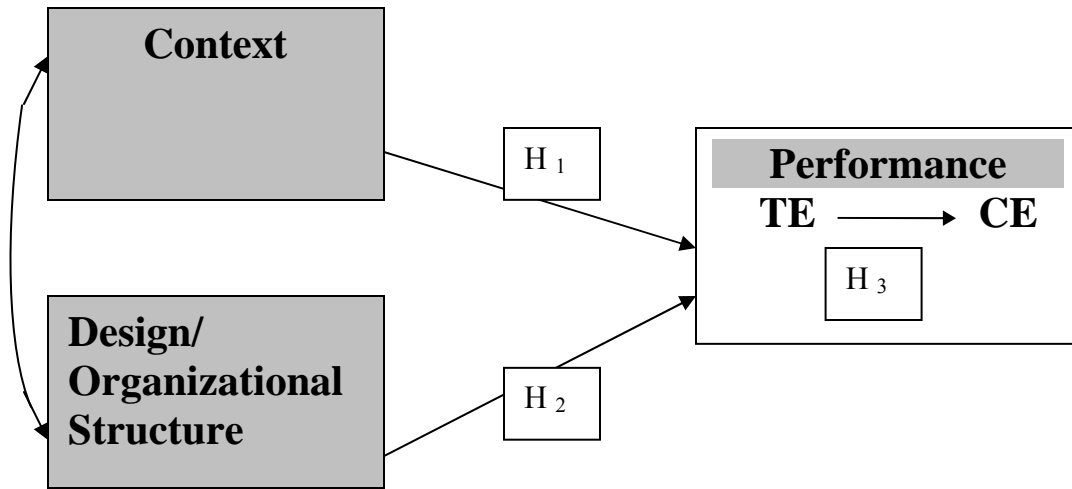


Figure 1: The Modified Context-Design-Performance (CDP) Framework for Assessing CHC Performance

Study Methodology

The study is a non-experimental panel study of 493 CHCs, with CHC as the unit of analysis. Data on all variables are compiled from the CHC administrative data systems for the period between 2000 and 2004. The CHC data file was merged with the Area Resource File to constitute a comprehensive research data set for exploring the relationships among the contextual, organizational structural (design), and performance variables. Analytical techniques include data mining with predictor tree analysis of high-performance CHCs, data envelopment analysis (DEA) of technical efficiency, and latent growth curve modeling of multi-wave performance indicators of technical efficiency and cost efficiency. Each hypothesis was

empirically tested. The analytical model of C-D-P was validated by multivariate modeling techniques.

Overview of Remaining Chapters

Chapter 2 reviews the literature on CHC performance with emphasis on efficiency, including the organizational and environmental determinants of CHC efficiency. Chapter 3 presents the theoretical framework used in the study. Chapter 4 introduces the research methods: research design, data sources, sampling, variable measurements and statistical approaches. Chapter 5 presents empirical results of the study, including descriptive statistics and validation of the overall model. Finally, Chapter 6 offers a summary of the empirical findings, tests of the hypotheses proposed in earlier chapters, policy implications of the results, limitations of the study, recommendations for future research and study conclusions.

CHAPTER TWO: LITERATURE REVIEW

Financial Challenges to the CHC Program

Financial Stability

Although CHCs have demonstrated success in providing primary care, they have been less successful financially. Many centers are on the brink of insolvency (McAlearney, 2002). During the 1998 – 2000 timeframe, the Health Resources and Services Administration (HRSA), a division of Health and Human Services (HHS) reported that about 10 percent of all health centers were in major financial difficulties (GAO, 2000). The factors contributing to poor financial performance are not fully understood, but include inadequate management, the burden of the uninsured, increasingly competitive health care markets, and insufficient funding. Examples of poor management practices are the inability to control expenditures, unfavorable contracts with other providers and managed care organizations, inappropriate or inadequate responses to market changes, and ineffective business operations (GAO, 2000).

The burden of the uninsured has increased. During the 10-year period immediately prior to the GAO study period of 1988 to 1997, the number of uninsured non-elderly persons in the U.S. grew by 30 percent (Lewin & Altman, 2000). The number of uninsured patients served by CHCs also grew. CHCs with greater increases in their percentages of uninsured users have incurred greater deficits per medical encounter (McAlearney, 2002). The increase in uninsured patients and in the need for care of the homeless and immigrants have raised the cost of providing services (Hawkins & Rosenbaum, 1997). As Medicaid managed care grew during the 1990s, CHCs faced more competition for Medicaid patients and the prospect of reduced Medicaid revenues. During the period 1996 - 1999, those CHCs serving Medicaid patients under

managed care patients performed worse than financially than did those whose Medicaid patients were not under managed care (McAlearney, 2002). During the years 1990 through 1998, CHC funding remained constant even though CHC operating costs increased (Lewin & Altman, 2000). About half of the community health centers and mental health centers (C/MHCs) had some operational or financial problems by the mid-1990's (GAO, 2000). For every year between 1997 and 1999, more than half of CHCs reported deficits (McAlearney, 2002). These perils threaten to erode the CHC safety net system and limit the healthcare access of vulnerable populations. It is imperative to better understand the factors that adversely affect CHC efficiency, so that it can be improved.

Related Research

Some studies have found CHCs to be inefficient. For example, a GAO (1976) study of CHCs found inefficiencies including overstaffing given the number of patients. Brecher and Forman (1981) compared costs of nine CHCs to those of private, for-profit group practices and found that CHCs had higher expenditures for their non-medical staff, which contributed to raising overall costs. In contrast to those studies, Goldman and Grossman (1983) found that CHCs were not necessarily cost-inefficient. Some studies found the cost of care per patient provided by CHCs to be less than that of other providers (Braddock, et al., 1994; Davis & Schoen, 1978; Sharfstein & Nafziger, 1976). Recent literature on CHC efficiency describes how CHCs are responding to the challenges in the current health care environment. Some studies describe how CHCs are responding to the impact of managed care on their financial performance by integrating and forming their own HMOs (Abrams, 1995; Lesser, Duke & Luft, 1997). Other studies analyze CHC performance of care from the patients' perspective. For example, Shi and

colleagues (2003) compared the quality of CHC patient care as reported by patients to that of HMOs and found that CHC users were more likely to rate their primary care providers as good except in the area of first contact.

Efficiency

Taxonomy

Farrell (1957) proposed that efficiency of a firm consists of two components: technical efficiency (TE), which is the ability of a firm to obtain maximal output from a given set of inputs, and allocative efficiency (AE), which is the ability of a firm to use the inputs in optimal proportions, given their respective prices and production technology. Allocative efficiency is also defined as the efficiency of a production process in converting inputs to outputs, where the cost of production is minimized for a given set of input prices. Allocative efficiency can be calculated by the ratio of cost efficiency to technical efficiency. These two measures are combined to provide a measure of total economic efficiency (TEE). The measures are bounded by zero and one. These efficiency measures assume that the efficient production function is known. In practice, the efficient production function is an estimate derived from sample data.

Cost efficiency (which is also known as economic efficiency) is the ratio of the minimum cost to the actual (observed) cost (Cooper, Seiford & Tone, 2000).

Shiell, Donaldson, Mitton and Currie (2002) in their discussion of health economics posit that for technical efficiency, an objective such as the provision of necessary healthcare services is axiomatic. Technical efficiency is about how best to achieve that objective; about ensuring the production of the same level of output with less of one input and no more of other inputs or,

equivalently, maximizing the output that one gets from given quantities of inputs. Technical efficiency is linked to cost effectiveness, in that the cost effective combination of technically efficient inputs minimizes the cost of achieving a given level of output.

Shiell, Donaldson, Mitton and Currie (2002) further posit that in allocative efficiency, all objectives compete with each other for implementation. For example, "should we allocate more resources to the prevention of childhood injury or improve clinics for children with chronic disease such as asthma?" is a question of allocative efficiency. Allocative efficiency questions whether to do something, or how much of it rather than how to do it. Allocative efficiency in health care is achieved when it is not possible to increase the overall benefits produced by the health system by reallocating resources between programs.

Productivity is the ratio of the unit's outputs to its inputs (Cooper, Seiford & Tone, 2000). Productivity is a function of production technology, the efficiency of the production process and the production environment. DEA does not measure productivity; it measures the efficiency of the production process (Cooper, Seiford & Tone, 2000). Productive efficiency (often just referred to as efficiency) is a measure of a unit's ability to produce outputs from a given set of inputs (Cooper, Seiford & Tone, 2000). The efficiency of a decision making unit (DMU) is always relative to the other units in the set being analyzed, thus the efficiency score is always a relative measure. A unit's efficiency is related to its radial distance from the efficient or efficiency frontier; it is the ratio of the distance from the origin to the inefficient unit, over the distance from the origin to the composite unit on the efficient frontier (Cooper, Seiford & Tone, 2000). Scale efficiency denotes optimality of the size of operation; if the size of operation is either reduced or increased, its scale efficiency will drop. Scale efficiency is calculated by dividing aggregate efficiency by technical efficiency. Slack represents the under production of output or

the over use of input. It represents the improvements needed to make an inefficient unit become efficient (Cooper, Seiford & Tone, 2000). These improvements are in the form of an increase/decrease in inputs or outputs. A unit is said to be technically efficient if it maximizes output per unit of input used. Technical efficiency is the efficiency of the production or conversion process and is calculated independently of prices and costs. The impact of scale size is ignored for the technical efficiency calculation, as the size of decision making units (DMU) is similar (Cooper, Seiford & Tone, 2000).

Technical Efficiency

Farrell illustrated his ideas by using a simple example of firms that use two inputs to produce a single output, assuming constant return to scale. Knowledge of the production function of fully efficient firms (the frontier) permits the measurement of technical efficiency. If a given firm uses quantities of inputs to produce a given quantity of output, the technical inefficiency of that firm could be represented by the amount by which all inputs could be proportionally reduced without a reduction in output.

Efficiency Measurement in This Study

In this study, CHC efficiency is treated as a latent construct that is measured by two related indicators of efficiency: technical efficiency and cost efficiency. This study assumes that CHCs attempt to maximize the number of patient encounters. Technical efficiency is calculated as a ratio of the number of encounters relative to three categories of clinicians/care providers: physicians, physician assistants (PA), and nurse practitioners (NP) to total cost. Technical inefficiency is the extent to which a CHC fails to achieve the maximum possible number of

encounters. Cost efficiency is computed by the total cost of CHC operations divided by the total number of encounters.

Factors Contributing to Efficiency

A number of factors that contribute to CHC efficiency have emerged from the literature. They are grouped into two categories: context and design (organizational structure). It is important to identify the relationships between the contributory factors and efficiency.

Contextual Factors

Variables representing environmental characteristics of CHCs are treated as contextual variables constituting multiple contingencies within organizations that can either facilitate or impede their performance (Wan, 1995). The environmental characteristics are median income (median income of the county where the CHC is located), Medicare (the percentage of the population that is Medicare eligible), poverty (the percentage of the population with income below 200 percent of poverty level), physicians (the number of physicians per thousand population), female (the percentage of the population that is female), birth rate (number of births per thousand population), uninsured (the percentage of the population that is uninsured), crude mortality rate, minority (percentage of the population that is African American and percentage that is Hispanic), region (the health center's DHHS region), and rurality (the health center's location in either an urban or a rural area). Each variable is explained in more detail below.

Poverty is defined as the number of persons living in poverty as a percentage of the county population. In this study the combined number of Medicaid enrollees and uninsured in the county is represented by the proxy variable “poverty”. This variable is important in the

study model as a demand characteristic because three-quarters of all community health center patients are below 200 percent of the federal poverty level and 85 percent are low-income (Rosenbaum et al., 2000). Minority: African American and Hispanic populations increase the demand for CHC services. More than half of CHC patients are from minority populations. In 1997, 26 percent of CHC patients were African American, and 31 percent were Hispanic (Kaiser, 2000). Each of these minority groups increases the demand for services such as pre-natal care and care for heart disease and stroke. On the whole, minority populations are more likely to be poor and to endure poverty-related conditions such as chronic illnesses, poor health behavior, and stress. African-American children are two-and-a-half times as likely as white children to die within the first year of life (National Association of Community Health Centers, 2003). Mexican-American women are more likely than non-Hispanic whites to have high blood pressure (American Health Association, 2003). Blacks and Hispanics have a higher age-adjusted incidence of diabetes than Whites have (National Council de la Raza website, 2004).

Design (Organizational Structure) Factors

The design variables used in this study are: size, which denotes the number of FTEs in the following professional categories of care: medical, dental, mental health, and substance abuse, and in other professional and enabling services, staffing, i.e. number of FTEs in each of the non-professional categories: administrative staff, facility staff, and patient services support staff, expressed as a percentage of total FTEs; payer mix, which denotes financial resources expressed as a percentage obtained by dividing grant revenue by total revenue; and integration or network alliance, i.e. participation in a network funded by the Integrated Services Development Initiative.

Factors Influencing CHCs' Efficiency

Cost of Care/Production

Most previous studies have analyzed costs on a cross-sectional basis, and costs relative to other forms of primary care. Few studies have analyzed the trends in CHC cost of care or productivity. Some of those studies have concluded that CHCs are less costly as compared to other providers (Zuvekas, 1990; Duggar, 1994). Other studies have shown that CHCs are not necessarily any less cost-efficient (e.g., Goldman and Grossman, 1983). Stuart and Steinwachs (1993), in their analysis of nearly 70,000 Medicaid recipients, found that after controlling for patient mix, those Medicaid recipients who identified a federally qualified health center as their usual source of care had overall more ambulatory care visits at less cost per visit than did those who sought care at a hospital outpatient department.

Physician Visits

Studies addressing CHC productivity usually, but not invariably, suggest that CHCs increase the overall rates of encounters per physician (Johns Hopkins Primary Care Policy Center for the Underserved, 1999). Goodrich and Gorry (1980) compared the rates of visits for ambulatory care before and after transferring patients from hospital outpatient clinics to CHCs and found that the visit rates to CHCs were higher. Okada and Wan (1980) found an increase in the number of CHC visits per person in 1975 compared to those in 1969.

Other Factors

Other factors empirically related to CHC efficiency in the literature include integration, expansion, managed care participation, growth in numbers of uninsured, Medicaid as a revenue source and staffing.

Since 1994, integration among CHCs and between CHCs and other safety-net providers has been facilitated through the federal Integrated Services Development Initiative (ISDI). Expected outcomes for the resulting networks included 1) cost efficiencies; 2) economies of scale (for functions such as billing and collections, claims management, and information management); 3) sharing of expertise and staff among collaborators; and 4) a “value-added aspect of higher performance” in areas such as revenue, staff utilization, and data capture (Bureau of Primary Health Care, 2000). As of 2000, approximately 36 percent of all health centers were in ISDI networks (Ortiz, Fottler, & Hofler, 2005), and since then the number of CHCs participating in the initiative has continually increased. Ortiz, Fottler, & Hofler (2005) examined the relationship between CHC participation in the federally-funded ISDI networks and their performance during the early years of network formation (first half of the 1990s). Their study found no evidence of cost efficiencies or higher performance in staff utilization in ISDI network member CHCs. Since more CHCs have participated in networks during the latter half of the 1990s, the financial effects of network participation call for ongoing assessment.

During the period of 1998 through 2003, 60 percent of the study panel of CHCs added sites. Table 2 shows the percentage of study panel CHCs that added sites for each of the number sites added. During 1998 – 2003, 22.2 percent of CHCs added two sites and 16.3 percent added five or more sites.

Table 2: Expansion in the Study Panel (1998 - 2003)

Number of Sites Added	Percent of CHCs
1	31.8%
2	22.2%
3	10.9%
4	12.1%
5	6.7%
>5	16.3%

Such internal CHC expansion has the potential to improve efficiency by achieving economies of scale and improving the use of capacity (Robinson, 1996). However, Dalton & Kesner (1985) found no evidence that large firms enjoy cost savings or more profits, although expansion may yield cost savings for small firms. Among the factors enabling an organizational strategy to succeed is the organization's ability to implement strategy, and also maintaining "organizational will," i.e. the organization's ability to engage in behaviors that move it toward its goals (Press, 2001). It is quite possible for there to be a time lag before the CHC expansion strategy yields more positive financial performance. Previous research suggests that favorable financial performance may result only after five or more years from the time of strategy implementation (Rhyne, 1986; and Shortell, 1988b). A study of the performance of rural hospitals after the adoption of one or more management strategies demonstrated how strategy-derived effects may be delayed. It was observed that the study hospitals actually performed worse (as measured by total margin, operating margin, and patient margin) in the year when strategies were adopted (Chung, 1995). Thus, the effects of expansion on CHC performance may be negative during the next few years before beginning to stabilize or improve in later years.

During the period between 1991 and 1996, the percentage of CHCs with managed care arrangements increased from 6 to 45 (Shi et al., 2000). Using 1996 data, Shi and colleagues studied the relationship between CHCs' participation in managed care and their ability to fulfill the CHC mission. They found that CHCs participating in managed care incur higher costs than non-managed-care centers have.

Forty percent of all CHC patients are "self pay" and are likely to be uninsured (Kaiser, 2000). Between 1980 and 1999, numbers of both uninsured and Medicaid patients served by federally-funded health centers increased. Between 1990 and 1997 the uninsured caseload for health centers grew by 50 percent, while for the nation it grew by 21 percent (Rosenbaum et al., 2000). During the period of 1998 – 2003 the number of uninsured patients in CHCs increased by 37.24 percent. Over the period 1990 – 1999 the number of CHC Medicaid patients doubled. The increasing numbers of uninsured are likely to increase the demand for CHC services and compel CHCs to provide more charity care. To maintain financial stability, CHCs might provide fewer enabling services. However, McAlearney (2002), in his study of CHC trends from 1996 – 1999, found the opposite: more centers had increased the number of enabling services they offered.

A large portion of the total CHC revenue comes from Medicaid. It represented 34.6 percent of the total revenue in 1997 (Kaiser, 2000). Medicaid collections as a percentage of total revenue remained fairly stable throughout the study period – 62.61% in 1998 and 63.87 percent in 2003 (UDS trend data for years 1996 through 2003). Note, however, that Medicaid revenue may not exceed reasonable cost of care for Medicaid patients (Kaiser, 2000).

A 1976 GAO study found that CHCs tended to be overstaffed for the number of patients being treated (Johns Hopkins Primary Care Policy Center for the Underserved, 1999). More recent studies (Shi et al., 1993 & 1994) found a positive association between center size and the

number of NPPs (non-physician providers), suggesting that larger centers may be able to reduce labor costs by using more NPPs. Brecher and Forman (1981) assessed various aspects of costs for CHCs as compared to those for private, profit-making group practices. They found that at some of the CHCs, high expenditures for non-medical providers substantially increased costs.

Relationships of CHCs' Contextual and Organizational Factors to Efficiency

In this study, the structural relationships of contextual and organizational (design) factors to CHCs' efficiency are examined by both cross-sectional and longitudinal analyses. Ideally, management style, leadership, strategic activities, care coordination, and other center-based patient care activities should be observed as design factors. However, the CHC database lacks those data at this time.

Critique of Related Studies

A systematic review of the empirical research on the study subject identifies the following concerns.

Limited Theoretical Specifications

The literature offers no theoretical underpinning to explicate research findings. This study's modified CDP theoretical framework addresses that deficiency.

Unidentified Traits of High-Performance CHCs

Between September, 1998 and January, 2000 the GAO conducted a study of CHCs, using health center data, interviews and case studies. The study found that successful centers adapt to

changes in the health environment. Some of the contributing factors to success were: integration into networks, participating in managed care, acquiring JCAHO accreditation, having patients with diverse payment sources, private donations, and strong billing and collections systems (GAO, 2000). This confirmatory study follows the exploratory GAO study to empirically examine the success characteristics identified by the GAO and other earlier research.

Lack of Methodological Rigor

A number of earlier case studies found CHCs to have weathered the changes in the health care market (Dievler & Giovannini, 1998). However, conclusions from these case studies may not be generalizable to other CHCs. The efficiency of CHCs must be examined for both the independent and additive function of organizational and environmental factors, so as to reveal the relative influences of relationships between these factors on efficiency. By identifying the determinants of CHC efficiency, this study discerns the common traits of the best performing CHCs and is therefore expected to be useful for guiding organizational improvement.

Lack of Longitudinal Analysis of CHC Performance

There have been no empirical longitudinal studies that assess CHC efficiency. To ascertain causal influence, it is necessary to examine CHC efficiency patterns and trends with their predictors empirically.

Lack of Evidence-Based Guidance for Performance Improvement

CHC efficiency improvement calls for evidence-based guidance. This study fills the gap in empirical research and offers, as well, a model based on a data-driven theoretical framework to derive indicators for efficiency improvement. Those efficiency indicators can establish an evidence base to guide efforts toward CHC efficiency/improvement.

CHAPTER THREE: THEORETICAL FRAMEWORK

Need for a Theoretically-Informed Framework and Conceptualization

An appropriate conceptual model to consider is based on the general systems framework of input, process, and output factors in combination with “a concern for the economics of production” (Myers, Smith, & Martin, 2005; Wan, 1995). Such a framework should guide the development of research hypotheses and the formulation of predictive models of the determinants of CHC efficiency, involving longitudinal observations. This analytical modeling of the determinants of CHC performance can identify the best practice CHCs and the factors influencing the variation in efficiency indicators.

Context-Design-Performance Framework

Figure 3 shows that the conceptual model used in this study; the context-design-performance (CDP) framework that allows observation and measurement of the interrelationships among a health center’s environment (context), organizational structure (design), and performance. CDP is derived as a strategic adaptation of the contingency theory. Contingency theory, articulated by Lawrence and Lorsch (1967) and Jay Galbraith (1973), is a natural, open type of organizational theory that is based on systems theory. Its main tenet is that “there is no optimal organizational response and no two responses are equal” (Wan 1995). For organizations with less complex functions and a small professional staff, a closed, rational theory such as Frederic Taylor’s industrial theory or Weber’s beurocratic theory may be apposite. For more organic organizational forms such as healthcare institutions with their higher density of professionals, an open, natural approach may be needed (Mick, 2002).

Contingency theory overemphasizes the structural and contextual influences and depreciates the role of effective managers, whose enlightened strategic management techniques can improve organizational performance (Wan 2003). Contingency theory also pays insufficient attention to the interplay between the context and organizational factors that influence organizational performance. This weakness in the conventional contingency theory can be ameliorated by considering the independent and additive influences of contextual and organizational factors in model specification. A longitudinal, panel design can ascertain the causal influences of contextual and organizational factors on CHC performance. This modified recursive framework has been articulated as a Context – Design – Performance framework (Wan 2003). Hendrick (2003) noted that the organization's successful adaptation to its environment is contingent on its fit with its environment. Hendrick (2003) also notes that the processes by which contextual and organizational process factors affect organizational performance are unclear.

Figure 2, adopted from Hendrick (2003), offers three plausible examples of causal relationships among the context-design-performance factors. The figure advances the original formulation of other investigators (Boals and Bryson, 1987; Wan, 1995) that articulated three paradigms for causal specification of the contingency theory. Paradigm A specifies that context directly affects design, which in turn directly affects performance. Paradigm B specifies that context and design may have both independent and additive effects on performance. Paradigm C specifies that the relationship between design and performance is contingent on context, suggesting an interaction effect.

CHCs are funded only if certain primarily contextual conditions are met: indicators of poverty, ethnicity, and lack of health insurance. The emphasis on contextual factors suggests that

contextual factors will be the dominant predictors of CHC efficiency. For this reason, paradigm B, which posits that context and design may have independent and additive effects on performance, is likely to be a paradigm more applicable to a study of CHC efficiency. The substantial direct effect of contextual predictors on CHC efficiency would militate against paradigm A, which specifies that context affects design which then affects performance, and against paradigm C, which specifies that the relationship between design and performance is contingent on context, suggesting an interaction effect.

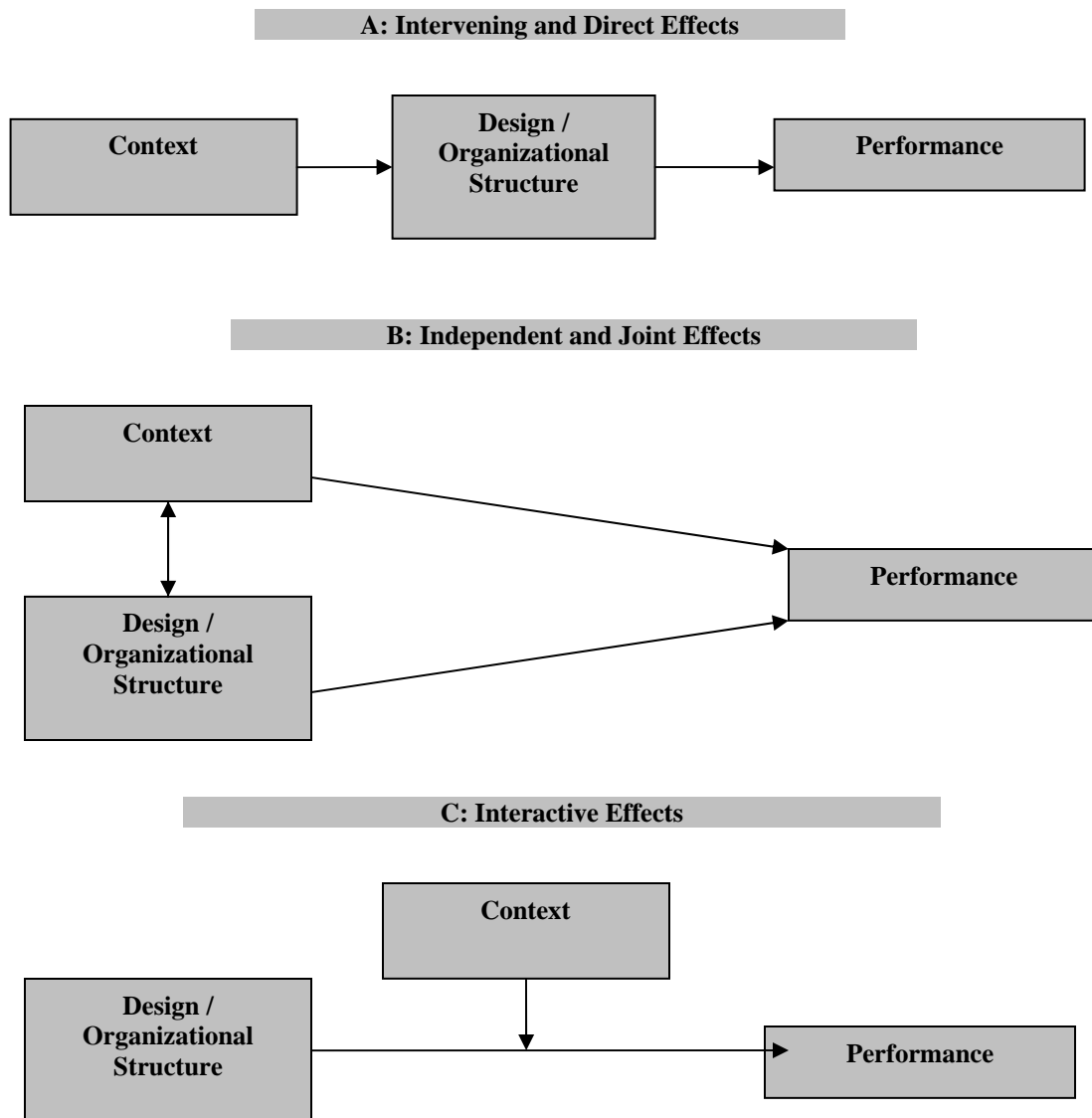


Figure 2: Possible Theoretical and Empirical Relationships among Context-Design-Performance

Paradigm B, which posits that context and design may have both independent and additive effects on efficiency as an indicator of performance, is assumed to be the one most applicable to this study of CHC efficiency. The reason for this assumption is that CHC funding is predicated on having met certain preconditions that are primarily contextual. Grantor emphasis

on contextual factors such as poverty, ethnicity, and lack of health insurance is derived from the core mission of CHCs: to serve the underserved. That mission confers dominance on contextual factors as predictors of CHC efficiency. A modified contingency framework is shown in Figure 3.

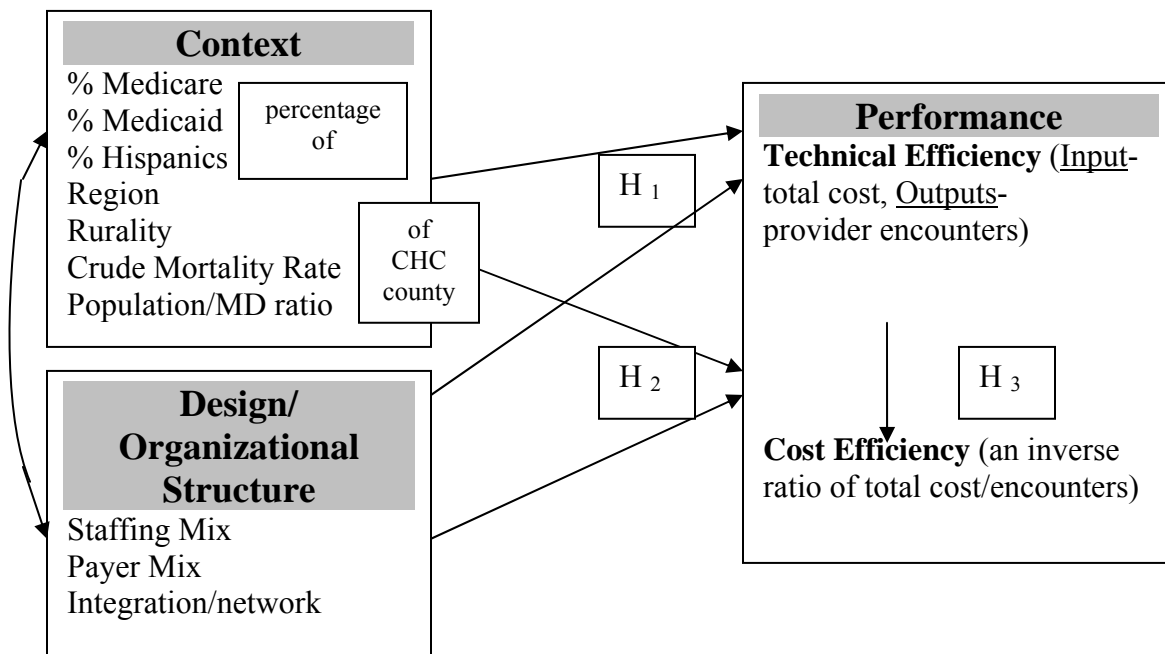


Figure 3: The Context-Design-Performance Framework for Assessing CHC Performance

Hypothesis Generation

The following section applied the tenets from the CDP framework, cited in Figure 3, to address the research questions raised in Chapter 1. Testable hypotheses were deduced from the contingency theory of organizational performance.

The Relationship of Contextual and Organizational Factors to Efficiency

Indicators of environmental characteristics such as Medicaid (McAlearney, 2002) and ethnicity (Kaiser, 2000) are usually treated as contextual variables influencing organizational performance. They can either facilitate or impede organization performance (Wan, 1995). Several related studies (Lewin & Altman, 2000, Rosenbaum et al., 2000) cited in the previous chapter suggest that the poor financial performance of community health centers is attributable to the burden of the uninsured, increasingly competitive health care markets, and insufficient federal fund availability.

As detailed in the literature review, the burden of the uninsured has increased. During the 10-year period immediately before the study period of 1988 to 1997, the number of uninsured, non-elderly persons in the U.S. increased by 30 percent (Lewin & Altman, 2000). With the growth of Medicaid managed care during the 1990s, CHCs faced the prospect of increased competition for Medicaid patients and decreased Medicaid revenues. During the period 1996 - 1999, those CHCs with Medicaid patients under managed care, performed worse financially than did those with Medicaid patients not under managed care (McAlearney, 2002).

Poverty is defined as the number of persons living in poverty as a percentage of the county population. This variable is important in the study model as a demand characteristic because three-quarters of all community health center patients are at or below 200 percent of the federal poverty level (Rosenbaum et al., 2000).

African American and Hispanic populations increase the demand for CHC services. More than half of CHC patients are from minority populations. In 1997, 26 percent of CHC patients were African American, and 31 percent were Hispanic (Kaiser, 2000). Black children are two-and-a-half times more likely than white children to die within the first year of life

(National Association of Community Health Centers, 2003). Mexican-American women are more likely than non-Hispanic whites to have high blood pressure (American Health Association, 2003). Blacks and Hispanics have a higher age-adjusted incidence of diabetes than Whites have (National Council de la Raza website, 2004).

As noted in the literature review, GAO (2000) found poor management practices among CHCs, including the inability to control expenditures, unfavorable contracts with other providers and managed care organizations, inappropriate or inadequate responses to market changes, and ineffective business operations. However, poor management is an elusive construct that cannot be measured by the instruments currently deployed to evaluate CHC performance and therefore is not available in the dataset used in this study.

Some studies that found CHCs to be inefficient related that finding to design (organizational structure) factors. For example, the GAO (1976) study of CHCs found various inefficiencies, including overstaffing given the number of patients. Brecher and Forman (1981) compared costs of nine CHCs to private, for-profit group practices and found that CHCs had higher expenditures for their non-medical staff that contributed to increased overall costs. In contrast to these studies, Goldman and Grossman (1983) found that CHCs were not necessarily cost inefficient. Several studies found the cost of care per patient provided by CHCs to be less than that of other providers (Braddock et al., 1994; Davis & Schoen, 1978; Sharfstein & Nafziger, 1976). Another organization structure (design) factor examined was network participation. Ortiz, Fottler, & Hofler's (2005) examined the relationship between CHC participation in the federally-funded ISDI networks and their performance during the early years (first half of 1990s) of network formation. Their study found no evidence of cost efficiencies in

ISDI network member CHCs but since more CHCs have participated in networks during the late 1990s, the financial effects of network participation need renewed assessment.

Other organizational factors that have been shown to relate to CHC efficiency are staffing mix, payer mix (percentage of grant/total revenue) (tpayermix) and network participation. More productive staff, less ready availability of grant funds and the synergy derived from network participation form a mix of factors that is deemed conducive to efficiency, forcing CHC managers to modify their organizational structure, operate more efficiently and focus on financial stability.

The hypotheses based on the relationship of the contextual and organization-structural factors to efficiency are formulated as follows:

- H₁. CHCs' technical efficiency is associated with contextual factors such as the percentage distribution of Medicare, Medicaid, and Hispanic population in the service areas and organizational factors such as staff mix and federal funding.
- H₂. CHCs' cost efficiency is associated with contextual factors such as the percentage distribution of Medicare, Medicaid, and Hispanic population in the service areas and organizational factors such as staff mix and federal funding.

The Relationship between Technical Efficiency and Cost Efficiency

Efficiency is a complex concept that consists of cost, process and technical aspects of production (Wan 1995). A commonly used measure of efficiency is the ratio output/input (Cooper, Seifeord & Tone, 2000). Such measures are sometimes referred to as "partial productivity measures" so as to distinguish them from "total factor productivity measures,"

because the latter ratio is obtained by accounting for all outputs and all inputs rather than for a segment of production such as productivity per employee, which the former ratio measures (Cooper, Seifeord & Tone, 2000). The lower the cost for the same output, the higher the technical efficiency and the lower the cost inefficiency. A production process is technically inefficient if production can be increased using the same amount of inputs. A production process is cost-inefficient if production could be maintained with a different combination of inputs at lower cost. Technical efficiency or productivity refers to producing the maximal output from a given vector of inputs.

No studies have addressed the causal relationship between technical efficiency and cost efficiency with regard to CHC efficiency. In an assessment of hospital performance by Wan (1995), cost efficiency was measured by costs per admission or costs per day, and process efficiency or productivity by proxy measures such as patient days per full time employee, admissions per FTE and physician visits per physician FTE (Wan, 1995). The study found that financial viability of hospitals was influenced by hospital efficiency (Wan, 1995). Technical efficiency calculated through DEA is an improvement over the typical ratio measures of productive efficiency (Wan, 1995). To examine hospital efficiency, weighted indices of technical efficiency using DEA are an improvement over crude measures (Wan 1995). DEA methodology aggregates multiple inputs and outputs into a single summary measure of efficiency predicated on Pareto optimality, not an arbitrary weighing scheme (Nunamaker, 1983). Nunamaker (1983) analyzed nonprofit hospitals' technical efficiency scores and total cost savings measured as cost/day of nursing services over two years and found that to discern inefficiency, DEA was a more sensitive method than the customary methods of government agencies. Technical efficiency is an indicator of productivity, which in turn is predicated on efficiency of processes

or work design, and can be expected to improve cost efficiency or organizational effectiveness (not studied here because data are unavailable). Other studies (Sherman, 1984; Grosskopf & Valdamanis, 1987; Valdamanis, 1990 and Ehreth, 1994) found that hospital technical efficiency has a positive relationship with hospital cost efficiency indicators.

In summary, it is expected that improved technical efficiency may enhance cost efficiency. Thus, the third hypothesis is postulated as follows:

- H₃. Among CHCs, the change in technical efficiency positively affects the change in cost efficiency.

CHAPTER FOUR: RESEARCH DESIGN AND METHODS

This chapter introduces research design, sampling, power analysis, classification of study variables and their measurements, analytical methods including data mining and tree analysis, data envelopment analysis (DEA), latent growth curve modeling and the steps of the analysis.

Research Design

The aim of this research is to examine the relationships among context, design (organizational structural) factors, and financial performance as measured by CHC technical and cost efficiencies.

Study Design

This study is a non-experimental panel study, with CHC as the unit of analysis. Data on all variables were compiled from the CHC administrative data systems for years 2000 through 2004.

Study Sample

A panel of 493 CHCs was used. The sample characteristics are presented in Table 3. The panel may be described by geographic area as follows: Northeast - 17.4 percent; Midwest - 17.4 percent; South - 34.7 percent and West - 27.0 percent. Approximately 85 percent of the panel CHCs are urban and 15 percent are rural.

Table 3: Number and Percentage Descriptions by Region of CHCs

	Frequency	Percent	Cumulative Percent
1.Northeast	86	17.4	20.9
2.Midwest	86	17.4	38.3
3.South	171	34.7	73
4.West	133	27.0	100.0

Sample Size and Power Analysis

A large panel of 493 CHCs with repeated measures for 5 years affords a sample size of 2,465, adequate to perform the longitudinal, multivariate statistical analyses. With 35 - 40 parameters in the proposed model to be estimated in structural equation modeling, the sample size of 2,465 meets the recommended sample size for the power of 0.80 with an alpha level of .05. Furthermore, Bollen and Curran (2004) and Bentler and Chou (1988) suggest that 5 to 10 cases per parameter are sufficient to generate proper parameter estimates.

The Classification of Study Variables and their Measurements

Table 4 shows the measurement variables classified into the contextual/ environmental factors, design/organizational structural factors, and CHC efficiency performance. A data warehouse was build to sort multiple variables into a systematic structure, informed by the theoretical constructs.

Table 4: Variables and Operational Definitions

Variable	Operational Definition
Context	
Medicare	Percentage of the population that is Medicare eligible
Poverty	Percentage of the population that is at or below 200 percent poverty level
Physicians	Number of physicians per thousand population
Minority	Percentage of population that is African American; percentage that is Hispanic
Region	US Census Region (1. Northeast, 2. Midwest, 3. South and 4. West)
Rurality- Location	Urban/rural location
Design	
Size (of staff)	Number of physicians + NPs + PAs
Staff Mix	Size/Total Staff
Integration	Member of an ISDI network (1 = member; 0 = non-member)
Financial Resources	
Federal Grants	Dollars revenue expressed as a percentage of total revenue
Total revenue	Total revenue in dollars
Performance	
Cost Efficiency	Cost per encounter
Technical Efficiency	Number of encounters (per total FTEs for three groups: physicians, PAs, NPs)

Note: The variables are measured for each of the five years (2000-2004).

Analytical Methods

Analytical techniques include data mining with predictor tree analysis of high-performance CHCs, data envelopment analysis (DEA) of technical efficiency, and latent growth curve modeling of multi-wave performance indicators of technical efficiency and cost efficiency.

Data Mining and Predictor Tree Analysis

Data mining extracts useful information from a set of data. Many techniques have been developed for data mining. In statistical analyses that assume no underlying theoretical model,

data mining is often approximated via stepwise regression methods wherein the possible relationships between a single outcome variable and potential explanatory variables are explored. A major benefit of data mining is to establish benchmarks (Wan, 2002).

However, predictor tree analysis has certain limitations. The statistical stability of the predictor tree must be established using random data with sub-samples (Wan, 2002). Size restrictions can inhibit logical and meaningful splitting of predictor trees (Wan, 2002). Causal inference cannot be generated from the cross-sectional data. Further replications of the exploratory model are necessary in order to establish reliability and consistency (Wan, 2002).

Data Envelopment Analysis (DEA)

As alluded to earlier, efficiency is a complex concept that consists of cost, process and technical aspects of production (Wan, 1995). A commonly used measure of efficiency is the ratio: output/input (Cooper, Seifeord & Tone, 2000). Ratio analysis suffers from certain weaknesses. The comparison implicit in ratio analysis does not assure that the most efficient organizations are being distinguished from poor performers (Chern & Wan, 2000). Furthermore, although ratio analysis can account for individual production, collectively, the ratios do not represent true efficiency (Sexton, 1978). Another major weakness of ratio analysis as a tool to evaluate overall performance is, subjectivity in selecting performance indicators (Chern & Wan, 2000).

Multiple regression analysis is the other conventional method to analyze efficiency of healthcare organizations (Chern & Wan, 2000). While multiple regression can use multiple inputs at one time to account for a single output, it also primarily yields estimates of average

relationships which may not be efficient unless all units being compared are efficient (Chern & Wan, 2000).

The fact that healthcare organizations such as CHCs use multiple inputs to produce multiple outputs at any given time, renders traditional ratio analysis and multiple regression techniques as suboptimal to distinguish efficient from inefficient organizations (Chern & Wan, 2000).

Data envelopment analysis (DEA) has emerged as a method to evaluate relative efficiency with applications to a manifold industries including airlines, banks, fast food establishments and healthcare (Chern & Wan, 2000). Data envelopment analysis (DEA), founded on the work by Farrell (1957) followed by Charnes, Cooper, Rhodes and Banker (1978; 1984), is a popular method for estimating frontier functions and thereby measuring efficiency of production. DEA is a nonparametric technique requiring no presupposition regarding the form of production (Wan, 2002). . DEA uses linear programming methods to construct the convex efficient production function. In order to measure both technical and allocative efficiencies for each CHC, a linear programming (LP) algorithm calculates radial distance from the actual production position of the CHC to the (fully efficient) position of that same CHC on the efficient production function curve. The availability of multiple waves of CHC performance data enables us to specify both input- and output-oriented DEA scores and to measure relative efficiency by using the ratio of weighted sum of outputs to weighted sum of inputs (Sexton, 1978). This study used an input oriented model with the reasonable assumption that CHCs have more control over inputs (resources) than outputs (provider encounters). The term “input orientated” indicates that an inefficient unit may be made efficient by reducing the proportions of its inputs but keeping the output proportions constant. The term “output orientated” indicates that an inefficient unit may

be made efficient by increasing the proportions of its outputs while keeping the input proportions constant.

Constant returns to scale may be assumed if an increase in a unit's inputs leads to a proportionate increase in its outputs i.e. there is a one-to-one, linear relationship between inputs and outputs. For example, if a 10% increase in inputs yields a 10% increase in outputs, the unit is operating at constant returns to scale. This means that no matter what scale the unit operates at, its efficiency will, assuming its current operating practices, remain unchanged. If an increase in a unit's inputs does not produce a proportional change in its outputs, then the unit exhibits variable returns to scale. This means that as the unit changes its scale of operations its efficiency will either increase or decrease (Cooper, Seifeord & Tone, 2000).

In this study, the potentially biased efficiency scores due to nonlinear relationships between service production (provider encounters), led to the choice of the more conservative VRS or variable return to scale model. DEA uses the frontier approach to estimate technical efficiency of decision making units abbreviated as DMUs. Decision making unit was the name used by Charnes, Cooper and Rhodes (1978) to describe the units being analyzed in DEA. The use of this term is intended to redirect the emphasis of the analysis from profit making businesses to decision making entities; thus the analysis which is performed can be applied to any unit based enterprise regardless of profitability. DEA calculates the maximum relative efficiency score of each decision-making unit (DMU) (Wan, 2002). DMUs assigned an efficiency score of unity are deemed technically efficient in comparison to their peers (Chern & Wan, 2000). Inefficient DMUs score between zero and one. Theoretically, the technically inefficient DMUs need more inputs to produce the same output in comparison to their more efficient counterparts (Chern & Wan, 2000). Efficiency scores are relative and not absolute, whose values depend on the choice

of peers (Chern & Wan, 2000). DEA can be used not only to ascertain the relative efficiency of scores but also to judge which inputs are used or outputs produced technically inefficiently; which in turn can guide performance improvement of inefficient units (Chern & Wan, 2000). DEA incorporates multiple outputs and inputs and can account for the multidimensional character of production by healthcare entities such as hospitals (Wan, 1995). CHCs also are multidimensional production facilities. DEA examines how resources (supplies, labor, and capital) produce a variety of outputs (research, teaching, patient care in a hospital setting) (Wan, 1995). DEA accommodates case mix differences and measures variables in their natural units without monetization (Wan, 1995).

The limitations of DEA include:

- Measurement error and other noise may influence the shape and position of the frontier.
- Exclusion of an important input or output can bias results.
- Efficiency scores obtained are relative only to the best CHCs in the sample. Inclusion of additional efficient CHCs may lower the measured efficiency of many inefficient CHCs.
- Care is required in comparing the mean efficiency scores from two different studies.

They reflect only the dispersion of efficiencies within each sample and say nothing about the efficiency of one sample relative to the other.

- With few observations and many inputs and/or outputs; many DMUs (such as CHCs) will appear to locate on the DEA frontier.
- Treating inputs and/or outputs as homogeneous commodities when they are heterogeneous, may bias results.

- Not accounting for environmental differences may give misleading indications of relative managerial competence.
- Standard DEA does not account for the multi-period optimization or risk involved in management decision-making.

The longitudinal analysis of CHC technical efficiency determines the stability and reliability of the measurement of technical efficiency over time. Thus a consistent set of input and output variables for performance evaluation of CHCs is ascertained from this study.

Latent Growth Curve Modeling

The dynamic relationships among multiple causes and effects of CHC efficiency cannot be adequately explained by conventional regression methods and are best assessed by growth curve modeling (Wan, 2002). Growth curve modeling is used for the following reasons: 1) the means, variances, and covariances of repeated measures of a continuous variable can be investigated by latent growth curve modeling; 2) random coefficients are used to capture individual CHC differences in the initial observation period and the growth trend; 3) both time-constant and time-varying covariates can be included as predictors or control variables for an endogenous variable; and 4) the change patterns of CHCs' efficiency over the time span of five years can be delineated so that we can test the concomitant presence of multiple factors contributing to efficiency (Wan, 2002). The latent growth curve model can be extended to include parallel processing factors when investigating change trajectories (patterns and trends) of performance (Wan, 2002). In this analysis, only statistically significant results ($p < 0.05$) are interpreted. The goodness of fit of the growth curve model is determined by statistics such as χ^2 ,

p -value, comparative fit index (CFI), Tucker-Lewis index (TLI), and root mean square error approximate (RMSEA) (Wan, 2002).

Analytical Approach

The following steps were used for analysis:

1. The five-year CHC-UDS data available from the HRSA (a division of BPHC) were merged, followed by merging of this new dataset with the ARF file and a commercially available Zip code database.
2. The data were cleaned. Missing and zero values were deleted. Outliers such as zero for cost were deemed unreasonable and deleted. The data from 1998 -1999 were not used because they lacked data elements essential for this study and contained inconsistent definitions of necessary data variables.
3. A hierarchical database for DEA was built. DEA scores were retrieved and then merged to create a research database to test for growth curve modeling.
4. Decision tree analyses were run, using DTREG software for data mining and developing important indicators/measures/predictors to assess performance.
5. Statistical modeling of the determinants of high performance CHCs was performed.
6. Since multi-wave (panel) data of repeated measures were included in the assessment; change trajectories of the performance were examined with the purpose of identifying the dynamic forces of CHC performance change.

7. The facility-based data were merged with the area characteristics compiled in the Area Resource File. The financial data from each center were used to compute indicators of technical efficiency for each center.
8. A parallel generic growth curve model was developed to examine the relationship between TE and CE.
9. Finally, the contextual and organizational covariates/control variables were included in the parallel growth curve model to construct a full model for assessing the effects of these variables on TE and CE.

CHAPTER FIVE: FINDINGS

Introduction

The empirical findings are presented in this chapter. The descriptive analyses of the contextual and design (organizational structural) variables is first presented, followed by the mean efficiency scores by year and by region derived from DEA and the cost efficiency scores by year and region . Next, results of the exploratory analysis of the predictors of TE and CE are noted, reporting the relative importance of the predictor variables of technical efficiency and the relative importance of the predictor variables of cost efficiency. Predictor tree analysis results are then presented. Next reported are the findings from multivariate longitudinal analyses using the growth curve models of TE and CE independently without predictor variables, and the relationship of contextual and organizational factors to technical efficiency and cost efficiency. Finally, the maximum likelihood estimates for the structural relationship between technical efficiency and cost efficiency, using a generic parallel growth curve model (without predictor variables) and a full model (with predictor variables), are presented.

Descriptive Analyses

Table 5 shows the descriptive statistical results for the study CHCs. The variables analyzed are: efficiency (technical efficiency, cost efficiency, totencounter, totalcost); contextual variables (% Medicare eligible, % poverty, % Medicaid eligible, % Hispanic, crude death rate, population/physician ratio, urban, region or rurality); CHC design-organizational structure variables (size = physicians+NPs+PAs), staffing mix, payer mix (% grant/total

revenue); and network participation. All variables were measured from year 2000 through year 2004.

Significant dispersion suggesting wide variability was observed to affect these context variables: total encounters and costs, percent poverty and Medicare eligibility; and these design variables: size, staffing mix and payer mix. Only 15 percent of the study CHCs were located in rural areas.

Table 5: Descriptive Statistics of the Predictor Variables

Variable	Label	Minimum Statistic	Maximum Statistic	Mean statistic	Standard Deviation
Continuous Context Variables					
% Medicare Eligible	permacare	.00	.31	.0730	.05
% Poverty	perpoverty	.00	.89	.1136	.14
% Medicaid Eligible	permcaid	.00	.57	.1323	.09
% Hispanic	perhispanic	.01	1.00	.3171	.31
Crude Death Rate	cdr	.00	24.44	8.8470	2.91
Population/Physician ratio	Doctor	.00	14.15	2.6675	2.30
Continuous Design Variables					
Size(Physicians+NPs+PAs)	size	478	.31	93851.43	10969.33
Staffing Mix	staffmix	.06	808.61	145.2957	107.88
Payer Mix(% grant/total revenue)	payermix	.02	56.20	1.3717	5.17
Categorical Context Variables					
			Frequency	Percent	Cumulative Percent
Urban	urban	rural	74	15.0	15.0
		urban	419	85.0	100.0
Region	region	1.00(Northeast)	86	20.9	20.9
		2.00(Midwest)	86	17.4	38.3
		3.00(South)	171	34.7	73
		4.00(West)	133	27.0	100.0
Categorical Design Variables					
Network01	Network0	.00	298	60.4	60.4
		1.00	195	39.6	100.0

Technical Efficiency Scores Derived from DEA

Table 6 shows the results of technical efficiency scores by year and by region. The average scores for technical efficiency among 493 CHCs for the study period are 0.2125 in 2000, 0.1987 in 2001, 0.1847 in 2002, 0.1800 in 2003, and 0.1738 in 2004. Interestingly, there is no statistically significant regional variation in the average technical efficiency scores. However, a consistently declining trend of technical efficiency is observed in all regions.

Table 6: Mean Technical Efficiency Scores by Year and by Region

REGION	Year				
	2000	2001	2002	2003	2004
1.00 (Northeast)	0.22	0.20	0.19	0.18	0.18
2.00 (Midwest)	0.21	0.20	0.19	0.18	0.18
3.00 (South)	0.21	0.19	0.19	0.18	0.17
4.00 (West)	0.23	0.21	0.19	0.19	0.18
Average Score	0.21	0.20	0.18	0.18	0.17

Cost-Efficiency Scores

Table 7 shows the results of cost-efficiency scores by year and by region. The average scores for cost efficiency among 493 CHCs for the study period are 107.76 in 2000, 112.95 in 2001, 118.96 in 2002, 123.09 in 2003, and 128.53 in 2004. Interestingly, there is no statistically significant regional variation in the average cost-efficiency scores.

Table 7: Cost Efficiency Scores

Variable	Label	Minimum Statistic	Maximum Statistic	Mean Statistic	Standard Deviation
Cost Efficiency year2000	Cost_eff0	24.07	410.07	107.75	40.53
Cost Efficiency year2001	Cost_eff1	28.40	482.65	112.95	36.68
Cost Efficiency year2002	Cost_eff2	33.59	490.45	118.96	38.34
Cost Efficiency year2003	Cost_eff3	27.65	433.63	123.09	38.07
Cost Efficiency year2004	Cost_eff4	33.15	414.47	128.53	39.20

Profiles of Highly Efficient CHCs (2000-2004)

Research Question 1 seeks to discern the profiles of highly efficient CHCs, irrespective of time points. Toward this goal, exploratory analysis of the predictors of technical efficiency (TE) and cost efficiency (CE) was performed, followed by analysis of predictor trees. The study found that the predictor variables affecting technical and cost efficiency in the predictor tree analysis failed to yield a consistent pattern. Thus, it is inappropriate to identify the profiles of highly efficient CHCs with the exploratory analysis.

Data Mining

Relative Importance of Predictor Variables of Technical Efficiency

Table 8 shows the results of exploratory analysis of the relevance of contextual and design (organizational structure) factors in explaining the variation in the technical efficiency score for each year. Exploratory analysis revealed that the contextual variables and organizational structural (design) variables of size (Physicians+NPs+PAs) and network participation do not rank in the relative importance hierarchy.

The study found that data mining and predictor tree analysis of factors influencing the variation in CHCs' technical and cost efficiency yield inconsistent results. No single predictor variable exhibits consistently highly important influence on the variation in technical efficiency throughout the five-year study period. The overall ranking for the first year (2000) was as follows: population physician ratio (the strongest), payer mix (2nd), region (3rd), crude mortality rate (4th), Medicaid eligibility (5th), poverty (6th), and region (7th).

The R square values, which explain the proportion of variance in each year, are 21.544%, 9.644%, 18.645%, 13.697% and 12.575% for the study years 2000, to 2004 respectively.

Data mining and decision (predictor) tree analysis identify important variables that are used to split the decision nodes (DTREG, 2006). The importance score for the most significant variable is a value of 100. Other predictor variables have lower values. Only the predictors with scores more than 0 are shown. The importance value of a variable is a relative score that does not explicate the percentage of explained variance (DTREG, 2006). For example, as shown in Table 8, the population physician ratio was the strongest predictor variable to explain technical efficiency for the year 2000 with an importance score of 100. The R square value, that explains the proportion of variance for the year 2000, was 0.21544 (explaining 21.544% of variance). This does not mean that the variable population physician ratio was the only predictor variable in year 2000 that can explain all of the 21.544% variance explained for that year, but that it was the most important, when compared with other variables: payer mix (2nd), region (3rd), crude mortality rate (4th), Medicaid eligibility (5th), poverty (6th), and region (7th).

The detailed explanation of the results of data mining for the relative importance of predictor variables of technical efficiency for the Year 2000 are presented in Appendix A.

Table 8: Relative Importance of Predictor Variables of Technical Efficiency by Year

Predictor Name	2000	2001	2002	2003	2004
Continuous Context Variables					
% Medicare Eligible (tpermcare)		100.000	76.870	100.000	29.090
% Poverty (tperpoverty)	52.991		88.742	67.258	30.315
% Medicaid Eligible (tpermcaid)	53.253				100.000
% Hispanic (tperhispanic)	62.875		91.272		34.123
Crude Death Rate (tcdrr)	59.486				
Population/Physician ratio (tdoctor)	100.000	10.038	1.738	1.818	1.106
Continuous Design Variables					
Staffing Mix tstaffmix			91.614		
Payer Mix(% grant/total revenue) (tpayermix)	79.976	38.672	64.483	98.352	
Categorical Context Variables					
Region	35.101	81.429	100.000	38.347	
Proportion of Variance Explained					
	0.21544 (21.544%)	0.09644 (9.644%)	0.18645 (18.645%)	0.13697 (13.697%)	0.12575 (12.575%)

Relative Importance of Predictor Variables of Cost Efficiency

Table 9 shows the results of data mining of predictors of cost efficiency. No single predictor variable exhibits consistently high influence on the variation in cost efficiency throughout the five-year study period. The overall result for the first year (2000) shows population physician ratio as the only significant variable.

Exploratory analysis revealed that the context variables such as percent poverty (tperpoverty), percent rurality, and network participation do not rank in the relative importance hierarchy. These variables are not shown in Table 9.

The R-square values that stand for the proportion of variance explained are 3.851%, 7.296%), 9.159%), 13.776%) and 14.771% for the study years 2000 to 2004, respectively.

The detailed explanation of results of data mining for the relative importance of predictor variables of cost efficiency for the Year 2000 is presented in Appendix B.

Table 9: Relative Importance of Predictor Variables of Cost Efficiency, by Year

Predictor Name	2000	2001	2002	2003	2004
Continuous Context Variables					
% Medicare Eligible (tpermacare)			97.717		
% Medicaid Eligible (tpermcaid)					65.620
% Hispanic (tperhispanic)			100.000		83.164
Population/Physician Ratio (tdoctor)	100.000	88.907	83.950	72.559	59.332
Continuous Design Variables					
Staffing Mix tstaffmix		100.000		100.000	
Payer Mix (% grant/total revenue) (tpayermix)					19.582
Categorical Context Variables					
Region (f 04439)				99.135	100.000
Proportion of Variance Explained					
	0.03851 (3.851%)	0.07296 (7.296%)	0.09159 (9.159%)	0.13776 (13.776%)	0.14771 (14.771%)

Predictor Tree Model with Splits for Technical Efficiency, Year 2000

Examination of the predictor tree model in Figure 4 below (depicting the technical efficiency score for year 2000) shows that the terminal node 10 has the highest DEA TE score, of 0.9939. The only CHC with fewer doctors (below 25th percentile), a lower percentage of Hispanics (50th percentile) and a higher number for poverty (75th percentile) had the highest

technical efficiency score, of 0.9939, for year 2000. The second most technically efficient CHC (N= 1) shown in terminal node 9, with an efficiency score of 0.9647, also had fewer doctors (below 25th percentile) and a lower percentage of Hispanics (50th percentile), but either a higher or lower number for poverty (100th or 50th and 25th percentiles) and a high percentage of patients with Medicaid (100th percentile). The same model also shows that terminal node 5, with a larger number (68) of CHCs, had the lowest DEA score, 0.1566. This indicates that CHCs with fewer doctors (below 25th percentile) and either a higher or a lower number of Hispanics (100th or 50th and 25th percentiles) and either higher or lower paymix (100th or 50th and 25th percentiles) had the lowest technical efficiency score, of 0.1566, for the year 2000.

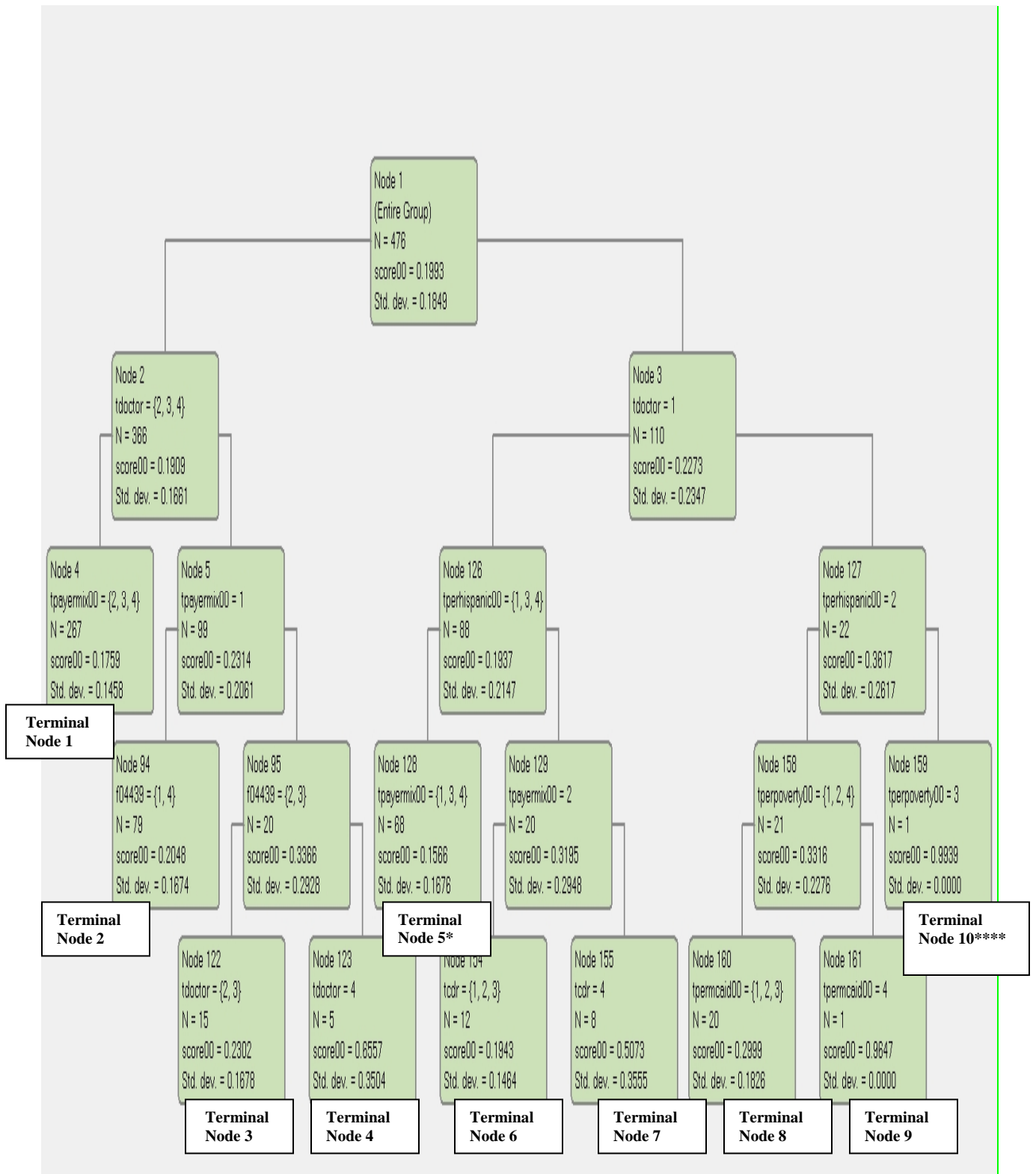


Figure 4: Predictor Tree Model with Splits for Technical Efficiency: Year 2000

Multivariate Modeling

Trends of Technical and Cost Efficiency in the Five-Year Period

In order to examine the trends or changes in efficiency of CHCs, multivariate modeling with the latent growth curve model was performed. This modeling approach assumes that the two growth components are related: the initial status (intercept) and the change (slope) in the efficiency measure are not independent.

Technical Efficiency (TE)

In analyzing the trend of TE in the study period as prompted by research question 2, a latent growth curve model of TE was developed and validated (figure 5). This model specifies that the initial status (intercept) of TE is associated with the growth trend (slope). Table 10 shows that a statistically significant inverse relationship was found between the intercept and the slope (-.344). This relationship suggests that highly technically efficient CHCs in the initial study period may improve less in later years than those with lower TE do. Model fit statistics show an excellent fit of the model, having a goodness of fit (GOF) index of 0.990, adjusted goodness of fit (AGOF) index of 0.969 and a summary score (RMSEA) of 0.058.

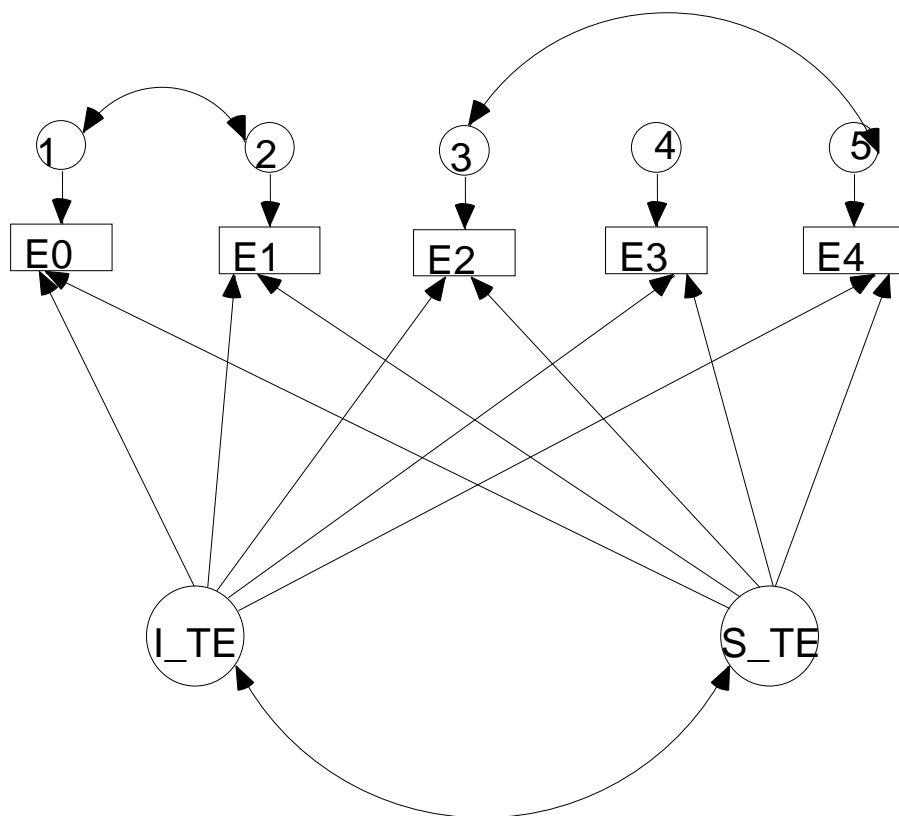


Figure 5: The Latent Growth Curve Model of Technical Efficiency (TE): 2000-2004

Table 10: The Maximum Likelihood Estimates for the Measurement Model of Technical Efficiency (TE): Growth Curve Model

Latent Variables and Their Indicators	Parameter Estimate	Squared Multiple Correlation
<u>TE intercept</u>		
TE_2000	.887	.787
TE_2001	.972	.871
TE_2002	1.031	.941
TE_2003	1.013	.912
TE_2004	1.026	.980
<u>TE slope</u>		
TE_2000	.000	
TE_2001	.138	
TE_2002	.292	
TE_2003	.431	
TE_2004	.581	
Correlation between intercept and slope	-.344*	
Chi Square: 13.174 Degrees of Freedom:5 Chi Square/Degrees of Freedom: 2.635 Goodness of Fit(GOF) Index: .990	Adjusted Goodness of Fit (AGOF) Index: .969 RMSEA: .058 P_Close: .316 Hoelter:414	

* Significant at 0.05 or lower level

Cost Efficiency

Research Question 2 seeks to discern any patterns and trends of cost efficiency observed among CHCs over the study period of five years. To analyze the trend of CE in the study period, a latent growth curve model of CE was developed and validated (figure 6). This model specifies that the initial status (intercept) of CE is associated with the growth trend (slope). Table 11 shows that a statistically significant inverse relationship was found between the intercept and the slope (-.531). This relationship suggests that highly cost-efficient CHCs in the initial study period may improve less in later years than those with lower CE do. Model fit statistics show an

excellent fit, with goodness of fit (GOF) index of 0 .996, adjusted goodness of fit (AGOF) index of 0 .989 and summary score (RMSEA) of 0 .000.

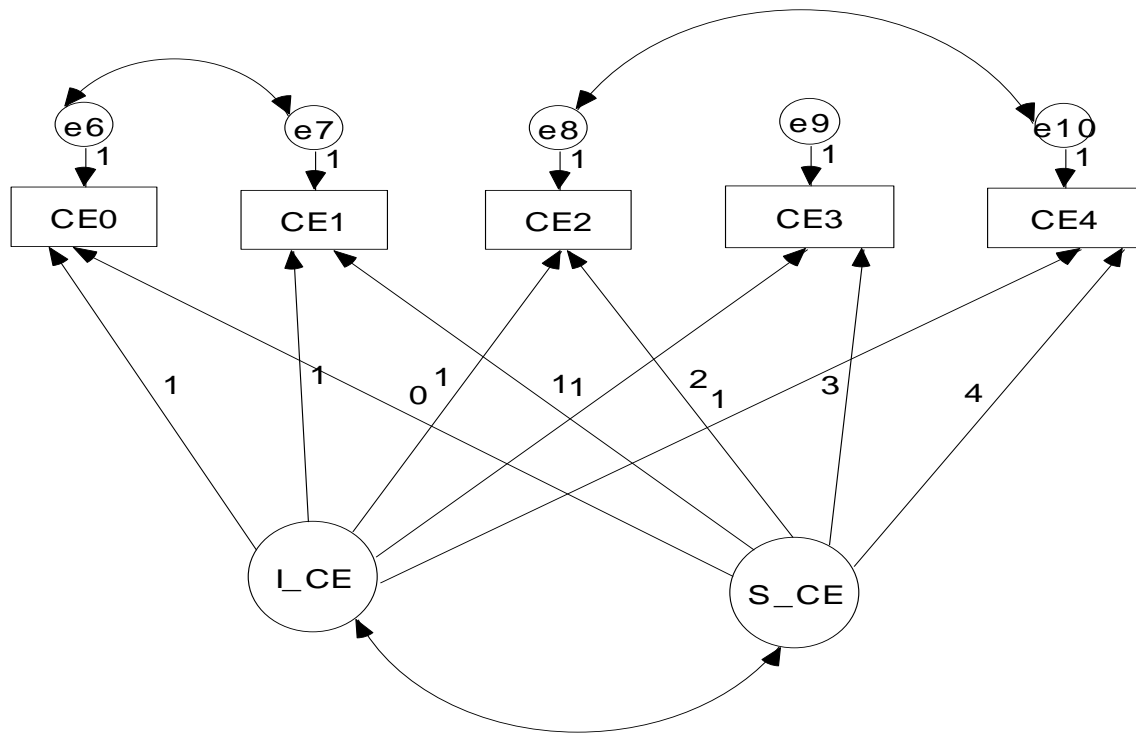


Figure 6: The Latent Growth Curve Model of Cost Efficiency (CE): 2000 to 2004

Table 11: The Maximum Likelihood Estimates for the Measurement Model of Cost Efficiency (CE): Growth Curve Model

Latent Variables and Their Indicators	Regression Estimation Lambda	Squared Multiple Correlation
<u>CE intercept</u>		
CE_2000	.881	.776
CE_2001	.969	.814
CE_2002	1.110	.954
CE_2003	1.112	.954
CE_2004	1.184	1.010
<u>CE slope</u>		
CE_2000	.000	
CE_2001	.142	
CE_2002	.325	
CE_2003	.488	
CE_2004	.693	
Correlation between intercept and slope	-.531*	
Chi Square: 4.337 Degrees of Freedom: 5 Chi Square/Degrees of Freedom: .867 Goodness of Fit(GOF) Index: .996	Adjusted Goodness of Fit (AGOF) Index: .989 RMSEA: .000 P_Close: .904 Hoelter: 1256	

* Statistically significant at the 0.05 or lower level

Predictors of Technical and Cost Efficiency of CHCs, 2000-2004

In order to discern the influences of contextual and organizational structural (design) predictors of efficiency observed among CHCs over the study years, multivariate modeling of these predictors with the latent growth curve model was performed.

Technical Efficiency

Research Question 3 seeks to discern the predictors of technical efficiency observed among CHCs over the study period of five years. To analyze the trend of TE in the study period,

a growth curve model of TE with contextual and organizational structural (design) predictor variables was developed and evaluated (figure 7). This model specifies that the initial status (intercept) and the growth trend (slope) of TE are independently affected by the contextual and organizational structural (design) predictor factors.

Hypothesis 1 (H_1), flowing from research question 3, seeks to confirm the association noted in the literature between CHCs' technical efficiency and both the contextual factors, such as the percentage distribution of Medicare, Medicaid, and Hispanic population in the service areas, and the organizational factors, such as staff mix and federal funding.

Table 12 shows the statistically significant predictors for initial technical efficiency (TE intercept) for the year 2000 in descending order of importance: (pmcare0), with a regression estimate of .219*; phisp0, with a regression estimate of .214*; and pmcaid0, with a regression estimate of .149*. The statistically significant predictor for the change in technical efficiency (TE slope) was pmcare0, with a regression estimate of -.178*. The explained variance was .126 or 12.6 percent, for the initial technical efficiency (TE intercept) and was .054 or 5.4 percent for technical efficiency (TE slope).

Findings from Table 12 confirm that certain of the variables deemed significant in the related literature: percentage of Medicare, Medicaid and Hispanic population are statistically important predictors of technical efficiency but reveal that certain other factors held important in the literature: poverty, staffing mix (professional provider staff size relative to total staff) and payer mix (grant dollars relative to total revenue) have no statistically significant relationship.

The somewhat low proportion of variance explicated suggests that other important factors such as management style, work design and healthcare technology deployment, which because of data nonavailability were not included, may be relevant.

The study findings support hypothesis 1.

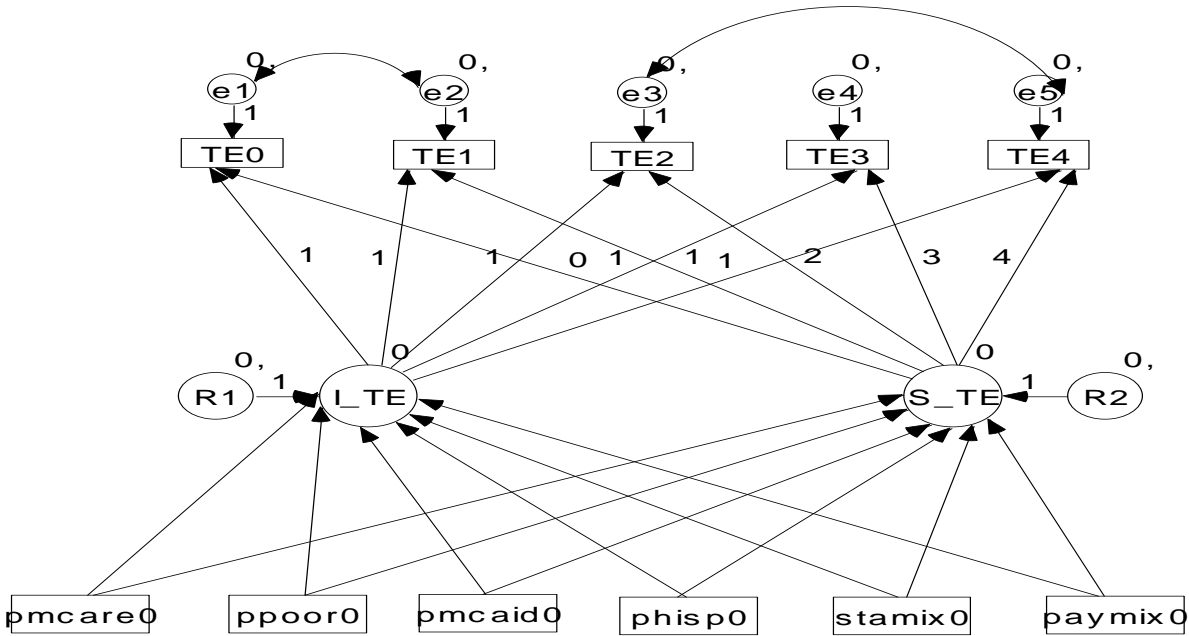


Figure 7: Measurement Model with Predictors for Technical Efficiency, 2000-2004

Table 12: The Maximum Likelihood Estimates for the Measurement Model of Technical Efficiency (TE): Growth Curve Model

Latent Variables and their Indicators	Regression Estimate ⁺	Critical Ratio(CR)	Squared Multiple Correlation
<u>TE intercept</u>			
pmcare0	.219*	4.684	
ppoor0	.074	1.554	
pmcaid0	.149*	3.193	
phisp0	.214*	4.511	
stamix0	-.063	-1.333	
paymix0	-.012	-.257	
<u>TE slope</u>			
pmcare0	-.178*	-2.532	
ppoor0	.002	.023	
pmcaid0	.064	.912	
phisp0	.022	.312	
stamix0	-.090	-1.260	
paymix0	-.101	-1.440	
R-square			
I_TE			.126
S_TE			.054
<u>Lambda (Parameter Estimate)</u>			
TE0	.725*		
TE1	.834*		
TE2	.944*		
TE3	.916*		
TE4	.970*		
Chi Square: 221.947 Degrees of Freedom: 39 Chi Square/Degrees of Freedom: 5.691 Goodness of Fit(GOF) Index: (TLI):.918	Adjusted Goodness of Fit (AGOF) Index: (CFI):.951 RMSEA: .098 P_Close: .000 Hoelter: 139		

* Statistically significant at 0.05 or lower level

+ Standardized regression coefficient

Cost Efficiency

Research Question 3 seeks to discern the predictors of cost efficiency observed among CHCs over the study period of five years. In analyzing the trend of CE in the study period, a growth curve model of CE with contextual and organizational structural (design) predictor variables was developed and evaluated (figure 8). This model specifies that the initial status (intercept) and the growth trend (slope) of CE are independently affected by the contextual and organizational structural (design) predictor factors.

Hypothesis 2 (H₂), flowing from research question 3, seeks to confirm the association noted in the literature between CHCs' cost efficiency and both the contextual factors such as the percentage distribution of Medicare, Medicaid, and Hispanic population in the service areas and the organizational factors such as staff mix and federal funding.

Table 13 shows the statistically significant predictors for the initial cost efficiency (CE intercept) for the year 2000 in descending order of importance: phisp0, with a regression estimate of .281*; pmcare0, with a regression estimate of .239*, Stamix0, with a regression estimate of .226*; paymix0, with a regression estimate of .206*; pmcaid0, with a regression estimate of .136*; and ppoor0, with a regression estimate of .128*. The statistically significant predictors for the change in cost efficiency (CE slope) are ppoor0, with a regression estimate of -.230*; phisp0, with a regression estimate of -.204*; stamix0, with a regression estimate of -.203*; and paymix0, with a regression estimate of -.163*. The total explained variance is .265 or 26.5 percent for initial cost efficiency (CE intercept) and .183 or 18.3 percent, for the slope of cost efficiency (CE slope).

Findings from Table 13 confirm that certain of the variables deemed significant in the related literature: percentages of Hispanics, Medicare, Medicaid and poor staffmix (professional

provider staff size relative to total staff) and payor mix (grant dollars relative to total revenue), are statistically important predictors of cost efficiency.

The somewhat low proportion of variance explicated suggests that other factors such as use of technology and care processes, which because of data nonavailability were not included, may be relevant.

The study findings support hypothesis 2.

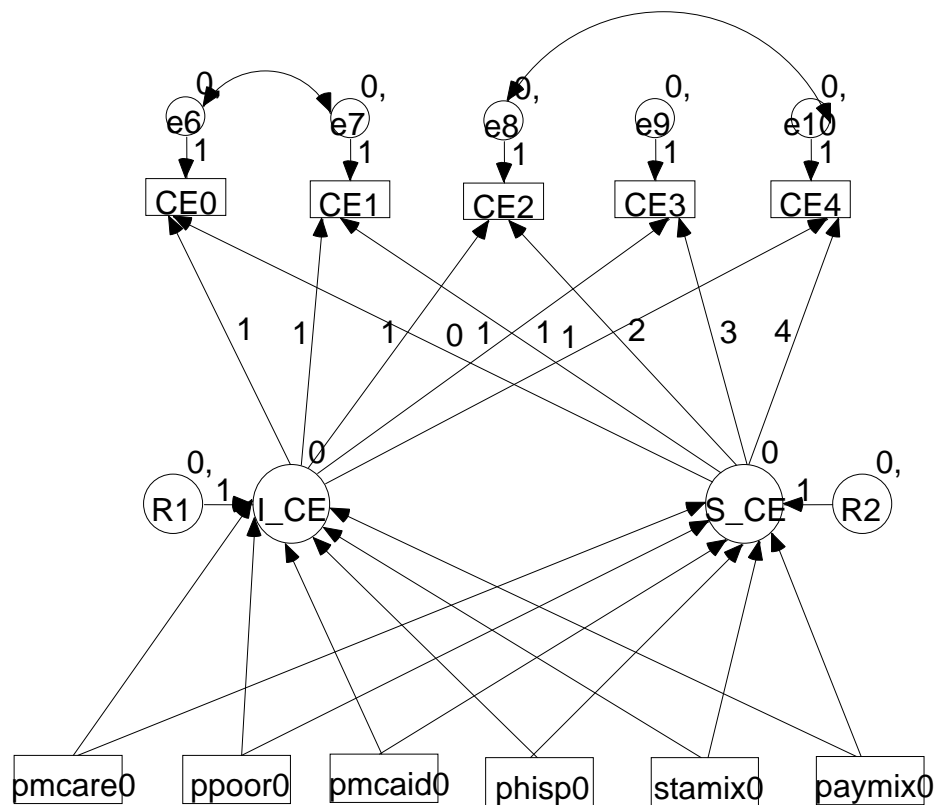


Figure 8: Measurement Model with predictors of cost efficiency (CE): 2000-2004

Table 13: The Maximum Likelihood Estimates for the Measurement Model of Cost Efficiency (CE): Growth Curve Model

Latent Variables and their Indicators	Regression Estimation ⁺	Critical Ratio(CR)	Squared Multiple Correlation
<u>CE intercept</u>			
pmcare0	.239*	5.387	
ppoor0	.128*	2.864	
pmcaid0	.136*	3.075	
phisp0	.281*	6.238	
stamix0	.226*	5.051	
paymix0	.206*	4.659	
<u>CE slope</u>			
pmcare0	-.128	-1.708	
ppoor0	-.230*	-3.046	
pmcaid0	-.066	-.886	
phisp0	-.204*	-2.685	
stamix0	-.203*	-2.678	
paymix0	-.163*	-2.179	
R-square			
I_CE			.265
S_CE			.183
<u>Lambda (parameter estimate)</u>			
CE2000	.682*		
CE2001	.763*		
CE2002	.955*		
CE2003	.905*		
CE2004	.987*		
Chi Square: 243.897 Degrees of Freedom: 39 Chi Square/Degrees of Freedom: 6.254 Goodness of Fit(GOF) Index: (TLI): .906	Adjusted Goodness of Fit (AGOF) Index: (CFI): .944 RMSEA: .103 P_Close: .000 Hoelter: 111		

* Statistically significant at 0.05 or lower level

+ Standardized regression coefficient

The Relationship between Technical Efficiency and Cost Efficiency: Growth Curve Modeling without Predictor Variables

Pursuant to research question 4, growth curve modeling without the contextual and organizational structural (design) predictors of efficiency was performed in order to examine the relationship between technical efficiency and cost efficiency (Figure 9).

Table 14 shows that the initial cost efficiency score (CE intercept) is positively affected by the initial technical efficiency (TE intercept), with a statistically significant regression estimate of .518*. The change in cost efficiency (CE slope) is positively affected by the slope of (change in) technical efficiency (TE slope), with a statistically significant regression estimate of .470* and by initial technical efficiency (TE intercept), with a statistically significant regression estimate of .122*. The change in cost efficiency (CE slope) is negatively affected by initial cost efficiency (CE intercept), with a statistically significant regression estimate of -.444*. The change (slope) in technical efficiency is negatively affected by initial technical efficiency, with a statistically significant regression estimate of -.241* and by the initial cost efficiency, with a statistically significant regression estimate of -.197*

The total explained variance is .268 or 26.8 percent for initial cost efficiency (CE intercept), .472 or 47.2 percent for the cost efficiency slope, and .146 or 14.6 percent for the technical efficiency slope. These findings lend support to Hypothesis 3, confirming that the change in technical efficiency positively affects the change in cost efficiency.

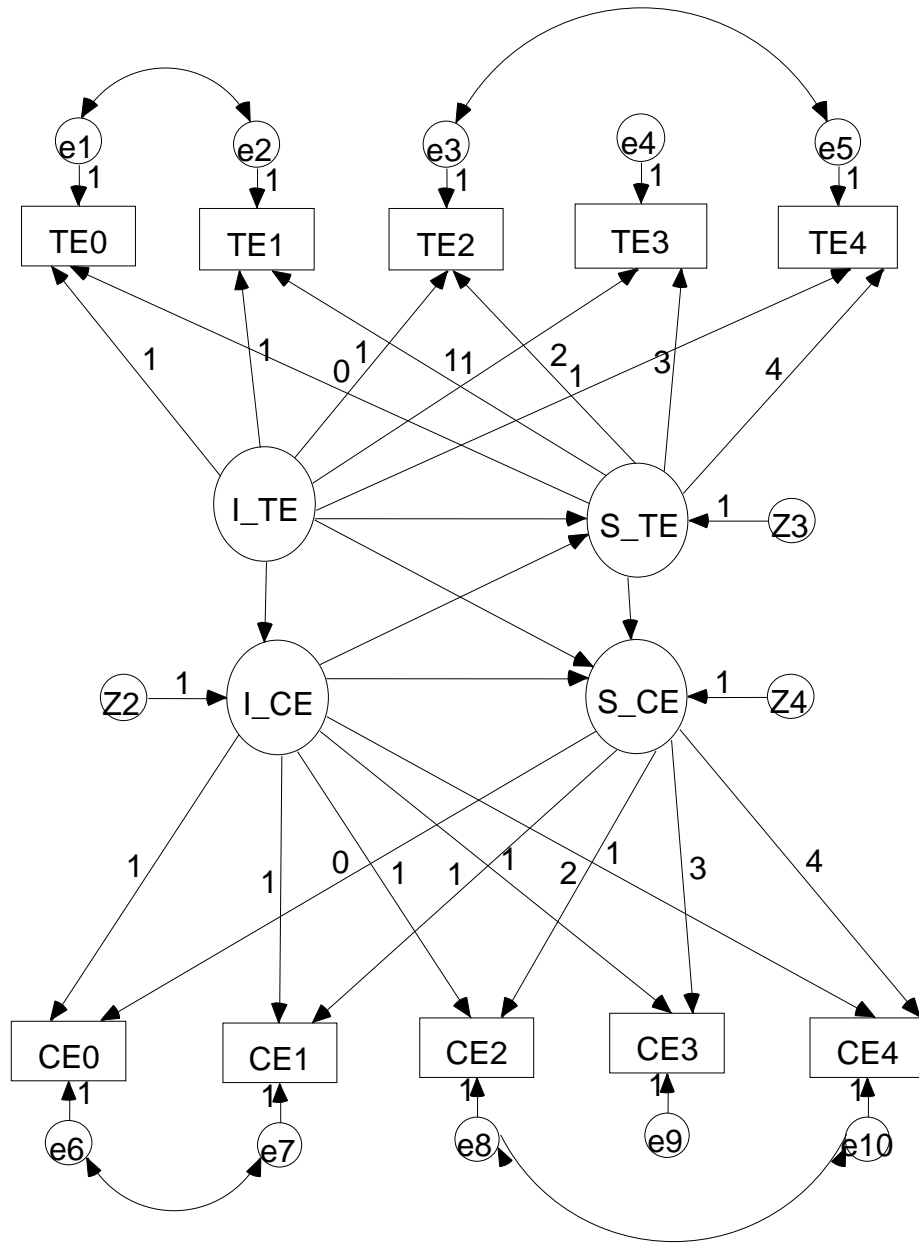


Figure 9: The Parallel Process Generic Growth Curve Model for the Relationship between TE and CE without Control Variables

Table 14: The Maximum Likelihood Estimates for the Structural Relationship between Technical Efficiency and Cost Efficiency: Parallel Growth Curve Model

Latent Variables and Their Indicators	Regression Estimation ⁺	Critical Ratio(CR)	Squared Multiple Correlation
I_CE<---I_TE	.518*	11.255	
S_TE<---I_CE	-.197*	-2.770	
S_TE<---I_TE	-.241*	-3.072	
S_CE<---I_TE	.122*	2.116	
S_CE<---S_TE	.470*	6.576	
S_CE<---I_CE	-.444*	-6.349	
R-square			
I_CE			.268
S_TE			.146
S_CE			.472
Lambda (parameter estimate)			
CE_2000	.786*		
CE_2001	.819*		
CE_2002	.952*		
CE_2003	.899*		
CE_2004	1.006*		
TE_2000	.794*		
TE_2001	.869*		
TE_2002	.940*		
TE_2003	.912*		
TE_2004	.979*		
Chi Square: 208.102 Degrees of Freedom: 31 Chi Square/Degrees of Freedom: 6.713 Goodness of Fit(GOF) Index: (TLI): .927	Adjusted Goodness of Fit (AGOF) Index: (CFI): .871 RMSEA: .108 P_Close: .000 Hoelter: 107		

* Statistically significant at 0.05 or lower level

+ Standardized regression coefficient

The Relationship between Technical Efficiency and Cost Efficiency: Growth Curve Modeling with Predictor Variables

Pursuant to research question 4, growth curve modeling with the contextual and organizational structural (design) predictors of efficiency was performed in order to examine the relationship between technical efficiency and cost efficiency, controlling for the statistically significant predictor variables of pmedicare, pmedicaid, phispanic staffmix and paymix (Figure 10).

Table 15 shows that initial technical efficiency (TE intercept) is positively affected by phisp0, with a statistically significant regression estimate of .220*; pmcare0, with a statistically significant regression estimate of .203*; and pmcaid0, with a statistically significant regression estimate of .168*.

Initial cost efficiency (CE Intercept) is positively affected by initial technical efficiency (I_TE) with a statistically significant regression estimate of .498*; stamix0, with a statistically significant regression estimate of .216*; paymix0, with a statistically significant estimate of .185*; pmcare0, with a statistically significant estimate of .137*; and phisp0, with a statistically significant estimate of .128*.

The following structural relationships among initial technical efficiency (TE intercept), initial cost efficiency (CE Intercept), change in technical efficiency (TE slope) and change in cost efficiency (CE slope) are identified. 1) The change in cost efficiency (slope) is positively affected by the change (slope) in technical efficiency, with a statistically significant regression estimate of .494*. 2) The change in cost efficiency (slope) is negatively affected by initial cost efficiency (CE intercept), with a statistically significant regression estimate of -.427*. 3) The change in cost efficiency (slope) is not affected by initial technical efficiency (TE intercept),

with a statistically insignificant regression estimate of .110. 4) The change (slope) in technical efficiency is negatively affected by initial cost efficiency (CE Intercept), with a statistically significant regression estimate of $-.249^*$, and by initial technical efficiency (TE intercept), with a statistically significant regression estimate of $-.204^*$.

The total explained variance is .502 or 50.2 percent for cost efficiency (CE slope), .420 or 42.0 percent for initial cost efficiency (CE intercept), .160 or 16.0 percent for the technical efficiency slope, and .118 or 11.8 percent for initial technical efficiency. These findings further support Hypothesis 3, that the change in technical efficiency positively affects the change in cost efficiency, holding contextual and organizational factors constant.

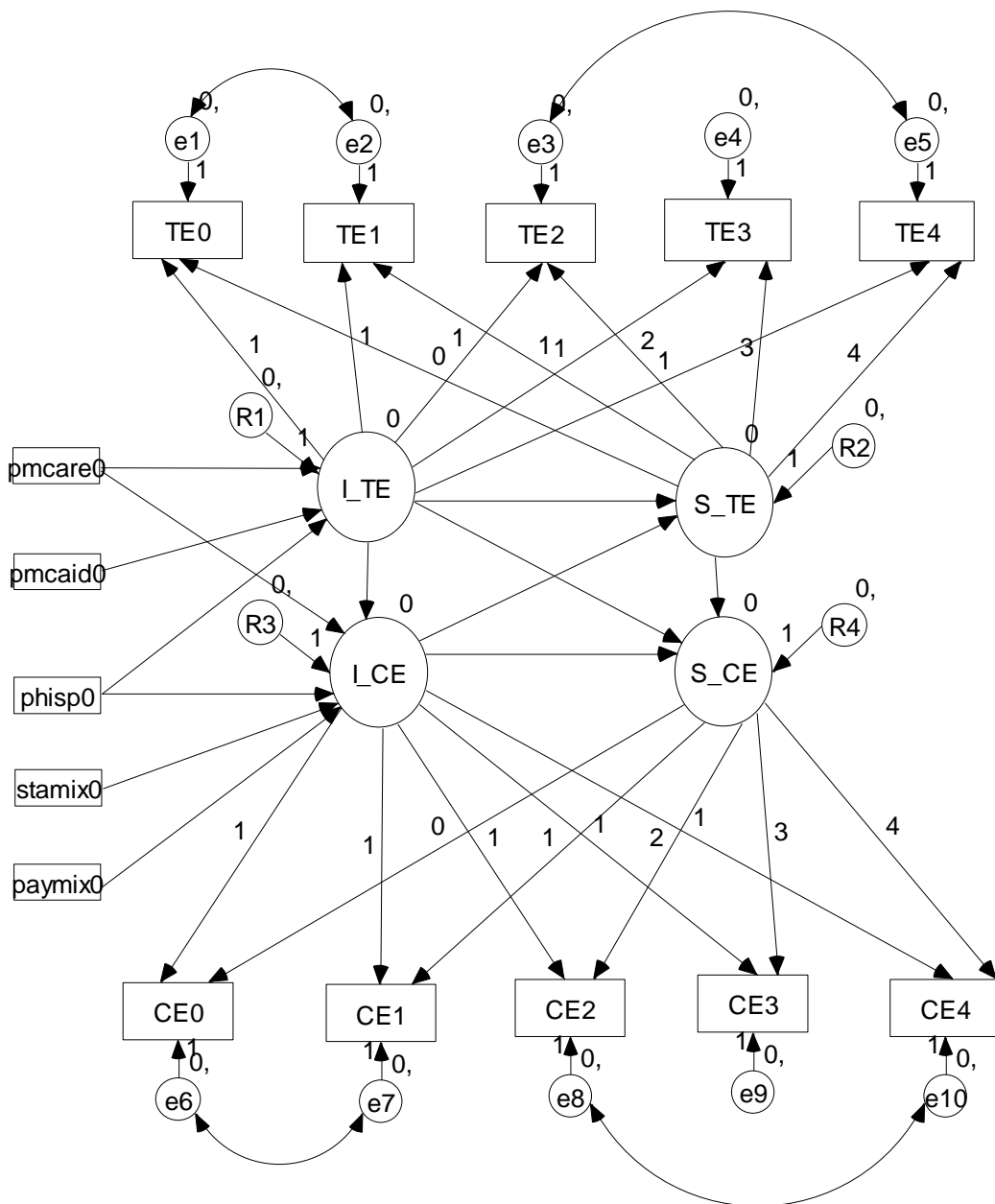


Figure 10: Generic Growth Curve Model for the Relationship between Technical Efficiency (TE) and Cost Efficiency (CE) with Control Variables: 2000-2004

Table 15: The Relationship between Technical Efficiency (TE) and Cost Efficiency (CE) with Predictor Variables

Latent Variable and their Indicators	Regression Estimate ⁺	Critical Ratio(CR)	Squared Multiple Correlation
<u>TE Intercept</u>			
pmcare0	.203*	4.576	
pmcaid0	.168*	3.793	
phisp0	.220*	4.892	
<u>CE Intercept</u>			
I TE	.498*	11.368	
phisp0	.128*	3.344	
stamix0	.216*	5.808	
paymix0	.185*	5.051	
pmcare0	.137*	3.650	
<u>Structural Relationship</u>			
S TE<---I CE	-.249*	-3.288	
S TE<---I TE	-.204*	-2.429	
S CE<---I TE	.110	1.841	
S CE<---S TE	.494*	6.413	
S CE<---I CE	-.427*	-5.785	
R-square			
I TE			.118
I CE			.420
S TE			.160
S CE			.502
<u>Lambda (parameter estimate)</u>			
CE_2004			1.006
CE_2003			.904
CE_2002			.953
CE_2001			.830
CE_2000			.801
TE_2004			.976
TE_2003			.913
TE_2002			.941
TE_2001			.865
TE_2000			.789
Chi Square: 396.722 Degrees of Freedom: 84 Chi Square/Degrees of Freedom: 4.723 Goodness of Fit(GOF) Index: (TLI): .941		Adjusted Goodness of Fit (AGOF) Index: (CFI): .959 RMSEA: .087 P_Close: .000 Hoelter: 132	

* Statistically significant at 0.05 or lower level.

+ Standardized regression coefficient

CHAPTER SIX: DISCUSSION, CONTRIBUTIONS/IMPLICATIONS AND CONCLUSIONS

Major Findings

Profile of High-Performing CHCs

The first research question for this study sought to discern the profiles of highly efficient CHCs, irrespective of time points. Exploratory analysis of the predictors of technical efficiency (TE) and cost efficiency (CE) and the predictor tree analysis found that they fail to yield a consistent pattern. No single predictor variable exhibited consistently high influence on the variation in technical and cost efficiency throughout the five-year study period. Furthermore, the R square values that explain the proportion of variance in each of the study years are modest. The predictor tree model for the year 2000 technical efficiency score, like the predictor tree models for other years for both technical and cost efficiency, showed that only a handful CHCs achieve exceptional (four times or more than the average) technical or cost efficiency. A majority of CHCs are underperforming. This is disconcerting, and presents the challenge to transform under performing CHCs into at least average performers, through managerial intervention and technical consultation. It is highly possible that with the assistance of a system for executive decision support, the majority of CHCs would learn how to optimize their resources to achieve at least an average level of efficiency. However, to expect achievement of a very high efficiency by the majority of CHCs in a short time is unrealistic.

In summary, the innovative use of exploratory analysis and predictor tree analysis, made in this study, is capable of identifying the high, average and low performing CHCs in terms of both technical and cost efficiency. However, assessment of the predictor variables affecting technical

and cost efficiency by these analytical techniques failed to yield a consistent pattern. Thus, predictor tree analysis fails to identify the consistent profiles of highly efficient CHCs.

Longitudinal Modeling with Multiple Waves of a Panel of CHCs

The inconsistent results of exploratory analysis and predictor tree analysis to identify the profiles of highly efficient CHCs call for a more rigorous multivariate approach, employing precise specifications of the structural relationships between the predictor variables and performance indicators of CHCs.

Examination of the Trends or Changes in Technical and Cost Efficiency of CHCs

Multivariate modeling with the latent growth curve model found, for technical efficiency (TE), a statistically significant inverse relationship between the intercept and the slope (-.344). This finding suggests that highly technically efficient CHCs in the initial study period may improve less in later years than to those with lower TE levels. This difference can be explained by the fact that the best performers have already optimized their technical efficiency in the initial study period, so achieving further marginal gains is very difficult. Similarly, for cost efficiency a statistically significant inverse relationship was found between the intercept and the slope (-.531), suggesting that highly cost efficient CHCs in the initial study period may improve less in later years, than compared to those with lower CE levels do.

Results from the influences of contextual and organizational structural predictors of efficiency among CHCs over the study years by multivariate modeling with the latent growth curve model show that the variation in technical efficiency (TE) may be explained by: the percentages of Medicare, Medicaid and Hispanic population, and market characteristics. Only a

limited amount of the total variance in TE is explained by these factors, however. The study's findings support those of the research literature, suggesting that TE is not related to poverty (Rosenbaum et al., 2000), professional provider- total staff ratio (GAO, 1976), or the grant dollars-total revenue ratio (GAO, 2000).

The somewhat low proportion of variance explained by the predictor variables for TE suggests that other organizational factors such as management style, work design and healthcare technology deployment, should be included in the analysis. Unfortunately, data on these important variables are not available for this research.

From multivariate analyses of the panel data, Hypothesis 1 is supported, confirming the association between CHCs' technical efficiency and the contextual factors: the percentage distributions of Medicare, Medicaid, and Hispanic population in the service areas; and the organizational factors of staff mix and federal funding.

For cost efficiency (CE), some of the variables deemed significant in the related literature: percentages of Hispanics, Medicare, and Medicaid; and poor staff mix (number of professional providers relative to total staff); and payor mix (grant dollars relative to total revenue) are statistically important.

From the multivariate analyses, Hypothesis 2 (H_2) is also supported, confirming that CHCs' cost efficiency is associated with these contextual factors: the percentages of Medicare, Medicaid, and Hispanic population in the service areas; and organizational factors: staff mix and federal funding. Compared with TE, a relatively larger amount of the variance in cost efficiency is explained by these contextual and organizational factors

Examining the relationship between technical efficiency and cost efficiency without predictor variables by using a parallel growth curve model revealed several important findings:

1) the initial cost efficiency score (CE intercept) is positively affected by the initial technical efficiency (TE intercept); 2) the change in cost efficiency (CE slope) is positively affected by the change in technical efficiency (TE slope) and by initial technical efficiency (TE intercept); 3) the change in cost efficiency (CE slope) is negatively affected by initial cost efficiency (CE intercept); and 4) the change (slope) in technical efficiency is negatively affected by initial technical efficiency and initial cost efficiency. These findings lend strong support to Hypothesis 3, confirming that the change in technical efficiency positively affects the change in cost efficiency.

The causal relationship between technical efficiency and cost efficiency was further examined with specific predictor variables included. By controlling for the statistically significant predictor variables of percentage of Medicare, percentage of Medicaid, percentage of Hispanic staffing mix and payer mix, the parallel growth curve model demonstrates that the initial technical efficiency (TE intercept) is positively affected by percentage of Hispanic 2000 , percentage of Medicare 2000, and percentage of Medicaid 2000. The initial cost efficiency (CE intercept) is positively affected by initial technical efficiency (I_TE), staffing mix 2000, payer mix 2000, percentage Medicare eligible 2000 and percentage Hispanic 2000.

Holding the contextual and organizational variables constant, the structural relationships among initial technical efficiency (TE intercept), initial cost efficiency (CE Intercept), change in technical efficiency (TE slope) and change in cost efficiency (CE slope) were further identified as follows: 1) The change in cost efficiency (slope) is positively affected by the change (slope) in technical efficiency, with the highest statistically significant regression estimate being .494. 2) The change in cost efficiency (slope) is negatively affected by initial cost efficiency (CE intercept). 3) The change in cost efficiency (slope) is not affected by initial technical efficiency

(TE intercept). 4) The change (slope) in technical efficiency is negatively affected by initial cost efficiency (CE intercept) and by initial technical efficiency (TE intercept). These findings further substantiate Hypothesis 3 and imply that technical efficiency positively affects cost efficiency, holding contextual and organizational factors being held constant.

The total explained variance is .502 or 50.2 percent for cost efficiency change (CE slope), .420 or 42.0 percent for the initial cost efficiency (CE intercept), .160 or 16.0 percent for the technical change (TE slope), and .118 or 11.8 percent for initial technical efficiency (TE intercept).

In summary, the initial cost efficiency score and the initial technical efficiency score are negatively associated with the growth trend of technical efficiency. This can be explained by the fact that for those CHCs that have already attained high levels of technical and cost efficiency, it is difficult to achieve marginal gains. The initial level of technical efficiency is not statistically significantly associated with the growth trend of cost efficiency. The two factors influencing the growth trend of cost efficiency are the growth trend of technical efficiency (with a positive influence) and the initial level of cost efficiency (with a negative influence). In analyzing the effects of contextual and organization-structural variables on the technical efficiency and cost efficiency of community health centers, the explanatory power of the predictors is much greater for cost efficiency than for technical efficiency.

This study lends support to a specific type of contingency theory (independent and additive influence of organizational and contextual factors on performance). The study also confirms the relative importance of contextual and organizational predictors in explaining the variation in both technical and cost efficiencies of CHCs. Moreover, the contextual factors exert a greater influence than the organizational-structural factors on CHCs' performance, irrespective

of the efficiency measures. The three study hypotheses supported by multivariate analysis are: 1) technical efficiency is associated with the contextual factors and organizational factors; 2) cost efficiency is associated with the contextual factors and organizational factors; and 3) change in technical efficiency leads to change in cost efficiency, when the contextual and organizational structural factors are held constant.

Study Contributions and Implications

The assessment of CHC performance vis a vis technical and cost efficiency, using longitudinal multivariate analyses, has made substantive, theoretical, methodological, and policy contributions to public affairs research.

Theoretical Contributions

The study supports the premise of a contingency theory perspective. It confirms the independent and additive influences of selected contextual and organizational factors on efficiency. It finds that the contextual factors influence the variation in CHC performance (in this study, technical and cost efficiency), independently of the influence of organizational structural factors. It also finds that the organizational structural factors influence CHC performance, independent of the influence of contextual factors. The study generates empirical findings to support Hendrick's proposition (2003) that not all contingency perspectives are the same. Moreover, the study demonstrates that context and design may act independently and also exert an additive effect on CHCs' performance in technical and cost efficiencies. This study provides evidence for theorizing causal relationships between CHCs' context and organizational structure (design), and their performance.

Methodological Contributions

Data Mining

The study applies data mining and predictor tree analysis in a novel way to ascertain the profiles of highly efficient CHCs. The study found these analytical methods to be incapable of identifying a systematic pattern of predictor variables that can discern high and low performers in both technical and cost efficiencies. Thus, the exploratory analytical techniques of data mining and predictor tree analysis are ineffective in identifying consistent profiles of highly efficient CHCs.

Longitudinal Modeling with Multi-Waves of Panel Data in CHCs

This study is the first longitudinal examination of CHC performance, using a national dataset. The availability of longitudinal data from 493 CHCs enables the exploration of plausible structural relationships among the context, organizational structure (design), and performance of CHCs. It offers an opportunity to examine the validity of a frequently used but poorly specified theory, contingency theory, in organizational research. The longitudinal, multi-wave design has strengthened the rationale for postulating and validating the causal influence of technical efficiency on cost efficiency.

Measurement of Technical Efficiency

This is the first study of CHC performance in terms of technical efficiency that uses data envelopment analysis (DEA). DEA is a well established tool that allows the researcher to

optimize the multiplicity of inputs and outputs simultaneously. The window-based analysis of a panel of 493 CHCs enabled us to derive relative values of technical efficiency for five years.

Determination of Structural Relationships/Causality

This study has thoroughly examined CHC performance, using a confirmatory approach of growth curve modeling to draw causal inferences about the predictors of CHC efficiency. This research methodology offers further evidence of the power of latent growth curve modeling for recognizing the predictors of organizational performance.

Policy Contributions

Identification of Predictors of CHCs' Efficiency

Prior studies with hospitals as the unit of analysis (Nunamaker, 1983; Sherman, 1984; Grosskopf & Valdamanis, 1987; Valdamanis, 1990 and Ehreth, 1994) found that hospital technical efficiency has a positive relationship with hospital cost efficiency indicators. No prior studies addressing the causal relationship between technical efficiency and cost efficiency were available in the literature on CHC efficiency. The most important finding in this study is that the change in cost efficiency (slope) is positively affected by the change (slope) in technical efficiency. The implication of this finding is that concerted efforts to enhance technical efficiency will improve cost efficiency. Thus it is clearly imperative to help mediocre CHCs improve their technical efficiency in order to achieve more cost efficiency. Since technical efficiency is the efficiency of the production or conversion process, it connotes the effectiveness of operational methods to morph inputs into outputs. The high technical efficiency of the “best

of the breed” CHCs suggests they are capable of parleying the same or similar resources into better or more outputs through their enlightened ability to optimize resource use or resource conversion. This ability is not necessarily limited to the managers of a high performing CHC; it can be inculcated in the managers of a poorly performing CHC, by transforming its organizational culture and/or reconfiguring its organizational work design. A high-performance learning institute could be established where a learning modality not unlike legendary Toyota Production Model could educate the executives of poorly performing CHCs. Innovative tools such as decision support systems and expert systems not only can accomplish that goal, but also can generate the knowledge base and data-warehousing functionality to sustain the gains. Ultimately, an executive decision support system developed from the evidence-based modeling approach, could make continued accountability to CHC stakeholders feasible and enable ongoing evaluation of CHC financial performance. This perhaps surreal scenario is a potential by-product of the study. The findings of the study can assist CEOs to maintain CHC financial stability by responding quickly and appropriately to market changes, rising costs and threats to revenue streams.

Study Limitations

This study has limitations in the areas of errors in the data, data set imperfections, and exclusion of other levels of the data from the analysis.

The study was designed to use existing administrative data. The analyses are limited by the availability of data elements in the administrative data set provided by the Health Resources & Services Administration, a division of the Department of Health and Human Services. These administrative data are not without errors and have missing values. The problems may not be

sufficiently overcome by the data cleaning procedures used and the specific procedures followed to handle missing values.

Ideally, the managerial information system of community health centers should contain important indicators such as the management practices that measure the ability to control expenditures, the extent to which a CHC is able to generate favorable contracts with other providers and managed care organizations, the flexibility to respond to market changes, and effectiveness in business operations (GAO, 2000). The current dataset contains no variables that allow the assessment of management practices. The dataset also does not contain variables that can help draw inferences about the influence of other important predictors of performance: organizational culture, leadership, and deployment of healthcare technology.

The examination of efficiency measures without assessing organizational effectiveness can provide only a partial evaluation of CHC performance. It must also be remembered that the salience of CHCs as safety net providers for the uninsured and the impoverished rests on a value-added proposition: that providing services with great efficiency is coupled with ensuring high quality and safe care. Currently, valid indicators of CHCs' quality of care are lacking. The Health Plan Employer Data and Information Set (HEDIS) scores used by the National Committee of Quality Assurance (NCQA) could be used to assess CHCs' performance in terms of their quality of care. Unfortunately, however, no such data are available for assessing the quality of care or effectiveness of the CHC delivery system. That serious shortcoming prevents comprehensive performance assessment of community health centers.

The level of analysis in this study is the organization. The unit of analysis is the community health center. No patient-specific data were collected. It is likely that the variability of CHC performance may be accounted for by the variability of patients' health status.

The small explained variance in the full model suggests that important variables may not be available for examination. More comprehensive data acquisition should alleviate this problem in future studies.

Recommendations for Future Research

Identification of Data Set Needs

GAO suggests that HRSA “. . . could improve its monitoring processes and oversight tools, especially its data collection efforts” (GAO, 2000, p. 35). The current data acquisition tools have major deficiencies. For example, the available instruments do not measure several variables shown in the literature to influence CHC performance including inadequate management (GAO, 2000). Inadequate management is known to be an important CHC performance contributor (GAO, 2000). Measurement of management, an elusive construct, also is not currently available in the CHC dataset.

The current CHC data collection does not report on the quality of care or the process of CHC delivery of care. Effectiveness indicators such as The Health Plan Employer Data and Information Set (HEDIS) scores used by the National Committee of Quality Assurance (NCQA) to assess managed care plan outcomes are critical for an orbicular and comprehensive assessment of CHC performance. A tool for comprehensive measurement of CHC performance would conflate valid effectiveness (i.e. quality of care) assessment with the efficiency measures developed in this study. Such tool would be a better measure of CHC value to all its stakeholders and would serve the disparate interests of managers, patients, and third-party payers. BPHC, the primary CHC funding agency, can develop fund allocation strategies

including “pay for performance” by using such an integrated instrument as a valid benchmark. Patients would then be more empowered when selecting a CHC facility and when necessary, pressing for improvement in the quality of care. And society would get a better return on its investment in caring for the less fortunate.

Conclusions

This study makes a novel use of various analytical techniques: data mining, predictor tree analysis, and multivariate modeling of CHC efficiency. The most important finding, that the change in CHC technical efficiency positively affects the change in CHC cost efficiency, has significant causal implication. Technical efficiency leads to cost efficiency in CHC operations. Put in practical terms, it is important to encourage managerial training and to help poorly performing CHCs to achieve more cost efficiency by optimizing their technical efficiency. As that translates into operational efficiency, the CHC program’s sustainability and cost effectiveness will improve. By augmenting the existing programs with appropriate technical assistance, or by employing innovative solutions such as availing CHCs of decision support software applications, we could expect improved CHC performance.

President's Bush's health centers initiative, to increase health care access to 1,200 of the Nation's neediest communities through new or expanded health center access points, recently was reauthorized. It is expected to cost the taxpayers approximately 1.8 billion dollars in the year 2007. Better tools should be employed to evaluate both the financial and the care performance of this important and expensive program. Spending more money without assessment of program outcomes including both efficiency and effectiveness is untenable. The findings of this study

offer an evidence-based strategy to guide much needed changes in the current evaluation of CHC program in efforts to improve its performance.

**APPENDIX A: THE EXPLANATION OF RESULTS OF DATA MINING:
RELATIVE IMPORTANCE OF PREDICTOR VARIABLES OF
TECHNICAL EFFICIENCY FOR THE YEAR 2000**

Medicare eligibility was not at all predictive in 2000 (the first year of the study), but it emerged as the strongest predictor for 2001 and 2003 with a score of 100; a moderately strong predictor for the year 2002 with a score of 76.87 and a weak predictor for the year 2004 with a score of 29. Medicare was overall the strongest predictor. Poverty was the fourth overall strongest continuous context variable, with a moderate score of 52.991 in the year 2000, exhibiting no predictivity in the year 2001 with a score of 0 and again showing moderate predictive scores of 88.742 and 67.258 for the years 2002 and 2003, respectively, and a weak score of 30.315 for the final study year of 2004. Hispanic ethnicity was overall the fifth strongest continuous context predictor, with a moderate score of 62.875 for the year 2000, a score of 0 for the years 2001 and 2003, but a high score of 91.272 for the year 2002 and a low score of 34.123 for the final year, 2004. Medicaid eligibility overall was the sixth strongest continuous context variable, with a moderate score of 53.253 for the first study year of 2000, scores of 0 for the years 2001, 2002 and 2003, and a high score of 100 for the final study year, 2004. Population physician ratio, a proxy variable for competition overall, was the seventh strongest continuous context variable among the six context variables. It exhibited a high score of 100 for the first study year, 2000, a low score of 10.038 for the year 2001 and very low scores of 1.738, 1.818 and 1.106 for the years 2002, 2003 and 2004 respectively. Crude death rate, a proxy for socioeconomic status overall was the weakest overall (ninth) of the predictor variables, with a moderate score of 59.486 for the first study year, 2000, and thereafter showing scores of 0 for the years 2001, 2002, 2003 and 2004.

Amongst the continuous design/organizational structure variables, funding (payer mix = % grant / total revenue), an indicator of direct financial support from the federal government, ranked as the overall second strongest variable, with the scores of 79.976, 38.672, 64.483 and

98.352 for the years 2000, 2001, 2002, and 2003, but a score of 0 for the final year, 2004. The overall eighth strongest continuous design variable, staffing, scored 0 for the years 2000, 2001, 2003 and 2004, and scored a high of 91.614 for the year 2002. The third continuous design variable, size (Physicians+NPs+PAs) showed no score for any of the five study years.

Amongst the categorical context variables, region was overall the third strongest variable exhibiting a moderately high influence with the scores of 35.101, 81.429, 100.000 and 38.347 for the years 2000, 2001, 2002 and 2003, respectively, but showing no score for the final study year of 2004. The only other categorical context variable, rurality, failed to register a score.

The only categorical design variable, Network participation, was not shown to be an important predictor according to the tree algorithm.

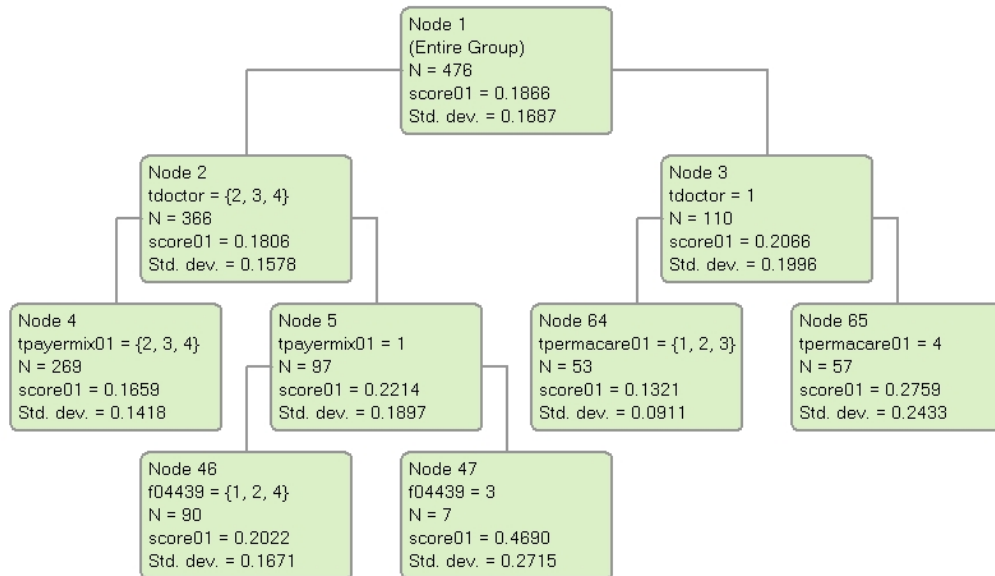
**APPENDIX B: THE EXPLANATION OF RESULTS OF DATA MINING:
RELATIVE IMPORTANCE OF PREDICTOR VARIABLES OF COST
EFFICIENCY FOR THE YEAR 2000**

Medicare eligibility ranked as the fifth (out of six) strongest predictive. Medicare was not at all predictive in the first study year of 2000 or in years 2001, 2003, and 2004, but showed a high predictivity for the years 2002, with a score of 97.717. Hispanic ethnicity was the fourth strongest predictor variable, with a highest score of 100 for the year 2002, a score of 0 for the years 2000, 2001 and 2003, but a high score of 83.164 for the year 2004. Population physician ratio, a proxy variable for competition, was the strongest predictor variable among the six variables that retained predictivity in data mining analysis. It exhibited the highest score of 100 for the first study year, 2000, a relatively high score of 88.907 for the year 2001, and high scores of 83.950, 72.559 and 59.332 for the years 2002, 2003 and 2004, respectively. The second strongest variable, staffing, scored 0 for the years 2000, 2002, and 2004 and scored a high of 100 for the years 2001 and 2003. Payer mix (% grant / total revenue) an indicator of direct financial support from the federal government, ranked as the sixth strongest variable, with scores of 0 for years 2000, 2001, 2002, and 2003, but a score of 19.582 for the final year, 2004. Amongst the categorical context variables, region was the only variable exhibiting a moderately high influence, with scores of 99.135 and 100.000 for the years 2003 and 2004, respectively earning a 3rd strongest rank as a predictor variable. The only categorical design variable, network participation, failed to register a score.

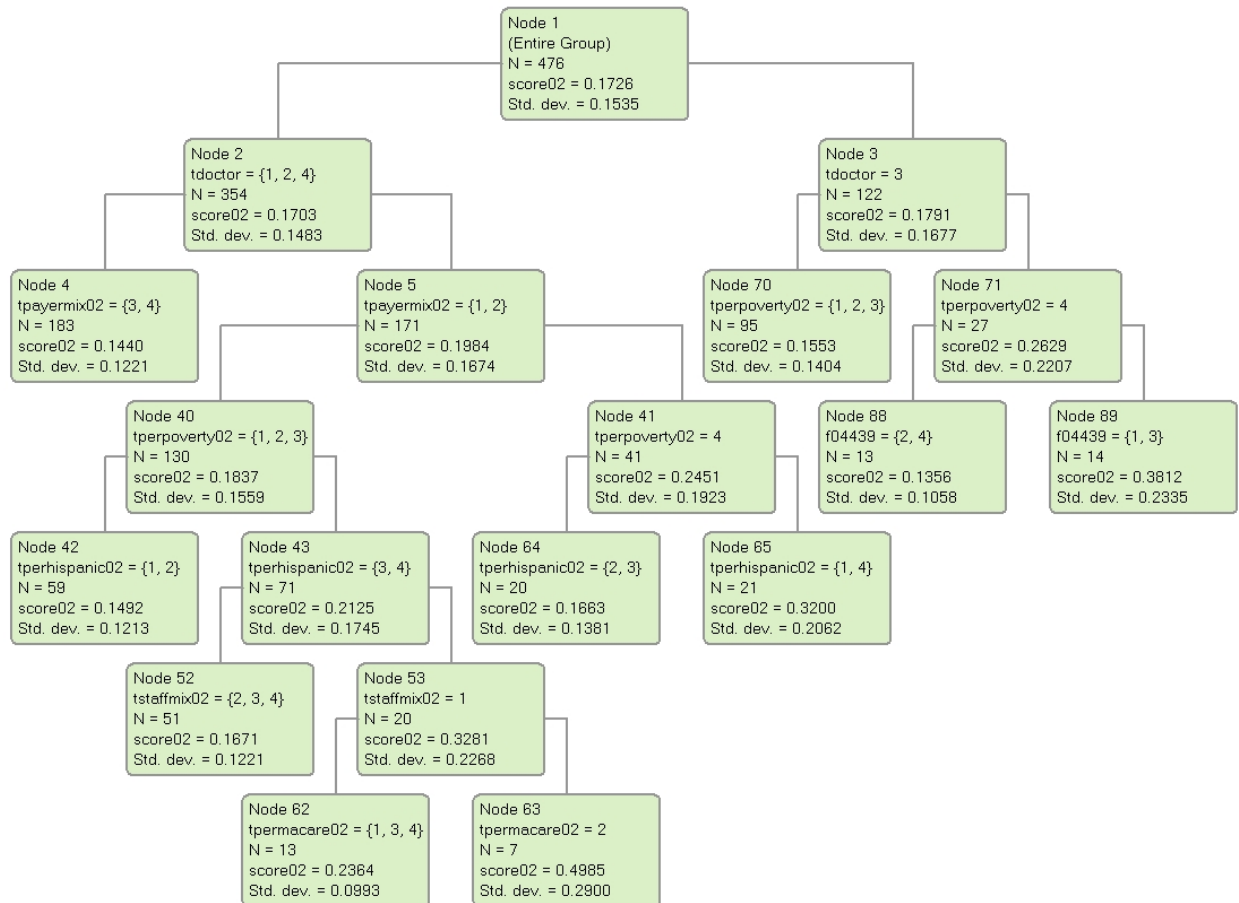
The ranking for predictor variables, suggesting their relative importance, was as follows. For the year 2000, the variable tdoctor was the only variable of importance, with a score of 100.000. For the year 2001, the variable tstaffmix was the variable of most importance, with a score of 100.000; tdoctor came in second with a score of 88.907. For the year 2002, the variable tperhispanic was the variable of most importance, with a score of 100.000; tpermacare came in second with a score of 97.717 and tdoctor came in third with a score of 83.950. For the year

2003, the variable tstaffmix was the variable of most importance, with a score of 100.000; region (f04439) came in second, with a score of 97.717. 99.135 came in third with a score of tdoctor 72.559 and for the year 2004, the variable region (f04439) was the variable of most importance, with a score of 100.000, and tperhispanic came in second, with a score of 83.164. Third was tpermcaid with a score of 65.620; tdoctor came in fourth, with a score of 59.332, and tpayermix came in fifth, with a score of 19.582.

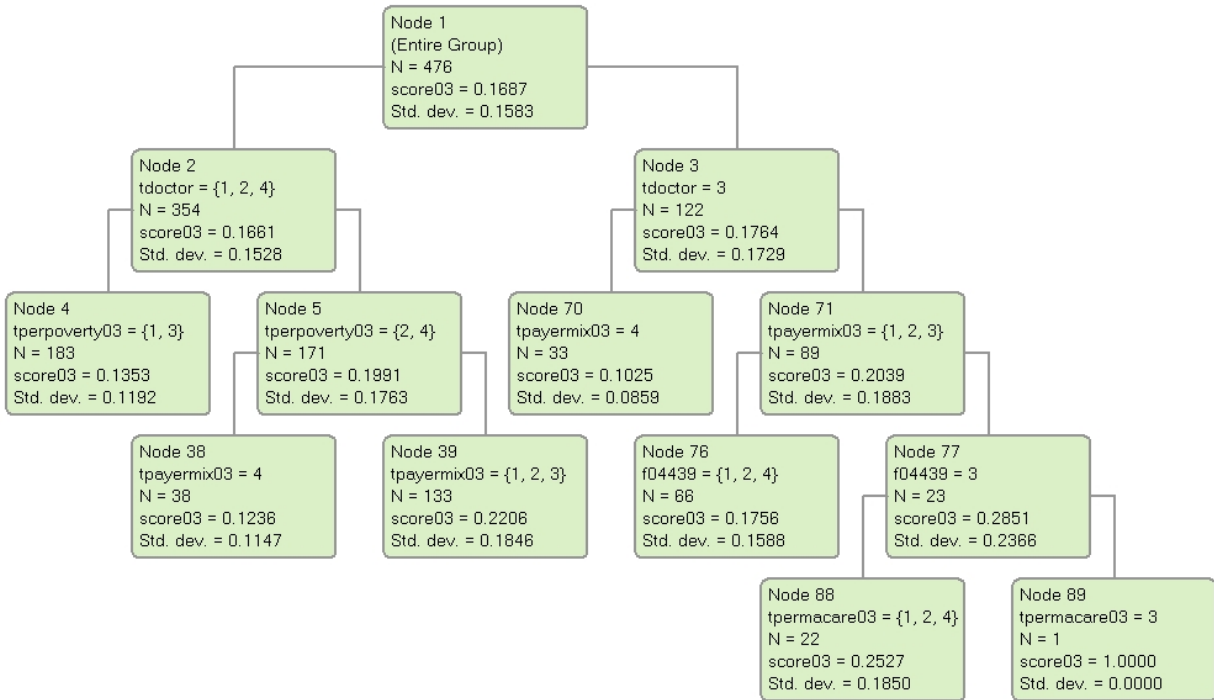
APPENDIX C: TREE MODEL WITH SPLITS FOR TECHNICAL EFFICIENCY FOR THE YEAR 2001



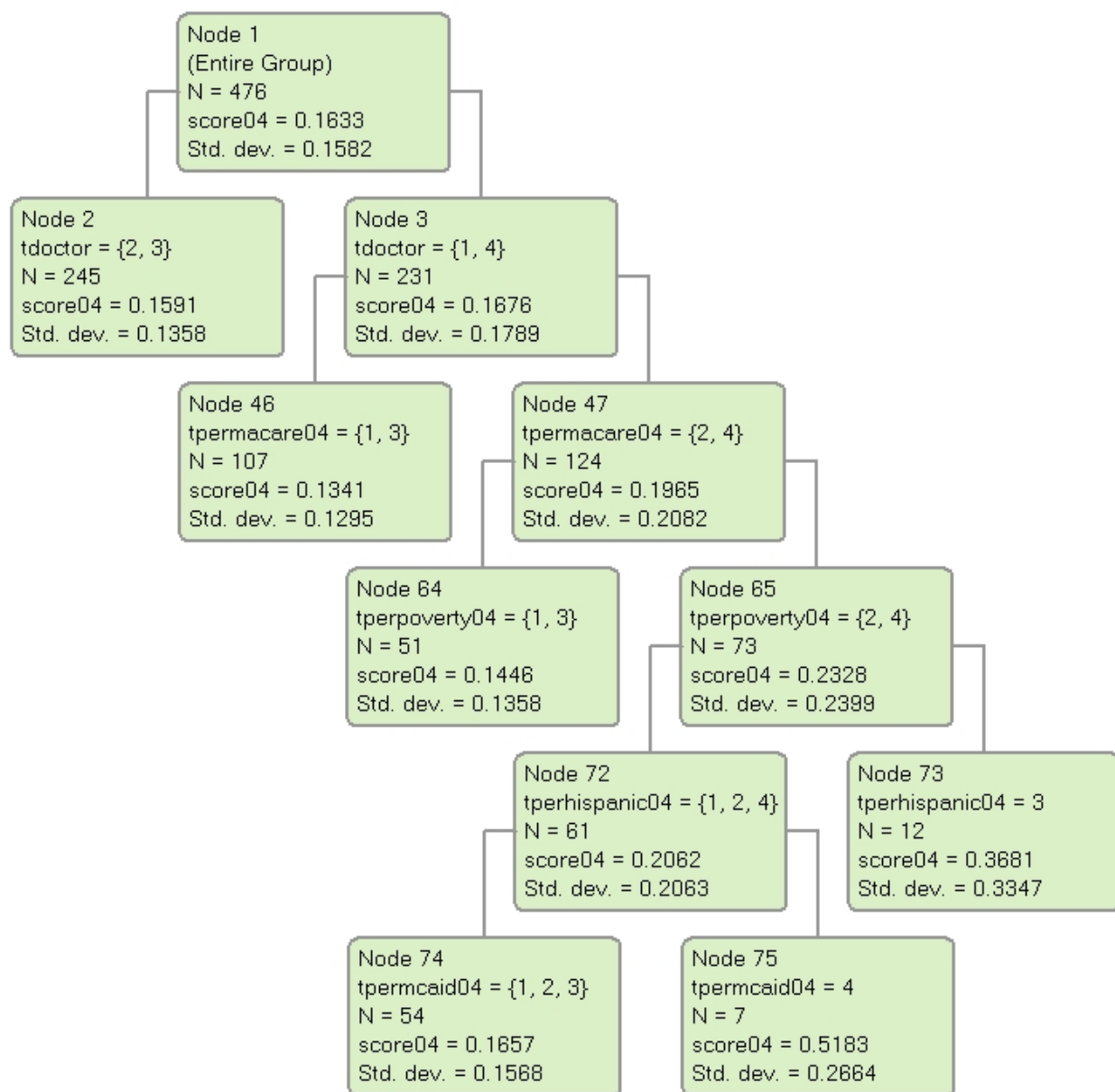
APPENDIX D: TREE MODEL WITH SPLITS FOR TECHNICAL EFFICIENCY FOR THE YEAR 2002



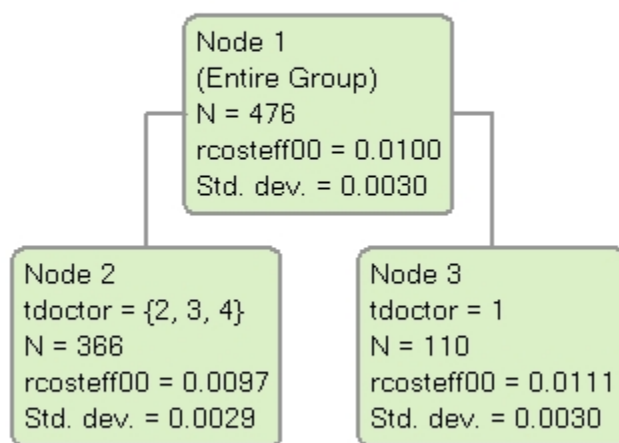
APPENDIX E: TREE MODEL WITH SPLITS FOR TECHNICAL EFFICIENCY FOR THE YEAR 2003



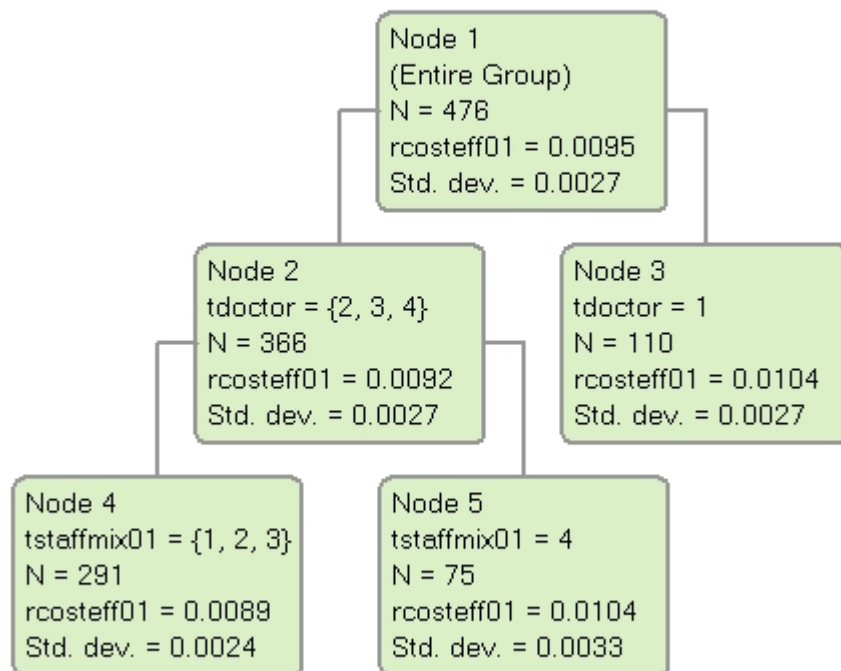
APPENDIX F: TREE MODEL WITH SPLITS FOR TECHNICAL EFFICIENCY FOR THE YEAR 2004



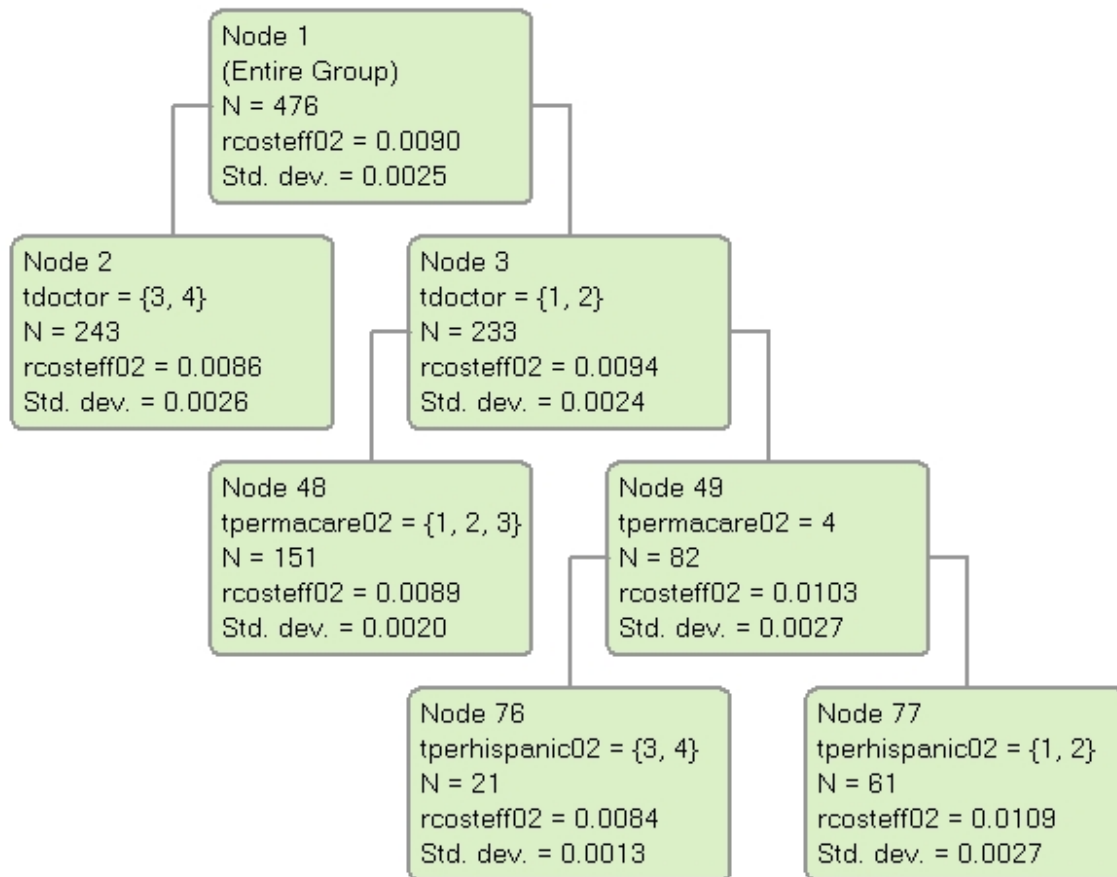
**APPENDIX G: TREE MODEL WITH SPLITS FOR COST EFFICIENCY
FOR THE YEAR 2000**



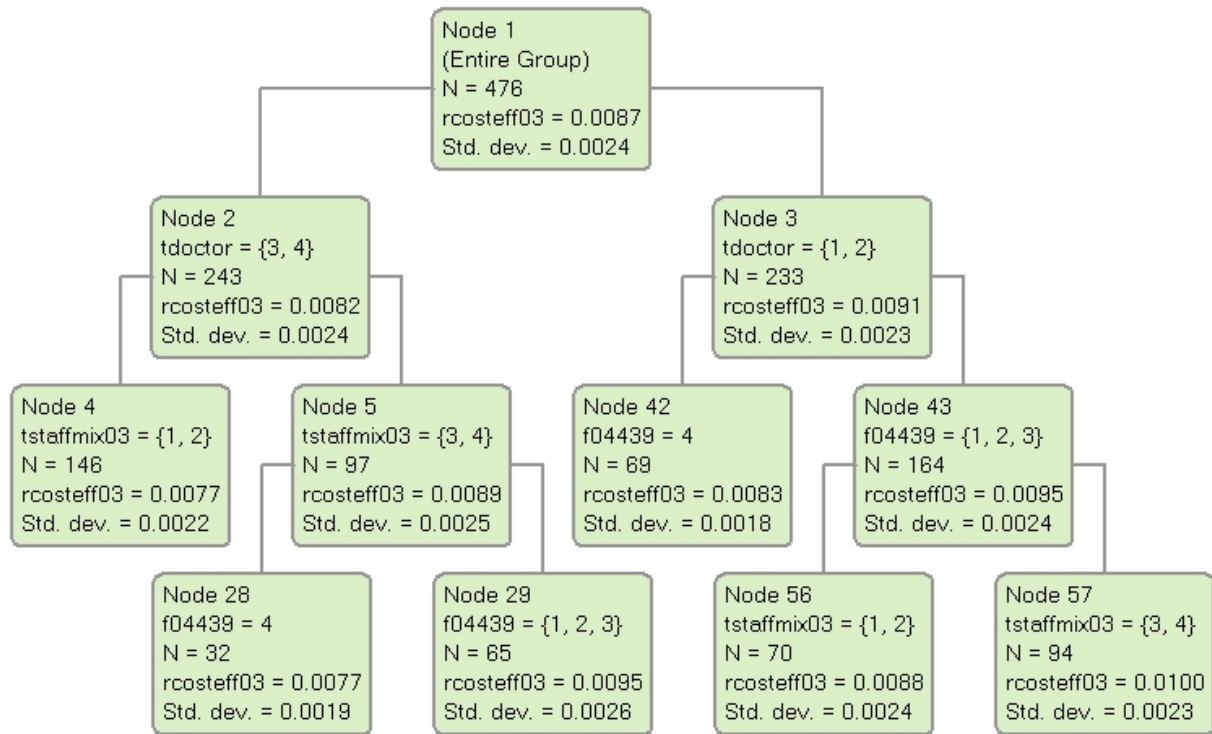
APPENDIX H: TREE MODEL WITH SPLITS FOR COST EFFICIENCY FOR THE YEAR 2001



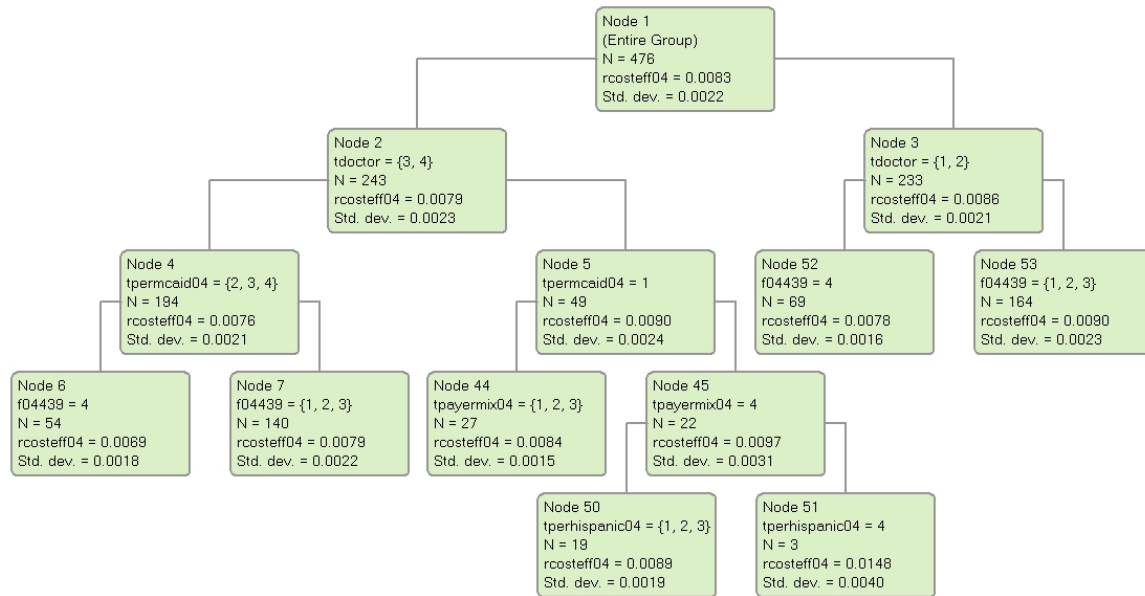
**APPENDIX I: TREE MODEL WITH SPLITS FOR COST EFFICIENCY
FOR THE YEAR 2002**



**APPENDIX J: TREE MODEL WITH SPLITS FOR COST EFFICIENCY
FOR THE YEAR 2003**



**APPENDIX K: TREE MODEL WITH SPLITS FOR COST EFFICIENCY
FOR THE YEAR 2004**



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