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Determinants Of Productivity In Hospital-based Rural Health Clinics A Growth Curve Modeling Approach

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DETERMINANTS OF PRODUCTIVITY IN HOSPITAL-BASED RURAL HEALTH CLINICS: A GROWTH CURVE MODELING APPROACH

by

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ABSTRACT

The Patient Protection and Affordable Care Act of 2010 expanded rural Medicaid and Medicare coverage. However, different vehicles of delivering care (e.g., hospitals, health clinics, etc.) have differing organizational capacity that may or may not enable them to overcome the challenges of expanded provision. Consequently, this research employed structural contingency and organizational performance models to investigate the impact of organizational factors on productivity growth, while recognizing that contextual factors also affect the delivery of care.

Latent growth curve modeling was used to study a national panel of 708 U.S. hospital-based Rural Health Clinics for the years 2005 to 2008. Productivity was measured through dynamic slacks-based data envelopment analyses. Unconditional and conditional linear growth curve models were fitted to data.

Findings revealed that 1) hospital-based clinics with higher baseline levels of productivity in 2005 had a slower rate of growth in productivity for the years 2006 to 2008, 2) hospital-based clinics with physicians had significantly higher productivity, 3) hospital-based clinics in urban focused areas had significantly higher productivity, 4) newer hospital-based clinics had significantly higher productivity, and 5) prospective payment system was negatively related to the rate of change in productivity growth.

Organizational and contextual factors included in this study significantly explained initial differences in productivity but were unable to explain productivity growth. Future research could improve the study by 1) including additional explanatory variables, such as the use of technology and disease management programs, 2) adjusting productivity measures by case mix measures, and 3) conducting truncated panel data regression with Monte Carlo simulation.

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LIST OF ACRONYMS/ABBREVIATIONS

AHRQ	Agency for Healthcare Research and Quality
ARF	Area Resource File
ARMA	Auto Regressive Moving Average model
CDC	Centers for Disease Control and Prevention
CDP	Context-Design-Performance model
CMS	Centers for Medicare & Medicaid Services
DEA	Data Envelopment Analysis
DMU	Decision Making Units
FIPS	Federal Information Processing Standards
FTE	Full Time Equivalent
GAO	Government Accountability Office
GCM	Growth Curve Modeling
GIS	Geographic Information Systems
HPSA	Health Professional Shortage Areas
HRSA	Health Resources and Services Administration
MLM	Maximum Likelihood Mean adjusted estimator
MUA	Medically Underserved Areas
OPT	Organizational Performance Theory
RHC	Rural Health Clinic
RUCA	Rural-Urban Commuting Area Codes
SCT	Structural Contingency Theory
SEM	Structural Equation Modeling
SPO	Structure-Process-Outcome model

CHAPTER ONE: INTRODUCTION

Access to health care in rural areas is a significant issue and will likely become even more critical in the coming few years. The Patient Protection and Affordable Care Act (PPACA) of 2010 introduced over a dozen of changes directly relevant to Rural Health Clinics (RHC) (Mueller, 2010). Some examples include expanded rural Medicaid (Section 2703) and Medicare coverage (Sections 3121–3127) in several vehicles of delivering care including RHCs as well as increasing and maintaining special benefits and payments to physician and non-physician providers (Sections 5101, 5303, 3102–3107).

However, different vehicles of care delivery (e.g., hospitals, health clinics, federally qualified health centers, etc.) have differing organizational capacity that may or may not enable them to overcome challenges of expanded provision. The differing organizational capacities also affect the ability of different vehicles of care delivery to respond to contextual factors. Consequently, it is important to examine these various vehicles.

In particular, the effect of delivery of care approaches on productivity needs further scrutiny, since a large number of provisions related to RHCs (Sections 5101, 5303, 3102–3107) concern overcoming workforce shortages. The current research attempts to move the issue forward by adapting structural contingency and organizational performance models in order to research the impact of organizational factors on the productivity of hospital-based RHCs, while recognizing that contextual factors also affect the delivery of care.

For the purposes of this study, productivity was defined as the maximization of outputs (visits or encounters) while minimizing inputs (FTEs) as computed by technical efficiency scores of Data Envelopment Analysis (DEA).

1.1 Background of the Study

Sixty-one million people live in rural areas of the U.S., a number that exceeds the populations of the U.K., Italy, Spain, or France (Rosenthal & Fox, 2000). Although the percentage of rural residents is decreasing over time, in raw numbers there are more rural Americans today than ever before. Despite health-practitioner shortages and resource deficits that riddle rural areas, patients still require essential health care services at both clinics and hospitals.

Unfortunately, health practitioners and resources remain in short supply. For instance, only one Primary Care Physician (PCP) is available for every 2,857 individuals in rural communities as compared to one for every 614 individuals nationally (Sinay, 2001). In response to the shortage of health practitioners in rural areas, the federal RHC program was instituted in 1977. The program provides RHCs with attractive reimbursements for services provided to Medicare and Medicaid beneficiaries. Although the program experienced slow growth during its first two decades, the number of RHCs increased twelve-fold from 314 in 1990 (Gale & Coburn, 2003) to approximately 3,800 in 2009 (U.S. Department of Health and Human Services, Center for Medicare and Medicaid Services [CMS], 2009).

Along with the growth of RHCs, the cost of the program on Medicare and Medicaid has increased substantially, reaching up to 630 million dollars in 2002 (U.S. Department of Health and Human Services, Office of Inspector General, 2005). RHC productivity (efficiency), effectiveness, and accessibility were subsequently questioned (Brown, 1996; Steinhardt, 1997). RHCs were found to have improved access to care (Cheh & Thompson, 1997). They were also found to have provided effective care (Probst, Laditka, & Laditka, 2009; Zhang, Mueller, Chen, & Conway, 2006).

However, RHCs were found to be less productive when examined in a cross-sectional manner (Sinay, 2001). Yet, it is not clear whether RHCs are showing growth or improvement in productivity if assessed in a longitudinal manner. If RHCs are not showing growth in productivity over time, it could be more difficult to continue and even raise the support given to RHCs in the light of impending fiscal austerity measures. More importantly, understanding organizational and contextual variables that could explain differential growth in productivity could help policy and practice interventions.

1.2 Statement of the problem

The RHC Services Act of 1977 defines an RHC as a primary care facility where at least one midlevel practitioner—a physician assistant (PA) or nurse practitioner (NP)—is available 50% or more of the time when the clinic is open (Gale & Coburn, 2003; Knott & Travers, 2002; Krein, 1999). Although physician services were desired by the Act, the Act did not require the availability of physicians as RHC staff. In other words, RHCs were primarily designed to be non-physician providers of care with periodic (once every fortnight) physician oversight in the light of the continued shortage of physicians (Gale & Coburn, 2003; Knott & Travers, 2002).

One of the least-studied problems of RHCs is how organizational variables affect productivity and productivity growth rates over time. Availability of physicians, ownership, age of clinics, and payment system are some of the potential determinants of productivity noted in literature. A study of RHCs in the Midwest indicated that facilities with physicians had higher productivity (Sinay, 2001). Non-profit ownership in RHCs was negatively related to cost-efficiency, although the relationship between ownership and productivity was not examined (Ortiz, Meemon, Tang, Wan, & Paek, 2009). Older RHCs were negatively related to cost-efficiency (Ortiz et al., 2009). But the relationship between age and productivity remained unexamined. Payment system (i.e., whether the RHC received capped or un-capped reimbursement) might relate to productivity (Gale & Coburn, 2003). However, RHC studies so far have not taken payment system differences into account.

Another set of problems related to RHCs is the influence of contextual variables on RHC performance. Many of the financial and operational challenges of RHCs emanate from the complexities of operating facilities in rural areas. Compared to urban areas, rural areas have a higher percentage of elderly, a higher proportion of non-insured residents, and a higher percentage of persons at or below the poverty index—subpopulations that place high demand on RHC staff and financial resources (Harris & Leininger, 1993). In spite of the high relevance of contextual variables, hardly any studies investigate how contextual variables affect trends and patterns of productivity.

1.3 Research Aims

For the years 2005 to 2008, the first objective was to examine whether growth trends and patterns of productivity were related to organizational determinants of productivity for U.S. hospital-based RHCs. For the years 2005 to 2008, the second objective was to investigate whether growth patterns and trends in productivity were affected by contextual determinants of productivity for U.S. hospital-based RHCs. A hospital-based RHC is defined as an integral and subordinate part of a hospital participating in Medicare that is operated with other departments of the hospital under common licensure, governance, and professional supervision (U.S. Department of Health and Human Services, Health Resources and Services Administration [HRSA], 2006).

1.4 Research Questions

1. For the baseline year of 2005, is there a significant variation in the initial levels of productivity among hospital-based RHCs? In other words, do hospital-based RHCs have similar baseline productivity levels?
2. For the years 2006 to 2008, is there a significant variation in the growth trends and patterns of productivity among hospital-based RHCs? In other words, taking into account any differences in baseline levels of productivity, is there a substantial growth in productivity from 2005 to 2008? If there is a growth in productivity, is productivity increasing or decreasing from 2005 to 2008? If productivity is increasing or decreasing over the study period, is the rate of increase or decrease in productivity similar across hospital-based RHCs?

3. For the years 2005 to 2008, is there a significant relationship between baseline levels of productivity and rate of change in productivity among hospital-based RHCs?
4. For the years 2005 to 2008, can the change trajectories in productivity be explained by time-varying (physician availability) and time-constant (age, ownership, payment system, poverty rate, minority population, Medicare-eligible population, uninsured population, rural classification, and geographic location) determinants of productivity? In other words, if hospital-based RHCs did show growth in productivity from 2005 to 2008, which set of determinants explained the growth in productivity? If hospital-based RHCs significantly differed in productivity growth rates, which set of determinants explained the differences in productivity growth rates?

1.5 Significance of the Study

The findings of the research had several implications for policy and practice. First, the four-year panel study on the most recent data (2005–2008) examined how RHC productivity growth related to time-constant and time-varying organizational and contextual variables. That examination addressed a number of questions that were of benefit to policy and practice.

Did hospital-based RHCs show a marked growth in productivity from 2005 to 2008? If there was a substantial growth in productivity, did the growth show an increasing or decreasing trend? Did hospital-based RHC productivity grow with similar rates? What variables explained differences in productivity growth rates among hospital-based RHCs? What variables explained growth in productivity among hospital-based RHCs? Answers to these questions indicated areas that are in need of policy and practice interventions.

Second, measuring overall organizational productivity with ratio analysis as done by CMS (i.e., total visits per total FTEs), is known by DEA experts to be inadequate (Cooper, Seiford, & Tone, 2007), for 1) ratio analysis does not take into account multiple inputs and outputs simultaneously, 2) ratios could not incorporate economies of scales, 3) ratio analysis is unable to account for productivity dependencies over time, and 4) ratios do not "benchmark" productivity against the best productivity frontier attained by the relatively productive RHCs. Applying DEA analysis addressed the aforementioned limitations of ratio analysis.

Last but not least, by exploring the spatial articulation of productivity through Geographic Information Systems (GIS), geographic variations were identified. The spatial exploration aided the identification of region-specific differences.

1.6 Scope of the Study

Hospital-based RHCs were the unit of analysis. There are two types of RHCs: independent and provider-based. Provider-based RHCs are operated by a hospital, nursing home, or home health agency, while independent RHCs are freestanding. In 2007, there were 1,701 provider-based RHCs in the U.S., which made up 45% of all RHCs (Ortiz et al., 2009). However, over 90% of provider-based RHCs are hospital-based RHCs (Gale & Coburn, 2003). In 1999, about 165 provider-based RHCs belonged to nursing homes or home health agencies (Gale & Coburn, 2003).

This study chose to focus on provider-based RHCs for several reasons: 1) after the Balanced Budget Act of 1997 (BBA), provider-based RHCs now face different systems of reimbursements that pose financial viability challenges distinct from independent RHCs (Krein, 1999; McAtee & Beverly, 2005); 2) in the mandated BBA implementation of quality assessment and performance improvement (QAPI) programs, provider-based RHCs tended to lag in the measurement of clinical effectiveness and productivity as compared to independent RHCs (Knott & Travers, 2002); 3) unlike free standing RHCs, provider-based RHCs operate without productivity standards (Gale & Coburn, 2003); and 4) data for provider-based RHCs were available from CMS Medicare Cost Reports free of charge.

For this study, the decision to focus on hospital-based RHCs from within provider-based RHCs was a matter of practicality: 1) a large majority of provider-based RHCs are hospital based, and 2) too few nursing homes and home health agencies provided data concerning their RHCs in CMS Cost Reports. Given the relatively small number and incomplete data of non-hospital based RHCs, the study focuses on hospital-based RHCs.

1.7 Theoretical Rationale

The study employed a context-design-performance (CDP) model of structural contingency and organizational performance theories. Structural contingency theory (SCT) is appropriate in the study for two key reasons.

First, according to SCT, the fit (alignment) between organizational variables and contextual variables will explain organizational performance. Hospital-based RHCs face different forms of reimbursements and certification requirements. In addition, they are located in rural areas, and rural areas show marked variations from place to place as compared to urban areas (Rosenblatt & Hart, 1999). Therefore, hospital-based RHCs could adapt to their environment in a variety of ways, making contingency theory a viable framework. Consequently, the growth patterns and trends of productivity were anticipated to show significant variation.

Second, the research aimed to identify determinants that account for variations in organizational performance. Contingency theory is useful when the research focus is on discovering the variations and growth trends in organizational performance rather than assessing congruence among organizations.

Organizational performance theory (as stipulated by Donabedian's Structure-Process-Outcome (SPO) model) is used as a supplement to structural contingency theory for two main reasons. To begin with, context-design-performance (CDP) model is an adaptation of the SPO model to the organizational level (Wan, 2002). Thus, such contingency models are shared by both structural contingency theory and organizational performance theory (Burke & Litwin, 1992). Second, not all contingences are equally important (Hendrick, 2003). In other words, the fit of contingencies may not be enough by itself. There is a need to focus on determinants of performance—variables that have a direct and consistent relationship with performance.

1.8 New Contributions

From a theoretical perspective, structural contingency theory was developed based on larger organizations, and the theory has been less applied in the study of small-scale organizations (Hollenbeck et al., 2002). The same can also be said of organizational performance theory. Consequently, applying contingency and organizational performance theories in a study of small organizations such as RHCs could contribute to knowledge in the field.

From a policy perspective, identifying recent trends and patterns of productivity change (growth, decline, or lack of growth) as well as variables that could explain such trends and patterns would benefit rural health policy makers. Since improved productivity is related to cost-efficiency (Ortiz et al., 2009), it is of benefit to understand determinants of changes in productivity. In addition, policy makers could be interested in regional variations in RHC productivity. That information could minimize the problem of a one-size-fits-all application of research findings.

In terms of practical contributions, the findings of the study indicated the need to attract and retain physician providers to rural areas. In addition, an uncapped cost-reimbursement system was associated with faster productivity growth rates. Moreover, proximity to urban areas was associated with higher levels of productivity.

From the research vantage point, some studies have explored RHCs' productivity (Ortiz et al., 2009; Sinay, 2001). However, hardly any known investigations have examined the simultaneous effects of organizational design and contextual factors on RHC productivity. Neither has there been a multi-year panel study of RHCs. Additionally, this study is the first to apply growth curve modeling to the study of RHCs.

In terms of the measurement of productivity, the research utilized the latest dynamic slacks-based four-wave DEA analysis of productivity, which accounted for 1) productivity dependencies over time, 2) impact of net-earning (financial viability) on productivity, and 3) underutilization or overutilization of inputs through slacks-based analyses. Moreover, the research is one of the first applications of dynamic DEA to rural health services research.

In addition, the research also improved on sample size and internal validity. McAtee and Beverly (2005) relied on a single case study; Sinay (2001) used 163 RHCs in the Midwest; Ortiz et al. (2009) used a nationwide survey of 134 provider-based RHCs. This study conducted a four-year panel analysis on a nationwide sample of 708 hospital-based RHCs. Panel studies use repeated measures of the same variables within the same organizations, which allows better statistical control for extraneous variables, thereby enhancing internal validity.

1.9 Limitations of the Study

The study has a number of limitations. First, a correlational and non-experimental research design cannot rule out all alternative explanations. For instance, productivity is measured through visits. Extraneous factors, such as individual patient characteristics, might affect the quality of outpatient visits. However, freely available data sources such as CMS Medicare Cost Reports do not provided individual (patient) level data.

Second, DEA is a relative and indirect measure of productivity. Therefore, DEA scores could not capture all aspects of productivity. Furthermore, DEA scores are truncated, given the limited range of values from 0 to 1. Moreover, DEA scores tend to be highly correlated with each other since they are computed on the basis of productive facilities. Such correlations tend to bias parameter estimates (Zhang, Unruh, & Wan, 2008).

Third, the study covered only hospital RHCs with complete data for 2005 and 2008. Missing data for 2006 and 2007 were imputed as long as values for the initial study period (2005) and final study period (2008) were available. Thus, the generalizability of the study was limited, given the non-random inclusion of hospital-based RHCs.

Fourth, contingency and organizational performance theories suggest additional variables that could not be addressed due to data limitations. For example, the use of technology (e.g., electronic medical records), organizational strategies (e.g., disease-management programs), organizational culture (e.g., interdisciplinary teams), and the disincentive of working in rural areas (e.g., professional and social isolation) are potential determinants of productivity.

Last, maximizing outputs (visits or encounters) is not the only objective in health care organizations. Therefore, determinants of productivity could relate differently to other performance measures such as quality of care, patient satisfaction, and cost-efficiency.

However, the impact of some of the limitations could be minimal given (1) the use of repeated measures of the same variables within the same hospital-based RHCs, making it possible to statistically control the effects of the extraneous variables; (2) the use of four-wave dynamic slacks-based DEA analysis that takes into account the influence of net earning on productivity; (3) the categorization of RHCs into groups on the basis of rural classification before conducting DEA analysis; and (4) the use of population-level risk adjustment for cause-specific mortality rates.

1.10 Summary

This chapter provided a brief background on RHCs, followed by a concise explanation of problems regarding the unexplored impact of organizational and contextual variables on facility-level productivity growth rates. The aim, significance, scope, and limitations of the study, as well as expected contributions, were subsequently discussed. In addition, the theoretical rationale behind the study was briefly noted. The next chapter provides a literature review on rural health settings in general and RHC studies in particular. Chapter 3 discusses the theoretical framework and the hypotheses developed on the basis of structural contingency and organizational performance theories. Chapter 4 presents the methodologies proposed to test the hypotheses. Chapter 5 narrates the findings of the study. The sixth and final chapter presents the discussions and conclusions.

CHAPTER TWO: LITERATURE REVIEW

This chapter has five sections. The first section discusses the background and contribution of RHCs. The second section presents specific information about hospital-based RHCs. The third section explores the current state of knowledge regarding RHC productivity studies. The fourth and fifth sections review literature regarding exogenous and endogenous variables, respectively.

2.1 Rural Health Clinics

The genesis of RHCs preceded their legislated enactment. The Rural Health Initiative program began in July 1975 as an attempt to combine the strengths of Community Health Centers and National Health Service Corps programs (Banahan & Sharpe, 1982). The Initiative culminated in the Rural Health Clinics Act of 1977 (P.L. 95-210), which was passed by Congress and signed into law by President Carter (HRSA, 2006).

The Act had two goals: 1) to increase the utilization of non-physician providers, even in the absence of a physician, and 2) to generate additional revenue for eligible rural practices to encourage continued service and outreach to a larger proportion of underserved populations, particularly Medicare and Medicaid beneficiaries (Cheh & Thompson, 1997; Krein, 1999; Travers & Dartt, 1995).

The Act also instituted a cost-based reimbursement mechanism for RHCs (HRSA, 2006). Moreover, the Act allowed RHCs to receive higher reimbursement rates from CMS and other payers. Higher reimbursement rates are intended to attract and retain physician and non-physician providers to medically underserved areas (Probst et al., 2009; Zhang et al., 2006).

2.1.1 RHC Certification Requirements

In order to qualify for RHC certification, a medical facility must be located in an area defined by the Census Bureau as non-urbanized and meet at least one of the following additional area designations: Health Professional Shortage Area (HPSA), Medically Underserved Area (MUA), or State Governor's Designated Shortage Area (GDSA) (Gale & Colburn, 2003; HRSA, 2006). Although the Census Bureau generally defines rural or non-urbanized areas as those with fewer than 2,500 residents, the RHC program allows areas up to 50,000 residents (Steinhardt, 1997). Therefore, RHCs do exist in counties that are classified as metropolitan or urban by the U.S. Census Bureau (Probst et al., 2009).

In addition to location-based requirements, RHCs themselves must meet various standards related to staffing, medical services, target population, and ownership. RHCs must have at least one of the following: Physician Assistant (PA), Nurse Practitioner (NP), or Certified Nurse Midwives (CNM) (Knott & Travers, 2002; Krein, 1999; CMS, 2009). In addition, each mid-level practitioner (PA, NP, or CNM) must be available 50% or more of the time when the clinic is open (Phillips & Kruse, 1995; CMS, 2009). Moreover, each mid-level practitioner in an independent RHC must provide at least 2,100 office visits annually (Gale & Coburn, 2003).

It is very important to reiterate that the absence of physician requirements does not ignore the crucial services of physicians but is rather a realistic reflection of acute physician shortages. In other words, RHCs were primarily designed to be non-physician providers with periodic (once every fortnight) physician oversight in the light of the continued shortage of physicians (Gale & Coburn, 2003; Knott & Travers, 2002).

The provision of primary care is required in RHCs. Primary care is defined as services typically performed in physician's office (HRSA, 2006). However, RHCs are not required to provide a full spectrum of primary care services (Probst et al., 2009). RHCs must furnish on-site routine diagnostic and laboratory services (CMS, 2009). More importantly, RHCs must either provide or have arrangements with other health care providers to furnish inpatient hospital services and specialty care (CMS, 2009; HRSA, 2006).

RHCs are not required to care for all individuals seeking care (Probst et al., 2009). Nor are RHCs obligated to provide service for the poor and the uninsured. As of September 2005, only 16% (590/3600) of RHCs stated they would take all patients regardless of ability to pay (U.S. Government Accountability Office [GAO], 2006). Although not required to accept uninsured patients, RHCs actually derive 15% of practice revenue from self-pay patients (GAO, 2001). In summary, the target populations of RHCs are Medicare and Medicaid beneficiaries (Zhang et al., 2006).

2.1.2 General Characteristics

RHCs are small organizations (Thometz, 1994). The median number of physicians, PAs, and NPs was 1.8 (Cheh & Thompson, 1997). The average numbers of FTEs were as follows: Physicians (1.7), PAs (1.2), and NPs (1.1). The average number for other clinical FTEs was as follows: Certified Nurse Midwives (0.09), Clinical Psychologist (0.06), and Clinical Social Worker (0.07) (Gale & Coburn, 2003). Thus, the number of non-physician FTEs other than PAs or NPs is negligible.

2.1.3 Typology

RHCs could be classified in several ways. In terms of ownership, RHCs can operate as public, private, or nonprofit entities (Zhang et al., 2006). Public RHCs could be local, state, or federal government owned. Nonprofit and for-profit owned RHCs could take the form of corporations, sole proprietorships, or partnerships (HRSA, 2006).

In terms of the nature of medical practice, RHC typologies are many. An RHC may be any type of primary care practice, including family practice, pediatrics, geriatrics, obstetrics/gynecology, or internal medicine (HRSA, 2006). However, an RHC must not be a rehabilitation agency (CMS, 2009).

The most popular classification uses autonomy as its criterion. That criterion was used by the RHC Act (P.L. 95-210) to designate two types of clinics. Independent RHCs are freestanding or office-based autonomous clinics similar to solo or small group provider practices. Provider-based RHCs must be "an integral and subordinate part of a hospital, skilled nursing facility, or home health agency participating in Medicare" (§42 CFR 405.2425). In 2007, 3,781 RHCs were reported by CMS (Ortiz et al., 2009). Of these clinics, 55% (2,080) were classified as independent, while 45% (1,701) were classified as provider based (Ortiz et al., 2009).

2.1.4 RHCs and Rural Health Services

Sixty-one million people live in the rural U.S. (Rosenthal & Fox, 2000). Although the percentage of rural residents is decreasing over time, from 25% (Harris & Leininger, 1993) to 20% (Gale & Coburn, 2003), there are more rural Americans today than ever before. Difficulties involved in delivering health care services to rural communities have been well documented.

Approximately one in three rural adults are in poor to fair health, and nearly one-half have at least one major chronic illness (Lindeke, Jukkala, & Tanner, 2005). However, rural residents are less likely to have health insurance, and a lack of health insurance has been linked to reduced access to care (Zuvekas & Weinick, 1999).

Moreover, managed care has been slow to penetrate rural markets (Miller, Weissert, & Chernew, 1998). More than two-thirds of the federally designated health manpower shortages are in rural areas. Yet, recruiting and retaining health practitioners in rural areas continues to be difficult (Harris & Leininger, 1993). Rural health care facilities have fewer physicians per capita than are found with urban providers (Ricketts & Heaphy, 1999; Rosenblatt & Hart, 1999). Only one Primary Care Physician (PCP) is available for every 2,857 individuals in rural communities as compared to one for every 614 individuals nationally (Sinay, 2001).

Rural residents make fewer physician visits than urban dwellers (Himes & Rutrough, 1994) and have less access to home health services (Cheh & Phillips, 1993). Rural areas also have fewer hospitals per capita (Ricketts & Heaphy, 1999). Consequently, RHCs are crucial for rural communities.

2.1.5 RHC Contributions

RHCs make several key contributions to rural health. First and foremost, RHCs are key access points for health care outside major urban centers. From 1995 to 1997, the number of Medicaid recipients served by RHCs increased by 16.4%. During that period, the increase in RHC utilization was accompanied by an 18.4% decline in Medicaid patients' receiving hospital outpatient services and an 11.4% decline in those receiving care in other clinics (Finerfrock, 1999, as cited by Gale & Coburn, 2003). In the absence of these RHCs, many patients would seek care from other health care providers. For example, the presence of an RHC in a community has been found to reduce emergency room use (Cheh & Thompson, 1997).

Second, RHCs are important safety-net providers in rural areas (U.S. Department of Health and Human Services, Agency for Healthcare Research and Quality [AHRQ], 2003; U.S. Department of Health and Human Services, Health Resources and Services Administration, Office of Rural Health Policy, 2002). Although it is not in their mandate, most RHCs choose to provide care for uninsured and underinsured patients (Gale & Coburn, 2003). The populations served by RHCs also include a high proportion of rural elderly and poor (Gaston, 1997). Even though self-pay, uninsured, and low-income patients make up a significant portion of the patient base of many RHCs, these facilities receive no specific reimbursement for the delivery of services to these populations (unlike community health clinics).

Third, RHCs contribute toward the retention of physicians and non-physician providers in rural areas (Probst et al., 2009). These practitioners provide a broader range of health services to smaller populations scattered over wider areas (Swan, Selvaraj, & Godden, 2008). Without more attractive reimbursement rates and expanded practice roles offered to physicians, the supply of health care providers in rural areas could have been more severe than it is now.

2.2 Hospital-Based Rural Health Clinics

This research focused on hospital-based RHCs. It should be stated again that hospital-based RHCs are the most dominant type of provider-based RHCs (about 90% of provider-based RHCs are hospital based). Much of the previous discussion on RHCs also holds true for hospital-based RHCs. However, hospital-based RHCs have several key features that set them apart from independent RHCs.

2.2.1 Background of Hospital-Based RHCs

In the first decade of the RHC program, the numeric growth of RHCs was dismal. In particular, less than 1% of RHCs were provider based. The RHC Act amendment of 1989 instituted changes to make hospital-based RHCs attractive by offering uncapped cost-reimbursement. The amendment was successful—perhaps too successful—so much so that Steinhardt (1997) argued that some hospitals created hospital-based RHCs to capitalize on the attractive financial arrangements rather than to improve access to care.

In the 1990s, provider-based RHCs were growing at a faster rate than independent RHCs. Only 5% of RHCs were provider based in 1990 (Krein, 1999); provider-based RHCs reached 48% by 1999 (Gale & Coburn, 2003). Of all provider-based RHCs, growth was fastest for hospital-based RHCs. The attractive, uncapped reimbursement rates to hospital-based RHCs were finally stripped away in the Balanced Budget Act of 1997. Except for hospital-based RHCs owned by hospitals with fewer than 50 beds, all other RHCs faced capped prospective reimbursement.

2.2.2 Hospital-Based RHC Certification Requirements

A hospital-based RHC must satisfy the same certification requirements as an independent RHC. However, the facility must meet additional requirements to receive the "hospital-based provider" designation. A hospital-based RHC is defined as an integral and subordinate part of a hospital participating in Medicare that is operated with other departments of the hospital under common licensure, governance, and professional supervision (HRSA, 2006).

Meeting the aforementioned definition of hospital-based RHCs is not sufficient for certification. Additional requirements are in place to assess the totality of relationships. For instance, the following administrative functions of hospital-based RHCs must be integrated with those of the hospital: billing services, records, human resources, payroll, employee benefit package, salary structure, and purchasing services (HRSA, 2006). More importantly, hospital-based RHCs and their parent hospitals need to be co-located on the same campus (HRSA, 2006).

2.2.3 Hospital-based Typology

Hospital-based RHCs could be grouped into two groups depending on the number of inpatient beds of a hospital: those that are owned by hospitals of fewer than 50 beds (56% of all hospital-based RHCs) and those owned by hospitals of 50 or more beds (44%). Both types together make up over 90% of all provider-based RHCs (Gale & Coburn, 2003).

2.2.4 Specific Contributions

Hospital-based RHCs share the contributions outlined for all RHCs. However, hospital-based RHCs are the largest outpatient primary care program for rural underserved communities (Krein, 1999). Hospital-based RHCs, by virtue of their placement in larger systems, offer more access to system-wide policies, procedures, support departments, and quality assurance procedures in ways not possible for independent RHCs.

In effect, they could be anticipated to have a different focus on quality and performance than independent RHCs (Edwards & Tudiver, 2008). Hospital-based RHCs contribute by enhancing the delivery of care in their parent organization (Probst et al., 2009). Although research in this area is sparse at present, evidence does show that RHCs were beneficial to a sponsoring hospital (Schoenman, Cheng, Evans, Blanchfield, & Mueller, 1999), conferring possible advantages on the community in which the hospital was located.

2.2.5 Particular Challenges

Hospital-based RHCs face a different set of financial constraints. As of January 1998, hospital-based RHCs owned by hospitals of 50 or more beds were subject to the same per-visit upper payment limit as other RHCs (Balanced Budget Act of 1997 [P.L. 105-33, subtitle C § 4205]). However, hospital-based RHCs owned by hospitals with fewer than 50 beds were exempted.

In addition, hospital-based RHCs tended to exceed their capped limit by a larger margin. The overall adjusted cost-per-visit rates reported by provider-based RHCs (that also include hospital-based RHCs) ($81.01) exceeded the cap on per-visit reimbursement that applied to hospital-based RHCs owned by hospitals of 50 or more beds ($61.85) (Gale & Coburn, 2003). Independent RHCs reported adjusted cost-per-visit rates of $66.31, indicating that hospital-based RHCs exceeded the capped limit about four times as much as independent RHCs ($19.16 versus $4.46).

Hospital-based RHCs operated differently on quality and performance challenges (Knott & Travers, 2002). Quality Assessment activities at hospital-based RHCs had a customer service orientation, likely influenced by their parent hospital. However, the prime focus on customer satisfaction seems to overshadow the mandate to improve the remaining three measures of performance: clinical effectiveness, access to care, and productivity.

In contrast, the top three tasks for independent RHCs were monitoring of immunization rates, the appropriateness and timeliness of procedures, and productivity (Knott & Travers, 2002). Therefore, it is crucial to investigate the performance of hospital-based RHCs in terms of productivity.

2.3 Current State of Knowledge

This third section has three components. The specific literature review is grouped into three parts: organizational determinants, contextual determinants, and productivity studies. As much as possible, the specific literature review focused on studies that 1) target RHCs or rural health settings, 2) investigated clinical settings similar to RHCs (e.g., ambulatory care settings, community health centers), 3) used productivity or efficiency as a performance measure, or 4) explicitly or implicitly subscribed to contingency or organizational performance theories.

2.3.1 Organizational Determinants

Physician staffing and ownership are two organizational determinants of productivity already utilized in RHC productivity studies (Ortiz et al., 2009; Sinay, 2001). Although they did not feature much in earlier RHC productivity studies, age of facility and payment system are potential determinants of productivity included in this study. The age of facilities could be related to productivity since newer facilities were found to have different management strategies as opposed to more established ones (Huang and McLaughlin, 1989). For facilities that are much more dependent on CMS, payment system could relate to productivity (McBride and Mueller, 2002).

Not all RHCs have access to physician services. In a descriptive study of RHCs, Sinay (2001) reported that the more productive RHCs had higher physician and non-physician total staffing levels. Similar results were reported for community health clinics (Marathe, Wan, Zhang, & Sherin, 2007). However, Sinay (2001) did not include RHCs without physicians in his DEA analyses. The exclusion of RHCs without physicians from productivity studies biases the results. Therefore, the present study included all RHCs and examined the influence of physician availability on RHC productivity.

This study explicitly investigated the relationship between physician availability and RHC productivity. For independent RHCs, the CMS RHC productivity standard for physician FTEs is 100% higher than for non-physician FTEs (minimum of 4,200 visits per annum versus 2,100 visits per annum). In other words, facilities with physicians could generate more visits that could lead to higher facility-level productivity. In contrast, however, there are no productivity standard requirements on provider-based RHCs (Gale & Coburn, 2003).

Non-profit ownership in RHCs was negatively related with cost efficiency, and older RHCs were negatively related with cost efficiency (Ortiz et al., 2009). But the relationship between age and productivity remained unexamined. The rationale for positing a relationship between ownership and productivity stems from the assumed incentive for for-profit firms to reduce direct costs as a means of maximizing profits.

Payment system (i.e., whether the RHC received capped prospective payments or un-capped cost reimbursement) might relate to productivity (Gale & Coburn, 2003). Payment system affected financial viability of a hospital-based RHC (McAtee & Beverly, 2005). However, RHC studies so far have not taken into account payment system differences.

2.3.2 Contextual Determinants

Generally, contextual (environmental) variables tend to relate to productivity and efficiency (Blank & Valdmanis, 2009; Worthington, 2004). In fact, in a panel study of community health clinics, only contextual variables were related to productivity (Marathe et al., 2007).

Compared to urban areas, rural areas in the U.S. have a higher percentage of elderly, a higher percentage of Medicare beneficiaries, more under-insured residents, and higher percentages of persons below the poverty line—a subpopulation that places high demand on RHC staff and financial resources (Harris & Leiniger, 1993). Geographic location, percentage of Medicare eligible, and minority population are other additional contextual variables commonly used in productivity studies (Marathe et al., 2007). Haque and Telfair (2000) found that use of health services increased in rural areas as the level of socio-economic distress increased.

Contextual variables are crucial in RHC productivity investigations, since 1) environmental variables are indicators of the demand for care, and 2) RHCs are anticipated to address health deprivation in medically underserved rural areas. In spite of the high relevance of contextual variables, hardly any studies investigated how contextual variables affected RHC productivity.

Although the relationship between geographic region and productivity was not investigated, provider-based RHCs in the Midwest were more cost efficient (Ortiz et al., 2009).

But the relationship between geographic location and productivity remained unexamined. Geographic location (as defined by the four U.S. Census regions) had no impact on productivity and cost efficiency of community health clinics (Marathe et al., 2007).

Earlier productivity studies did not examine the relationship between poverty rate, minority population, Medicare-eligible population, and uninsured population with RHC productivity. Although poverty rate was not related to productivity in some studies (Marathe et al., 2007; Rosenbaum, Shin, Markus, & Darnell, 2000), it serves as a proxy measure for demand of care from the Medicaid-eligible population.

Minority and Medicare-eligible populations had a positive relationship with productivity of community health clinics (Marathe et al., 2007). Rural areas tend to have more uninsured residents as compared to urban areas (Harris & Leiniger, 1993). In any rate, the relationship between uninsured population and RHC productivity remains unexamined.

2.3.3 Productivity Studies

Data Envelopment Analysis (DEA) has been extensively used to measure productivity (efficiency) in not-for-profit firms and governmental units (Hollingsworth, 2008; Huang & McLaughlin, 1989; Worthington, 2004). Previous research suggests that DEA is an effective technique for measuring efficiency and productivity of hospitals (Grosskopf & Valdmanis, 1987; Lee, Yang, & Choi, 2009; Nayar & Ozcan, 2008), of rural hospitals (Ozcan, Luke, & Haksever, 1992), and of nursing homes (Rosko, Chilingerian, Zinn, & Aaronson, 1995; Sexton, Leiken, Sleeper, & Coburn, 1989).

There were two reported uses of DEA to measure productivity in RHCs (Ortiz et al., 2009; Sinay, 2001). In RHCs, Sinay (2001) reported that RHCs had lower productivity. Lower number of patient visits could have contributed to lower productivity (Chang & Troyer, 2009; Sinay, 2001). On average, productive RHCs have more physician FTEs (Sinay, 2001). However, productive RHCs tended to have higher total medical cost (Sinay, 2001).

In a study of 134 provider-based RHCs, productivity was positively related to cost efficiency (Ortiz et al., 2009). Consequently, improvements in productivity could enhance financial success. On the basis of the four U.S. Census Bureau regional classifications, provider-based RHCs in the Midwest were the only ones positively related with cost efficiency. Nonprofit RHCs had no relationship with cost efficiency (Ortiz et al., 2009).

Neither the study of Sinay (2001) nor Ortiz et al. (2009) used productivity as a dependent variable. Huang and McLaughlin (1989) conducted a panel study on 163 rural health primary-care programs from 1978 to 1983. Although that study did not include RHCs, productivity was used as a dependent variable. Table 1 presents a synopsis of key literature.

Table 1 Summary of Empirical Papers Reviewed

Authors	Statistical method	Unit of analysis	Dependent variables	Independent variables	Significant findings	Discussion
Sinay (2001)	Descriptive statistics	163 RHCs in the Midwest for the year 1994 as reported in CMS Cost Reports	None	Size Productivity Cost	1) On average, productive RHCs are larger than less productive RHCs 2) On average, productive RHCs have more physicians FTEs 3) Productive RHCs have higher total cost	1) The relationship between physician availability and productivity was not inferentially tested 2) A regional study on small sample size that has limited generalizability
Ortiz et al. (2009)	Regression	402 RHCs in the US for the year 2007 (134 provider-based)	Cost efficiency	Productivity Non-Profit Region	1) Productivity is positively related to cost efficiency 2) Provider-based RHCs in the Midwest were more cost-efficient 3) Non-profit status bore no relationship to cost-efficiency	1) Productivity was not studied as a dependent variable 2) The influence of rural classification was not taken into account. RHCs at frontiers were compared to RHCs in urban focused areas.

Authors	Statistical method	Unit of analysis	Dependent variables	Independent variables	Significant findings	Discussion
Marathe et al. (2007)	Growth curve model	A panel study of 493 Community Health Clinics (2000-2004)	Productivity Cost efficiency	Size, Network PayerMix StaffMix Region Poverty Minority Medicare	1) Changes in productivity affect changes in cost-efficiency but not the other way around 2) Only contextual variables were related to productivity 3) A small amount of variation in productivity was explained	1) The rural urban distinction in community health clinics was not explicitly modeled 2) There were no time-varying predictors, so impact of time-dependent variables is unknown
McAtee & Beverly (2005)	Descriptive	One hospital-based geriatric RHC in Arkansas	None	Outpatient prospective payment system Net Profit Billable visits	1) The capped payment system created a financial viability challenge 2) Geriatric-focused RHC helped to meet the needs of rural elderly	1) Another hospital-based RHC that still continued to receive uncapped payment systems was not used as a case study control 2) Limited generalizability

Authors	Statistical method	Unit of analysis	Dependent variables	Independent variables	Significant findings	Discussion
Huang & McLaughlin (1989)	Logistic regression	193 Rural Primary Health Care Programs (1978-1983)	Productivity	Staffing Total Cost Age Population size	1) Productivity is negatively related to population size 2) Neither age of program nor total medical cost were related to productivity	1) the relationships between physician availability and productivity were not investigated 2) DEA was found to be a better measure of productivity than both ratio analysis (visits per FTE) and regression analysis
Silverman et al. (1995)	ANOVA	Random-ized trials in 4 hospital-based clinics and 4 physician offices	Utilization Clinical effective-ness	Type (provider-based clinics versus community physician offices)	1) Hospital-based RHCs showed no difference in levels of utilization as compared to community-based physician offices	1) hospital-based RHCs were significantly better in measures of clinical effectiveness 2) Utilization (total number of visits) was not divided by total clinical FTEs (hence productivity level is unknown)
Anderson & Hampton (1999)	Logistic regression	29,095 outpatient visits from urban and rural hospitals	Utilization	Payment source Staff Ownership Region	1) Utilization of non-physicians was 8 times higher in rural hospitals than in urban hospitals 2) Utilization is not related to payment source	1) Utilization was not divided by total number of FTEs (hence productivity level is unknown) 2) Payment sources (Medicaid, Medicare, HMO, private insurance, self-pay) were all not related to utilization

2.4 Gaps

After the accessibility, effectiveness, and productivity of RHCs were questioned (Brown, 1996; Steinhardt, 1997), a number of studies attempted to address gaps in RHC studies. A randomized control trial found RHCs to have improved access to care (Cheh & Thompson, 1997). RHCs were also found to have provided effective care (Probst et al., 2009; Zhang et al., 2006). However, RHCs were reported to be less productive (Sinay, 2001). Therefore, examining determinants of productivity would be of great benefit.

The study of Sinay (2001) had a number of limitations. First, it was a descriptive study that did not examine organizational and contextual determinants of productivity. Second, it was a regional study with limited sample size. Third, the study disregarded the homogeneity requirement of DEA and proceeded to compute DEA scores for all RHCs.

As mentioned before, provider-based and independent RHCs have key distinctions, including differing reimbursements for services rendered and the absence of productivity standards in provider-based RHCs. Moreover, rural areas are very heterogeneous. Therefore, comparing the productivity of RHCs in all kinds of rural areas yields a biased assessment. Consequently, DEA scores should be computed separately on the basis of rural classification and provider type.

The study of Ortiz et al. (2009) did compute DEA scores separately for provider-based RHCs. However, that study did not compute DEA scores separately per rural classification. Several limitations stand out. First, given the absence of productivity standards in provider-based

RHCs, physician availability could have been a useful determinant of productivity and cost efficiency.

Second, the differences in payment systems among provider-based RHCs were not taken into account. Third, the study included 134 provider-based RHCs with cross-sectional focus. Thus, the generalizability and stability of relationships over time remain unknown. Since productivity levels depend on earlier years of productivity, a cross-sectional investigation will not be able to address dependencies of productivity over time.

The Huang and McLaughlin (1989) panel study did not include RHCs, given their relative newness at the time of study (1978–1983). That study, too, had several limitations. First, the homogeneity requirement of DEA was not met, since the analysis included all vehicles of care delivery in rural areas. Second, the evaluation was at the program level, which had limited applicability to facility-level productivity. Third, population size was a crude measure for demand of care. Using several variables, such as Medicare-eligible population, Medicaid-eligible population, and uninsured populations, could have served as a better proxy of the differing patterns of health and health care use from key segments of the population.

The present research addressed the aforementioned gaps and limitations. First, both organizational and contextual determinants of productivity were included. Moreover, productivity was measured at a facility level. Second, a four-year longitudinal panel design on the most recent data was used to test both the strength and stability of relationships over time. Third, a panel study offered statistical control over extraneous variables by conducting repeated measures of productivity within the same hospital-based RHCs over time.

Fourth, productivity was analyzed through a four-wave dynamic slacks-based DEA analysis methodology that takes into account dependencies over time. Moreover, the productivity scores were computed after controlling for the lag effect of net-earning (financial viability). Fifth, RHCs were grouped on the basis of RUCA (Rural-Urban Commuting Area Code) four-level classifications of rural areas. DEA analysis was run separately for each group. In that way, productivity of RHCs in frontiers (isolated rural areas) was assessed in comparison to other frontier clinics rather than in comparison to RHCs located near urban areas.

Sixth, determinants of *changes* in growth patterns and trends of productivity were examined. Specifically, latent growth curve models examined the development (growth) of individual RHCs on productivity over a four-year period. Growth models also assessed whether initial levels of productivity affected productivity growth on subsequent years.

And last, both time-constant and time-varying determinants of productivity were included. For instance, some variables, such as ownership, would remain stable (constant) over the study period while others, such as physician availability, might vary from year to year. Thus the simultaneous investigation of both time-constant and time-varying variables assisted in explaining variation in productivity as well as changes in productivity growth.

2.5 Exogenous Variables

This section presents a brief literature review for each of the ten exogenous (independent) variables that were used in the study (Table 2). The variables could be grouped into two categories: organizational and contextual. Contextual variables include county-level data for poverty rate, minority population, Medicare-eligible population, percentage of uninsured residents, and geographic location. RUCA four-level rural classifications were assigned on the basis of RHC zip codes. Organizational characteristic variables include physician availability, ownership, payment system, and age of facility.

Table 2 List of Variables that Pertain to Rural Health Clinic Productivity Study

Construct	Type	Classification	Variable	Authors
Contextual	Exogenous	Time-Constant	- Poverty rate as percentage of population below poverty line[1]	Krein (1999); Haque & Telfair (2000)
	Exogenous	Time-Constant	- Percentage of uninsured as of total county population[1]	Harris & Leiniger (1993); Probst et al. (2009)
	Exogenous	Time-Constant	- Percentage of Medicare-eligible population as of total county population[1]	Marathe et al. (2007); Woolf et al. (1981)
	Exogenous	Time-Constant	- Percentage of minorities as of total county population[2]	Probst et al. (2009); Marathe et al. (2007)
	Exogenous	Time-Constant	-Rural classification on the bases of Rural Urban Commuting Area (RUCA) zip-code approximations[3]	Hart, Larson, & Lishern (2005)
	Exogenous	Time-Constant	- US Census Bureau geographic locations (North east, Midwest, West and South) [2]	Woolf et al. (1981); Anderson & Hampton (1999) ; Rosenthal & Fox (2000)
Organizational Design	Exogenous	Time-Varying	- Physician availability (facilities with no physician FTEs versus facilities with physician FTEs) [4]	Sinay (2001); Shortell & Kaluzny (2006)

Construct	Type	Classification	Variable	Authors
	Exogenous	Time-Constant	- Ownership (Nonprofit or government owned versus for profit owned) [4]	Ozcan et al. (1992); Worthington (2004)
	Exogenous	Time-Constant	- Age of facility in years[4]	Leatt & Schneck (1982); Ortiz et al. (2009)
	Exogenous	Time-Constant	- Payment system (cost-reimbursement versus prospective payment)[4]	Gale & Coburn (2003); McAtee & Beverly (2005)
Organizational Performance	Endogenous	Time-Varying	- Productivity as measured through Data Envelopment Analyses scores.	Sinay (2001); Huang & McLaughlin (1989)

[1] Data Source: Area Resource File

[2] Data Source: US Census Bureau

[3] RUCA classifications of rural areas from WWAMI Rural Health Research Center

[4] Centers for Medicare and Medicaid Services

2.5.1 Rural Classification

For health services research, Hart, Larson, and Lishner (2005) recommended the use of "RUCA zip-code approximation" classification of rural areas. The RUCA zip-code approach is an improvement over the RUCA (Rural-Urban Commuting Area Code) methodology developed by the Office of Rural Health Policy (ORHP) of the Health Resources and Service Administration (HRSA), the Department of Agriculture's Economic Research Service (ERS), and the WWAMI Rural Health Research Center (RHRC).

The developers of RUCA methodology recommend the use of "categorization A": a four-level classification of rural areas (WWAMI, 2010). The levels are Urban Focused Areas, Large Rural Towns, Small Rural Towns, and Isolated Rural Areas. Productivity DEA scores were computed separately for hospital-based clinics that fall under each classification, so clinics in isolated areas were compared only to other clinics in similar rural conditions, and so on.

2.5.2 Poverty Rate

Poverty rate was previously used in a hospital-based RHC study since it served as a proxy measure for the potential Medicaid-eligible population (Krein, 1999). Although the relationship between poverty and productivity was not significant in some studies (Marathe et al, 2007; Rosenbaum et al., 2000), that might be different for RHCs. In the current study, poverty rate served as a contextual control variable. It also served as a time-constant exogenous variable.

2.5.3 Minority Population

Percentage of minorities (e.g., percentage of nonwhite county residents) was reportedly related to productivity of health care providers in community health centers (Marathe et al., 2007). The variable serves as a proxy measure for the potential Medicaid-eligible population as well as a proxy measure for differing patterns of health and health care use among minorities (Marathe et al., 2007). Although there were hardly any RHC productivity studies that used the variable of minority population, it was found to be significantly related to RHC effectiveness (Probst et al., 2009). Hence, it was included as a time-constant control variable.

2.5.4 Percentage of Uninsured

Percentage of uninsured residents is a contextual variable that could affect the utilization and productivity of health care organizations in rural settings much more than in urban settings (Harris & Leiniger, 1993). The variable could be used as a proxy measure for health care demand coming from residents who are *not* members of the Medicaid- and Medicare-eligible populations. Although there were hardly any RHC productivity studies that used the variable, it was included in the RHC effectiveness study (Probst et al., 2009). Percentage of uninsured residents was used as a time-constant control variable in the present study.

2.5.5 Medicare-eligible Population

Percentage of Medicare-eligible population was known to relate positively to productivity (Marathe et al., 2007). Percentage of the population over 64 years of age was related to health-practitioner supply (Woolf, Uchill, & Jacoby, 1981). The Medicare-eligible population was used as a time-constant control variable.

2.5.6 Geographic Location

Regional location of patients, on the basis of U.S. Census Bureau classification, affected utilization of PAs and NPs (Anderson & Hampton, 1999). Since utilization (visits) is the numerator of productivity measures, regional location could also affect productivity. Geographic location was also reported to be a determinant of productivity in many other studies (Worthington, 2004). Geographic location was used as a categorical variable with four levels: Northeast, Midwest, South, and West. Geographic location was used as a time-constant control variable.

2.5.7 Physician availability

For the purposes of this study, physician availability was defined as hospital-based RHCs that had non-missing values for physician FTEs as reported in Medicare Cost Report for Hospitals. Physician availability was used as a time-varying exogenous variable. RHCs with physicians were found to be more productive (Sinay, 2001). However, earlier studies excluded RHCs without physicians from productivity analyses (Ortiz et al., 2009; Sinay, 2001). Therefore, reported findings in the literature were biased toward RHCs with physicians.

2.5.8 Ownership

The utilization aspect of rural hospitals depended on whether the facility was government, for-profit, or voluntary nonprofit owned (Anderson & Hampton, 1999). The rationale for positing a relationship between ownership and productivity stems from the assumed incentive of for-profit firms to reduce direct costs as a means of maximizing profits. For instance, productivity differs by ownership (Burgess & Wilson, 1998; Grosskopf & Valdmanis, 1987; Lee et al., 2009; Ozcan et al., 1992).

However, studies that sought to determine whether for-profit ownership is positively related to productivity had mixed results (Fottler, 1987; Hollingsworth, 2008; Valdmanis, 1992). The Hollingsworth (2008) meta-analysis indicated, with caution, that public (not-profit) ownership, rather than for-profit ownership, seemed to relate positively to productivity, while others found to the contrary (Hofler & Rungeling, 1994; Lee et al., 2009). In any case, ownership served as a time-constant control variable.

2.5.9 Age of Facility

For the purposes of this study, age of hospital-based RHCs was defined as the number of years between the initial study time of 2005 and the original date of certification as an RHC. Age is an organizational contingency variable used in health services research under contingency theory (Leatt & Schneck, 1982; Zinn & Mor, 1998). As provider-based RHCs were found to be significantly newer than independent RHCs (Ortiz et al., 2009), it is possible that age might be a factor when modeling the growth trends of productivity. Hence, age of facility was used as a time-constant control variable.

2.5.10 Payment System

On the basis of payment systems, hospital-based RHCs could be grouped into two categories. Hospital-based RHCs with fewer than 50 beds receive un-capped cost-reimbursement rates, while hospital-based RHCs with 50 or more beds obtain capped reimbursement under a prospective payment system (Gale & Coburn, 2003; McAtee & Beverly, 2005). Although Gale and Coburn's descriptive study of RHCs indicated that such payment system distinctions might be an important factor, hardly any known studies in RHC performance included the variable. Payment system was used as a time-constant control variable.

2.6 Productivity

Productivity of hospital-based RHCs is the endogenous (dependent) variable of interest. Productivity is measured as a time-varying variable. Productivity is generally defined as ratio of outputs to inputs (Flood, Zinn, & Scott, 2006; Hollingsworth, 2008). For the purposes of this study, productivity is defined as maximization of visits (encounters) as outputs while minimizing labor inputs as computed by technical efficiency scores of DEA. DEA is used as an indirect measure of productivity in health services research (Hollingsworth, 2008; Worthington, 2004).

Hollingsworth (2008) conducted a meta-analysis of DEA use in health care settings based on 317 published papers from the U.S. and Europe. Worthington (2004) conducted a literature review on 38 DEA studies in health care. Over 90% of the studies were based on hospitals, nursing homes, primary care physician offices, renal care, and dental services. Less than 10% of studies were in other health care setting, to which RHCs would belong (Hollingsworth, 2008).

In terms of output variables for DEA measures, the ideal measure of efficiency and productivity in health organizations is the health gains of individual patients, which is the ultimate final output (Hollingsworth, 2008). However, most research published so far has used intermediate outputs (throughputs), in terms of numbers of patients treated (Hollingsworth, 2008; Worthington, 2004). Consequently, over 91% of health care DEA use throughput (process) measures of physical performance, such as inpatient days or discharges (Hollingsworth, 2008;

Siciliani, 2006). Huang and McLaughlin (1989) argued that process outputs offer a measure of quality of medical services within administrative data sets.

As for input variables, the majority of DEA studies mainly used measures of staff and capital employed (Hollingsworth, 2008; Worthington, 2004). In addition, many efficiency and productivity studies used technical efficiency (Hollingsworth, 2008).

In one of the earliest DEA studies in rural health setting, Huang and McLaughlin (1989) stated that productivity is best assessed through Data Envelopment Analysis (DEA). More often than not, RHC's productivity rate is measured by annual visits for each medical team (Gale & Coburn, 2003). Such simple ratios of visits per FTE are known to be a poor measure of productivity (Huang & McLaughlin, 1987; Siciliani, 2006; Sinay, 2001).

DEA experts give a number of reasons why ratio analysis is inadequate (Cooper et al., 2007): 1) it does not take into account multiple inputs and outputs simultaneously, 2) it could not incorporate economies of scales, 3) it is unable to account for productivity dependencies over time, and 4) it does not "benchmark" productivity against the possible productivity frontier attained by the relatively productive Decision Making Units (DMUs).

2.7 Summary

This chapter has provided an overview of RHCs in general and hospital-based RHCs in particular. The literature findings on the current state of knowledge in RHCs were reported, focusing on organizational determinants, contextual determinants, and productivity. Relevant studies were critiqued, and knowledge gaps were identified. Relevant literature on endogenous (dependent) and exogenous (independent) variables was discussed. The next chapter describes the theories used to develop the conceptual model.

CHAPTER THREE: THEORETICAL FRAMEWORK

This chapter explores the theoretical framework literature review consisting of structural contingency theory (SCT) and organizational performance theory (OPT). In particular, it examines the context-design-performance (CDP) model that belongs to both OPT and SCT. The chapter is structured into four main sections. The first section reviews key theoretical papers to disclose assumptions, propositions, and gaps with regard to SCT. The second section reviews additional theoretical papers related to OPT in general and the CDP model in particular. The third section discusses the formulation of testable hypotheses. The last section discusses the limitations of SCT and OPT.

3.1 Structural Contingency Theory

Contingency theories emerged during the 1950s in response to the then-prevailing theories of management that emphasized the "one best way" to organize (Weill & Olson, 1989). The contingency approach is generally theorized into main ways (Kast & Rosenzweig, 1973, as cited in Weill & Olson, 1989, p. 60). One mode of theorizing attempts to understand the interrelationships within and among organizational subsystems. Another mode of theorizing attempts to understand the interrelationships between organizational system as an entity and its external environment. The focus of this dissertation topic is on the latter conception of SCT.

The term "contingency variable" refers to any environmental or organizational variables that were assumed to exert *direct* or *indirect* influence on organizational performance. The most frequently cited contingency variables are external environment and technology (Donaldson, 2001; Morton & Hu, 2008). Contingency theories have two main theoretical branches in relation to how contingency variables were approached. Structural contingency theory considers environmental contingency variables as hard-to-control constraints. Thus, for managers, organizational contingency variables are the "only" modifiable components to address organizational performance (Leatt & Schneck, 1984). Strategic contingency theory, on the other hand, assumes that managers are able to manipulate environmental contingency variables.

Contingency theory is the preferred framework for two key reasons. First, according to the theory, organizations adapt to organizational and environmental contingencies in a variety of ways (Strasser, 1983). Hospital-based RHCs face different systems of reimbursements and certification requirements from those of freestanding RHCs. In addition, they are mostly located in rural areas, and such areas show marked variations from place to place as compared to urban areas (Rosenblatt & Hart, 1999). Moreover, hospital-based RHCs operate without productivity standards (Gale & Coburn, 2003). Therefore, hospital-based RHCs could adapt to their environment in a variety of ways, making contingency theory a viable framework. Consequently, the growth patterns and trends of productivity are anticipated to show marked variation from one hospital-based RHC to another.

Second, the research aimed to explore variations in organizational performance. Contingency theory is useful when the research focus is on discovering the variations in organizational performance rather than assessing similarities (trends of consistency) among organizations.

SCT dominated the study of organizational performance from the 1960s to the 1980s. But the inability of SCT to resolve theoretical and empirical problems promoted basic changes in SCT, as was argued by Drazin and Van de Ven (1985) and Schoonhoven (1981). Despite the doom and gloom predictions on SCT, SCTs have gained a pivotal standing within the field of organizational studies (Pennings, 1992), and contingency theory is still “the most widely utilized contemporary theoretical approach to the study of organizations” (Scott & Davis, 2007, p. 104). Similarly, Lawrence (1993) reiterated that “contingency theory continues to be the strongest, research-based body of knowledge [in organizational research]” (p.16). Contingency theory is relevant as it asserts that the range of differences in organizations are neither random nor isomorphic but could vary systematically depending on contingency factors such as technology, external environment, and, possibly, other factors such as age and ownership (Leatt & Schneck, 1982).

There are two theoretical gaps in the literature of SCT that this dissertation research could address. First, very few studies explicitly tested the link between contingency variables and organizational performance (Bergeron, Raymond, & Rivard, 2001; Drazin & Van de Ven, 1985; Weill & Olson, 1989). The majority of studies focused on the fit within and among contingency variables.

For example, the fit between environmental uncertainty and organizational structure was the most reported in contingency literature (Pennings, 1992). Of the six types or models of fit - moderation, matching, mediation, co-variation, profile deviation and gestalts (Venkatraman, 1989) – this study focused on fit as moderation. In other words, determinants of productivity will be anticipated to moderate productivity growth rates. Second, there are even fewer studies that explored the link between contingency variables and performance over time (Meilich, 2006).

3.2 Organizational Performance Theory

SCT alone could not generate an adequate theoretical framework. First, SCT assumes that all contingencies are equally important to performance. Thus SCT has the air of an "it all depends" approach (Burke & Litwin, 1992). Organizational performance theory (OPT) adds more precision by focusing on variables that have a determinant influence on performance. In other words, the focus is on variables that have *direct* and consistent influence on performance.

Second, the list of contingency variables in SCT is plentiful, including strategy, structure, size, environment, technology, task, and individual behavior (Weill & Olson, 1989). Thus, it is often very difficult to identify which of the contingency variables are pertinent in a particular setting. The linking of SCT with OPT generates a contingency model of organizational performance that aids in the selection of determinant variables.

Organizational performance theory (OPT) is a set of models and an assortment of organizational theories rather than a distinctive theory. Nonetheless, organizational performance theory could be taken as a systems theory where "input-throughput-output with a feedback loop is the basic model" (Burke & Litwin, 1992, p. 524).

OPT is pertinent for the research on two counts. First, OPT is useful when the focus of study is on variation of performance and growth trends rather than on trends of consistency. Second, not all contingences are equally important (Hendrick, 2003). In other words, the fit of contingencies may not be enough by itself. There is a need to focus on determinants of performance.

Third, the context-design-performance (CDP) contingency model is actually the application of Donabedian's Structure-Process-Outcome (SPO) model to organizational level research (Wan, 2002). SPO model is one of the prominent OPTs in health services research (Flood et al., 2006). Consequently, contingency models such as CDP are also considered to be part of OPT (Burke & Litwin, 1992).

Context-Design-Performance (CDP) is also a strategic adaptation of another contingency model of SCT: the Context-Structure-Performance (CSP) model (See Figure 1). It is important to note that this dissertation research focused on the CDP model. However, it would still be beneficial to underline the distinctions between the CSP and CDP models.

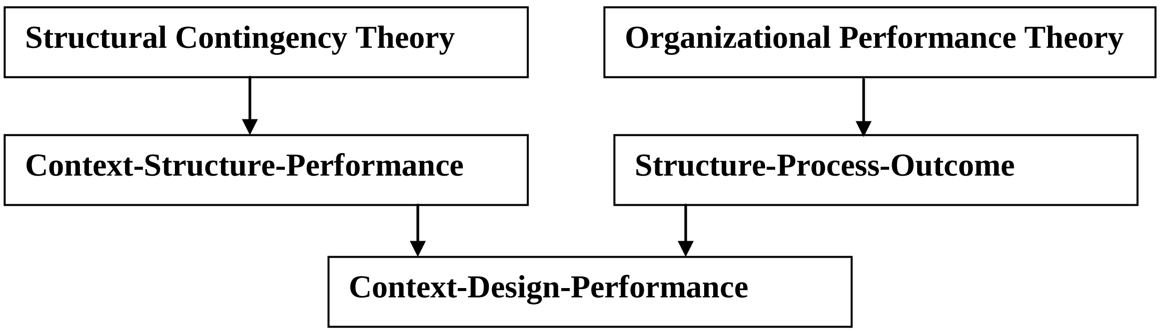


Figure 1 Context-Design-Performance Model

The term organizational “structure” in the CSP model generally refers to the degree of organizational structure as a form, e.g., functional U- (unitary) forms or divisional M- (multidivisional) forms (Donaldson, 1987). Hence organizational structure is defined as level of coordination, communication, and specialization (Bergeron et al., 2001); as de-standardization, decentralization, and professionalization (Schoonhoven, 1981); or as the arrangements among people for getting work done (Perrow, 1967). However, such definitions of organizational structure are narrow, as organizational design is much more than the form/structure of an organization.

Consequently, the Context-Structure-Performance framework of SCT (Drazin & Van den Ven, 1985) was adapted into a Context-Design-Performance model where organizational design could include measures of capability and capacity such as staffing and payer mix. Such conception of organizational "design" in the CDP model overlaps with the notion of "structure" in Donabedian's Structure-Process-Outcome (SPO) model. "Structure" in SPO is defined as human and organizational resources associated with the provision of care, such as professional staffing and facility operation capacities (Burns, 1995; Donabedian, 1966, 1988; Zinn & Mor, 1998). Consequently, the notion of "structure" in SPO is similar to that of "design" in the CDP model but different from the term "structure" in the CSP model.

The conceptualization of the term "context" in CDP models includes characteristics of organizational culture, environment, technology, or size (Drazin & Van de Ven, 1985). "Context" takes on different meanings depending on the level of analysis (Leatt & Schneck, 1984). For instance, if the level of analysis is the subunit level, then context often means the internal environment of organizations, such as size and individual dispositions.

If the level of analysis is at the organizational level, the term context often refers to the external environment, such as market competition, resource dependency, and geographic location. For the dissertation research at hand, context in CDP is taken as a set of external environmental variables. That choice is reasonable, since county-level contextual variables are inherently external to hospital RHCs.

The term "performance" is often conceptualized as measures of finance (e.g., profitability, rate of return on assets) or measures of volume (e.g., patient volume, sales).

Performance is also conceptualized as including outcomes, quality, efficiency, productivity, and effectiveness (Flood et al., 2006).

Having clarified the terms “context,” “design,” and “performance,” it is now possible to discuss the context-design-performance (CDP) model behind the proposed study (Figure 2).

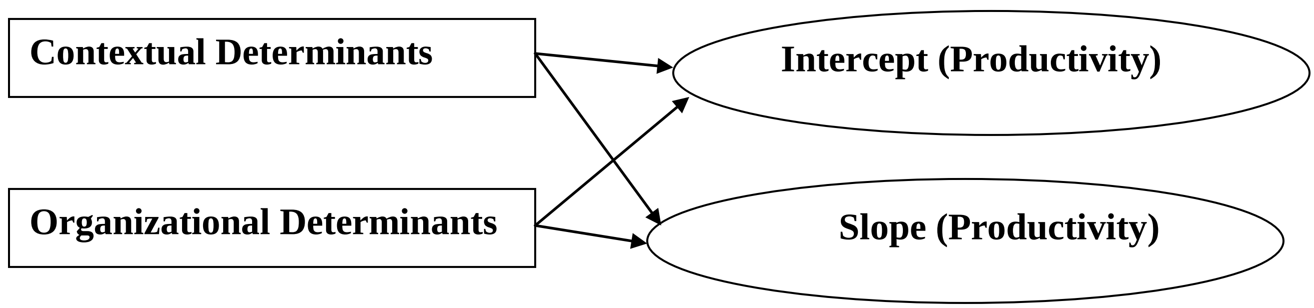


Figure 2 Growth Curve Conceptual Model

Productivity is measured as a latent construct with two latent variables (Intercept and Slope). Intercept measures the initial differences in productivity, while slope measures the patterns and trends of growth in productivity. In other words, intercept measures the trends in productivity at the beginning year of a study, while slope measures the rate of change in productivity in subsequent years.

Organizational variables that are potential determinants of productivity were assumed to have an impact on both growth factors (slope and intercept) of productivity. Simultaneously, contextual variables that are possible determinants of productivity are assumed to have an impact on both growth factors (slope and intercept) of productivity.

The organizational determinants of productivity that are included in the study were physician availability, age of facility, ownership, and payment systems. The rationales for including these variables are as follows. Since hospital-based RHCs are primarily non-physician providers of care, the availability of physicians could be a distinguishing factor that influences productivity. Newer facilities often adopt differing management strategies to bolster productivity in ways that may not be common in relatively established facilities. The profit aspect of productivity renders ownership as a potential determinant.

The contextual determinants of productivity that are included in the study were poverty rate, minority population, Medicare-eligible population, estimated rate of uninsured residents, rural classification, and geographic location. Poverty rate and minority population are proxy measures of demand of care from Medicaid beneficiaries (Marathe et al, 2007). Demand of care will affect productivity measurements by influencing number of visits or encounters.

Since Medicare and Medicaid beneficiaries are the mandated target population of RHCs, they are pertinent determinants of productivity. However, since RHCs may also serve uninsured population, there will be demand of care arising from non-Medicaid or Medicare beneficiaries. More remote/rural areas or regions might deter productivity through reduced volume of patients. Consequently, rural and geographic locations might affect productivity.

There are two theoretical gaps in the literature of OPT that this dissertation research could partly address. First, a large portion of OPT is based on post-hoc explanations of statistical relationships rather than on theoretically specified models (Lenz, 1981). In fact, studying the correlations of a large number of organizational variables with performance variables formed the basis of OPT in health care (Fottler, 1987; Georgopoulas, 1978, 1985).

Second, testing the CDP model over time, as is done in a panel study, is a more reliable way of identifying organizational and contextual determinants of productivity. Moreover, geographic information systems (GIS) allowed the spatial exploration of productivity to better gauge regional variations.

3.3 Development of Testable Hypotheses

The application of the CDP model to the research questions aided in the development of testable hypotheses. The first research question was “For the baseline year 2005, is there a significant variation in the initial levels of productivity among hospital-based RHCs?” In other words, “do hospital-based RHCs have similar baseline productivity levels”?

Hypothesis 1A: Hospital-based RHCs will differ in the levels of productivity for the year 2005.

Hypothesis 1B: Hospital-based RHCs will show significant variability in baseline levels of productivity for the year 2005.

Applying SCT, we can hypothesize that there will be a significant variation in the initial levels of productivity for hospital-based RHCs. The theory posits that both contextual and organizational variables will show marked variation across organizations and across rural counties. However, the ability of organizations to respond to such differences will be varied. Thus, contingency theory anticipates varied responses by organizations, leading to a variation in the initial levels of productivity in hospital-based RHCs.

The second research question was “For the years 2006 to 2008, is there a significant variation in the growth trajectory of productivity among hospital-based RHCs?” In other words, taking into account any differences in baseline levels of productivity, was there a substantial growth in productivity from 2005 to 2008? If there is a growth in productivity, is productivity increasing or decreasing from 2005 to 2008? If productivity is increasing or decreasing over the study period, is the rate of increase or decrease in productivity similar across hospital-based RHCs?

Hypothesis 2A: Hospital-based RHCs will differ in the rate of change of productivity for the years 2006 to 2008. In other words, there will be growth in productivity.

Hypothesis 2B: Hospital-based RHCs will show significant variability in the rate of change of productivity for the years 2006 to 2008. In other words, the rate of increase or decrease in productivity will be different across hospital-based RHCs.

Applying SCT, we can hypothesize that there will be a significant variation in the rate of change in productivity for hospital-based RHCs. In other words, the growth patterns and trends of productivity will vary from one hospital-based RHC to another. The direction of growth could be either increasing or decreasing. However, productivity is not assumed to remain stable or unchanged from 2005 to 2008.

As was discussed in Chapter 2, hospital-based RHCs face different payment systems (Gale & Coburn, 2003; McAtee & Beverly, 2005), show marked variation on quality and performances challenges (Knott & Travers, 2002; Krein, 1999), and differ in productivity and effectiveness (Ortiz et al., 2009).

In addition, hospital-based RHCs are located in rural areas, and rural areas show marked variations from place to place as compared to urban areas in many contextual measures (Rosenblatt & Hart, 1999). Thus, it is plausible to anticipate that the productivity growth of hospital-based RHCs would show marked variability rather than remain stable over time.

The third research question was “For the years 2005 to 2008, is there a relationship between hospital-based RHC’s initial levels of productivity in 2005 and their rate of change in productivity from 2006 to 2008?”

Hypothesis 3: Holding other organizational and contextual variables constant, initial levels of productivity in hospital-based RHCs will be negatively related to rate of change in productivity.

According to organizational performance theories, productivity in health care facilities could not increase indefinitely without having a performance trade-off in other measures, such as quality, financial viability, and patient satisfaction (Flood et al., 2006). Hospital-based RHCs with higher productivity levels in 2005 might focus on the improvement of other dimensions of performance.

In contrast, hospital-based RHCs with lower productivity levels in 2005 might need to focus more on boosting productivity for 2006 to 2008 to be operationally active. Rather than waiting for patients to visit their facilities, facilities with lower productivity might venture out to provide more community-based visits to boost their productivity and revenue. Consequently, initial levels of productivity in the baseline year of 2005 are anticipated to be negatively related to rate of change in productivity for the years 2006 to 2008. For OPT, the presence of performance trade off supports the notion that once higher productivity level is attained, further increases in productivity could have a trade-off effect on other measures of performance like quality and cost-efficiency.

The possibility of performance trade-offs in OPT relate to some tenets of economic theories particularly the laws of diminishing returns. Since the marginal utility of increased performance decreases with each attainment of higher performance levels, health care facilities could not increase productivity indefinitely even if no concomitant performance trade-off occurs. Therefore, OPT needs to be accompanied with such economic rationale.

3.4 Limitations of Theoretical Frameworks

For SCT, the lack of consistent relationships across structural contingency and context-design-performance (CDP) studies is often used to challenge the validity of the theory. However, the inconsistent results often emanate from two problems. The first problem is the misspecification of the CDP model, which is inherently causal. That is, unless all three (context, design, and performance) measures are included, results could be inconsistent.

A second problem relates to the fact that SCT was "developed in the context of large-scale organizations…and the predictions may not generalize to small organizations" (Hollenbeck et al., 2002, p. 600). Therefore, testing SCT and CDP in small organizations such as RHCs could contribute to the development of theory.

OPT has a number of limitations, some of which are shared with SCT. First, attribution problems are prevalent, especially when measures of performance inherently have quality dimensions. Patients vary in terms of physical, social, financial, genetic, and other characteristics that may affect the outpatient care provided to them by hospital-based RHCs.

Second, OPT assumes that the main intent of organizations is to maximize performance. However, maximizing number of visits as productivity may not be the only objective of RHCs.

Third, not all measures of performance are compatible, leading to the possibility of performance trade-offs (Cameron, 1986; Campbell, 1977). In other words, determinants of productivity could relate differently to other measures of performance such as quality of care, patient satisfaction, and cost-efficiency.

3.5 Summary

Context-Design-Performance (CDP) of structural contingency and organizational performance theories provided the theoretical guideline for the study. A conceptual model was developed that measures productivity as a latent construct explained by a number of environmental and organizational determinants of productivity. On the basis of the theoretical frameworks discussed in this chapter, combined with the empirical literature review in Chapter 2, four research hypotheses were developed. The chapter closed with limitations of the theoretical framework as applied in the study. The next chapter discusses the methodology that was applied to test the hypotheses.

CHAPTER FOUR: METHODOLOGY

The previous chapter discussed the theoretical framework and conceptual model that framed the formulation of the research hypotheses. The current chapter provides an overview of the research design, addressing the selection of hospital-based RHCs, the operational definition of study variables, and the analytical strategy. It also describes data sources and methodological limitations.

4.1 Study Design

This research was conducted as a four-year longitudinal panel study from 2005 to 2008. The purpose of panel studies is to test the stability of the data and relationships over time. In particular, this study used a non-experimental and correlational research design. Both time-constant and time-varying determinants of productivity were included.

Panel data are more useful in detecting causal relationships among study variables compared to contemporaneous (cross-sectional) data. Since the same variables are measured within the same hospital-based RHCs, it is possible to statistically control the effects of the extraneous variables. This in turn enables the researcher to clearly identify the structural relationships between the exogenous and endogenous variables.

The study design used multivariate modeling approaches, including Structural Equation Models (SEM) and latent Growth Curve Modeling (GCM). Growth curve modeling is one methodology that is used to investigate panel development phenomena and temporal causality (McArdle & Epstein, 1987). Cheong, MacKinnon, and Khoo (2003) defined growth curve modeling as “a way to investigate individual differences in change over time and explore the predictors of these individual differences” (p. 242). Growth curve modeling is a particularly useful way to understand the interactions between multiple causal and effect variables over a period of time. Wan (2002) also indicated that growth curve modeling is a more flexible, powerful, and versatile methodology to investigate growth patterns and trends.

While cross-sectional studies are commonplace in health-services research, the use of the aforementioned multivariate approaches (SEM and GCM) with panel data is rare in rural health services research. Additionally, the study design incorporated spatial exploration using the Geographic Information Systems (GIS). Counties are identified through Federal Information Processing Standards (FIPS) five-digit codes, while hospital-based RHCs are located through their county FIPS code and zip-code addresses.

The study design was based on secondary data analysis. However, data were leveraged and merged from several national databases, including CMS Medicare Cost Report for Hospitals 2005–2008 (CMS, 2005–2008), Area Resource File Access System for 2005 (U.S. Department of Health and Human Services, Health Resources and Services Administration, Bureau of Health Professions, 2005), U.S. Census Bureau American Fact Finder system (U.S. Census Bureau, 2010), and WISQARS database (U.S. Department of Health and Human Services, Centers for Disease Control and Prevention [CDC], 2010).

Physician availability, age of facilities, ownership and payment system were obtained from CMS Cost Reports. Poverty rate, percentage of Medicare population, and percentage of uninsured population were obtained from Area Resource File. RHC zip codes, which were used in RUCA zip code approximation classification of rural areas, were obtained from the complete CMS listing (CMS, 2011). Percentage of minority population was obtained from U.S. Census

Bureau. The most prevalent cause-specific mortality rates were identified from WISQARS database.

4.2 Research Participants

Hospital-based RHCs were the unit of analysis. The national study attempted to include all hospital-based RHCs as reported in the CMS Cost Reports for years 2005 to 2008 (N=1,596). However, only those hospital-based RHCs with complete data for 2005 and 2008 were included. Missing data for 2006 and 2007 were imputed as long as values for the initial study period (2005) and final study period (2008) were available. In effect, 708 hospital-based RHCs or 44% of all hospital-based RHCs were included in the study.

4.3 Research Procedure

The analytical strategy is composed of two key components: linear growth curve modeling as the analytic model of choice and structural equation modeling as the preferred statistical procedure. GCM is second generation SEM procedure (Wan, 2002).

4.3.1 Linear Growth Curve Model

Linear growth curve modeling is second generation structural equation modeling procedure (Wan, 2002; Curran & Muthen, 1999). When used in a structural equation modeling framework, growth curve modeling uses two growth factors in the form of continuous latent variables (Curran & Muthen, 1999; Wan, 2002): (1) the intercept, which refers to the initial status of the productivity growth curve, and (2) the slope, which refers to the trajectory (rate of change) of productivity growth. The intercept indicates the starting point of the trajectory at the initial time of the study (2005) and can be obtained by holding all other factor loadings of the repeated measures to 1 (Curran & Muthen, 1999). The slope indicates the growth rate of productivity, and the factor loadings can be either fixed or freely estimated.

Linear growth curve models can be developed by using Mplus software (Muthen & Muthen, 1998–2010). Mplus is a structural modeling software that is capable of handling multiple latent and observed variables at a time. The variables can be continuous, categorical, or a combination of both. Thus, by applying linear growth curve modeling on Mplus version 6 (Muthen & Muthen, 2010), the growth patterns of productivity over a time span of four years from 2005 to 2008 were examined.

A linear growth curve model can be implemented into ways: as a univariate multi-level model or as a multivariate single-level model (Muthen & Muthen, 1998–2010; Wan, 2002). The current study opted to use a multivariate single-level approach. According to Muthen and Muthen (1998–2010), multilevel modeling normally takes a univariate approach to growth modeling where a dependent variable measured at four occasions gives rise to a single dependent variable.

In contrast, a single-level multivariate modeling of GCM is flexible, since differences in residual variances over time, correlated residuals over time, and regressions among the dependent variables over time could be incorporated (Muthen & Muthen, 1998–2010). These three aspects could be useful in addressing the hypotheses of the study. In addition, Sivo, Fan, Witta, and Willse (2006) indicated that the three aspects are often needed in GCM fitting.

4.3.2 Structural Equation Modeling (SEM)

SEM is a powerful statistical methodology that is associated with confirmatory analysis or hypothesis testing (Byrne, 2001.) SEM is used in health care studies (Wan, 2002). SEM allows GCM (Wan, 2002; Curran & Muthen, 1999). SEM combines a number of factor analyses with a set of multiple regression analyses over multiple endogenous (dependent) variables and latent constructs.

SEM basically consists of two types of models: measurement models and structural models. Measurement models relate to latent constructs, which means variables that could not be directly observed. In the current study, growth factors (intercept and slope) were the two latent variables. Thus, the first stage of SEM involved developing measurement models in which the latent variables were theoretically defined and measured by multiple observed variables (indicators) through confirmatory factor analysis.

In the current study, productivity was a latent endogenous (dependent) construct measured by two latent variables (intercept and slope). The DEA productivity measurements of each year from 2005 to 2008 served as indicators for the two latent variables.

Once the measurement model of productivity was evaluated and found to be valid, the next step was to combine the measurement model along with the hypothesized relationships to create a structural model. In GCM terminology, the measurement model corresponds to the unconditional GCM (i.e., GCM without exogenous variables), while the structure model corresponds to the conditional GCM (i.e., GCM with exogenous variables).

The unconditional and conditional GCM were statistically tested to find out whether the model was in line with the actual data. If the goodness-of-fit was found to be statistically satisfactory, then the hypothesized relationship between the variables would be considered credible. If the goodness-of-fit was not found to be adequate, then the plausibility of the proposed model would be rejected.

Examples of software that can be used to build SEM and GCM models include AMOS, LISREL, EQS, SAS PRO CALIS, and Mplus. Mplus version 6 was used for modeling, and SAS version 9.1 was used for data management and statistical analysis.

4.3.2.1 Rationale for using SEM

The decision to use SEM was based on several factors. First, when the phenomena underlying research questions and hypotheses are complex and multidimensional, SEM is the analysis tool that allows complete and simultaneous tests of all hypothesized relationships (Ullman, 2007). Second, a single SEM model combines the strengths of both multiple regression and confirmatory factor analysis (Hays, Revicki, & Coyne, 2005).

Third, according to Byrne (2001), SEM provides a precise estimate for systematic and random measurement errors. This is critical in avoiding inaccuracies, particularly when the errors are significant. Last, unlike most other multivariate analyses that could focus only on observed variables, SEM has the capacity to simultaneously analyze both observed and unobserved (latent) variables (Schumacker & Lomax, 2010).

4.3.2.2 Assumptions

Wan (2002) identified the following assumptions in SEM: 1) variables are characterized by linear relationships whose effects add up linearly, 2) temporal precedence exists in SEM in which “causes” (exogenous/independent variables) are assumed to occur before “effects” (endogenous/dependent variables), 3) continuous variables are preferred over nominal and ordinal variables in SEM, though all of them could be included, 4) observations are independent of each other, 5) homoscedasticity or equal variance exists among exogenous (independent) variables, 6) residual terms may not be correlated, 7) multicollinearity should be avoided among exogenous variables, and 8) variables may be standardized in order to generate weight-adjusted results.

Ullman (2007) supplied additional assumptions: 1) absence of univariate and multivariate outliers among all variables, 2) multivariate normality of all variables, 3) absence of singularity, and 4) after model estimation, normally distributed residuals (i.e., the frequency distribution of the residual covariances should be symmetrical and the residuals themselves need to be small and centered around zero).

4.3.2.3 Power Analysis

According to Miles (2003), the power of a statistical test refers to “the probability that the test will find a statistically significant effect in a sample of size N, at a pre-specified level of alpha, given that an effect of a particular size exists in the population” (p. 6). In SEM, power analysis is especially sensitive to sample size. Consequently, SEM on small sample sizes often lacks power, minimizing the effect size of reported findings.

MacCallum and Austin (2000), on the other hand, cautioned against relying entirely on power analysis to determine sample size, because a minimum sample size needed to obtain accurate parameter estimates, for instance, may be different from a minimum sample size determined by using power analysis. There is no universally accepted standard on determining sample size, but a rule of thumb is a minimum of 10–15 cases per estimated (free) parameters (Bentler, 1995).

Using the Schumacker and Lomax (2010) guideline of free parameters, the current GCM model has 30 free parameters (23 structure coefficients, 4 measurement error covariances, and 2 prediction error variances, 1 prediction error covariance). Therefore, the minimum sample size needed was 30 times 15, or 450 clinics for each year of study. The study had 708 hospital-based RHCs for each year. Therefore, there was more than sufficient statistical power.

4.3.2.4 Hypotheses Testing Using SEM

Multivariate modeling using SEM and GCM followed the theoretical and methodological guidelines elucidated by Wan (2002), Ullman (2007), Sivo and Fan (2008), and Sivo, Fan, and Witta (2005). In SEM, if a hypothesized model is found to fit the data, then the model is assumed to explain the covariance among the parameters. If the model fits the data, the model is kept as is, but if not, the model will have to be modified until it fits the data.

In other words, the null hypothesis states that the specified theoretical model fits the data. Therefore, the primary goal of an SEM model is to support a null hypothesis (hence the desire to get a non-significance test). Consequently, the goal of SEM is quite different from the goals of many other hypothesis testing statistical methodologies that seek to reject the null hypothesis.

4.3.2.5 Goodness-of-Fit Indices

One of the unique advantages of SEM is the method's ability to estimate how well the proposed model fits the actual data (Hays et al., 2005; Schumacker & Lomax, 2010). Normally, the decision to accept or reject SEM models is based on the values of the goodness-of-fit indices. The statistical significance of a model is determined only after it is found to fit the data sufficiently well (Byrne, 2001; Schumacker & Lomax, 2010).

If the model is not found to fit the data, then the Modification Indices (M.I.) can be used to re-specify the model until it sufficiently fits the data. There is no general consensus on which indices to use, though several researchers have forwarded recommendations (Byrne, 2001; Fan & Sivo, 2005; Schumacker & Lomax, 2010; Sivo et al., 2006; Ullman, 2007). The following indices were used to determine the goodness-of-fit in this study.

CMIN (minimum discrepancy), also known as chi-square (χ^2) or chi-square goodness-of-fit (Garson, 2009), is a test that represents the discrepancy between predicted and observed or between an unrestricted and restricted covariance matrix (Byrne, 2001). Significant chi-square values indicate poor model fit. A model can be rejected if chi-square is less than .05. Chi-square is generally considered conservative, and this can easily lead to Type II (false negative) errors.

The recommended practice is to use relative chi-square that is adjusted by degrees of freedom (CMIN/DF). Generally, a ratio between 2:1 and 3:1 is considered indicative of a good fit. The key problem of the chi-square test is its sensitivity to large sample sizes (more than several hundred observations). For large samples, chi-square is known to flag trivial differences as significant (Ullman, 2007). In addition, chi-square fit inadequately deals with distributional misspecifications of models. Consequently, alternative goodness-of-fit indices were used (Hu & Bentler, 1999).

For the power aspect of models, RMSEA (root mean square error of approximation) is taken as the best alternatives (Sivo et al., 2006; Ullman, 2007). A value of < .08 is considered as a good indicator of fit. Although some suggest a cutoff value of less than or equal to .06 (Hu & Bentler, 1999) or .05 (Schumacker & Lomax, 2010), the empirical evidence is in favor of a .08 cut-off value (Fan & Sivo, 2005; Sivo et al., 2006).

For comparison of nested models (Byrne, 2001; Schumacker & Lomax, 2010; Ullman, 2007), CFI (comparative fit index) is the more desirable index, with values ranging between 0.00 and 1.00. A good fit is indicated by values greater than .95.

For a focus on the complexity of models, where simpler models are rewarded, TLI (Tucker-Lewis index) is one of the most preferred indices (Schumacker & Lomax, 2010). TLI values range between 0.00 and 1.00. A good fit is indicated by values greater than .90, although some impose an even higher cut-off value of .95 (Schumacker & Lomax, 2010).

For a focus on unexplained residual aspect of models, standardized root mean square residual (SRMR) is the most desirable test (Sivo et al., 2006; Ullman, 2007). In general, and for most purposes, CFI and RMSEA are perhaps the most popular and frequently used goodness-of-fit measures (Schumacker & Lomax, 2010; Sivo et al., 2006; Ullman, 2007).

4.3.2.6 Path Diagram Conventions

There are several conventions in the path diagrams used to build structural equation models (Ullman, 2007). Latent constructs, also known as latent variables or unobserved variables, are represented by circles or ovals in path diagrams. Observed variables, also known as indicator or manifest variables, are represented by squares or rectangles. Hypothesized relationships between variables are indicated by lines; lack of a line connecting variables implies that no direct relationship has been identified.

There are two kinds of lines in path diagrams. Straight and one-directional arrows represent a hypothesized direct relationship between two variables, and the variable with the arrow pointing to it is called endogenous (dependent) variable. A curved line with arrows at both ends indicates correlation or covariance (i.e., has no implied direction of effect).

4.4 GIS

In health services research, Geographic Information Systems (GIS) is used as a tool to 1) present spatial patterning of performance measures, and 2) construct maps to present data in a practical and accessible manner (Gatrell, Löytönen, & European Science Foundation, 2003). Because of the large number of counties within the proposed study, the GIS application of choice was ArcGIS.

ArcGIS consists of the following applications: ArcView, ArcEditor, and ArcInfo. ArcGIS 9.3 was used to construct geographical maps that explore the spatial patterning of changes in productivity for hospital-based RHCs from 2005 to 2008. The use of GIS is mainly geared towards illustrating potential implications for practice and policy.

4.5 Operational Definition of Variables

Table 3 presents the operational definition, measurement levels and data sources of study variables. Two variables were repeatedly measured: physician availability and productivity. Productivity was the endogenous variable of interest that was measured from 2005 to 2008. Physician availability was the time-varying exogenous variable measured annually from 2005 to 2008.

Table 3 Operational Definitions, Measurement Levels and Data Sources

Constructs	Variables	Definition of Study Variable	Remark	Data Source
Contextual determinant variables	POVR	Poverty rate in 2005	Number of persons below federal poverty line divided by total number of persons in county	ARF[1]
	%MIN	Percentage of non-white population in 2000	Total number of persons in county minus number of persons self-identified as white divided by total number of persons in county	USCB[2]
	%MDC	Percentage of Medicare-eligible population in 2004	Number of persons above age of 64 eligible for Medicare divided by total number of persons in county	ARF
	UINS	Estimated % population without health insurance in 2000	Number of estimated persons above age of 17 without insurance divided by total number of persons in county	ARF
	REGION	1 = Hospital-based RHC in North-East	RHC located in CT, ME, MA, NH, NJ, NY, PA, RI or VT	USCB
		2 = Hospital-based RHC in West	RHC located in AK, AZ, CA, CO, HI, ID, MT, NV, NM, OR, UT, WA or WY	-
		3 = Hospital-based RHC in South	RHC located in AL, AR, DE, DC, FL, GA, KY, LA, MD, MS, NC, OK, SC, TN, TX, VA or WV	-
		4 = Hospital-based RHC in Mid-West	RHC located in IL, IN, IA, KS, MI, MN, MO, NE, ND, OH, SD, or WI	-

Constructs	Variables	Definition of Study Variable	Remark	Data Source
	RURAL	1 = Hospital-based RHC in isolated rural areas	RHC zip code matches RUCA-zipcode rural classification of 10.0, 10.2, 10.3, 10.4, 10.5, or 10.6	WWAMI[3]
		2 = Hospital-based RHC in small rural towns	RHC zip code matches RUCA-zipcode rural classification of 7.0, 7.2, 7.3, 7.4, 8.0, 8.2, 8.3, 8.4, 9.0, 9.1, or 9.2	-
		3 = Hospital-based RHC in large rural towns	RHC zip code matches RUCA-zipcode rural classification of 4.0, 4.2, 5.0, 5.2, 6.0, or 6.1	-
		4 = Hospital-based RHC in urban focused areas	RHC zip code matches RUCA-zipcode rural classification of 1.0, 1.1, 2.0, 2.1, 3.0, 4.1, 5.1, 7.1, 8.1, or 10.1	-
Organizational determinant	PH5-PH8	0 = Hospital-based RHC without physician FTEs	0 physician FTEs	CMS[4]
		1 = Hospital-based RHC with physician FTEs	> 0 physician FTES	
	PAYS	0= Capped reimbursement	>= 50 hospital beds	CMS
		1=Un-Capped reimbursement	< 50 hospital beds	-
	FORPRO	0= Nonprofit or Government.	Dichotomous	CMS
		1= For Profit	-	-

Constructs	Variables	Definition of Study Variable	Remark	Data Source
	AGE	Length of certification as RHC	2005 minus year of certification as RHC	CMS
Productivity	P_05-P_08	Four-Wave Dynamic slack-based DEA score with:	A DEA score between 0 and 1	CMS
		Inputs: Total FTEs 05 - 08 as grand sum of:	Numerical	CMS
		Physician FTEs 05 - 08	-	-
		Physician Assistant (PA) FTEs 05 - 08	-	-
		Nurse Practitioner (NP) FTEs 05 - 08	-	-
		Visiting Nurse FTEs 05 - 08	-	-
		Clinical Psychologist FTEs 05 - 08	-	-
		Clinical Social Worker FTEs 05 - 08	-	-
		Outputs: Total Visits 05 – 08 as grand sum of:	Numerical	CMS
		Physician Visits 05 - 08	-	-
		Physician Assistant (PA) Visits 05 - 08	-	-
		Nurse Practitioner (NP) Visits 05 - 08	-	-

Constructs	Variables	Definition of Study Variable	Remark	Data Source
		Visiting Nurse Visits 05 - 08	-	-
		Clinical Psychologist Visits 05 - 08	-	-
		Clinical Social Worker Visits 05 - 08	-	-
		Control links: Net Earning 05 – 08	Net Earning = Total Outpatient Revenue Minus Total Health Services Cost	CMS
		Total Health Services Cost 05 - 08	-	-
		Total Outpatient Revenue 05 - 08	-	-
	CMR	**Multiplier**: Cause-specific mortality rate for the four leading causes of death at the county level divided by U.S. average	Sum of mortality rates for heart diseases, malignant neoplasms, cerebro-vascular disease, and chronic low respiratory disease at the county level divided by sum of mortality rates for heart diseases, malignant neoplasms, cerebro-vascular disease, and chronic low respiratory disease at national level	CDC[5]

1. Area Resource File
2. U.S. Census Bureau
3. WWAMI Rural Health Research Center 4 level classification
4. Centers for Medicare and Medicaid Services Cost Reports
5. Centers for Disease Control and Prevention WISQARS leading causes of death database, 1999–2007

All contextual variables, age of facility, payment system, and ownership were treated as time-constant exogenous variables. Time-constant variables were generally measured at the initial study period (2005). However, data limitations required some contextual variables to be measured as early as 2000 (to benefit from U.S. Census Bureau as well as ARF data sources). In addition, Table 3 indicates the clustering of variables under theoretical constructs: organizational determinants of productivity and contextual determinants of productivity.

4.5.1 Exogenous Variables

Figure 3 presents the proposed linear growth curve model. Intercept and slope measure changes in the endogenous variable productivity over the four year period (2005–2008). The intercept measures initial differences in productivity between hospital-based RHCs while controlling for each of the nine time-constant exogenous variables (AGE, PAYS, FORPRO, POVR, %MIN, %MDC, REGION, RURAL and UINS).

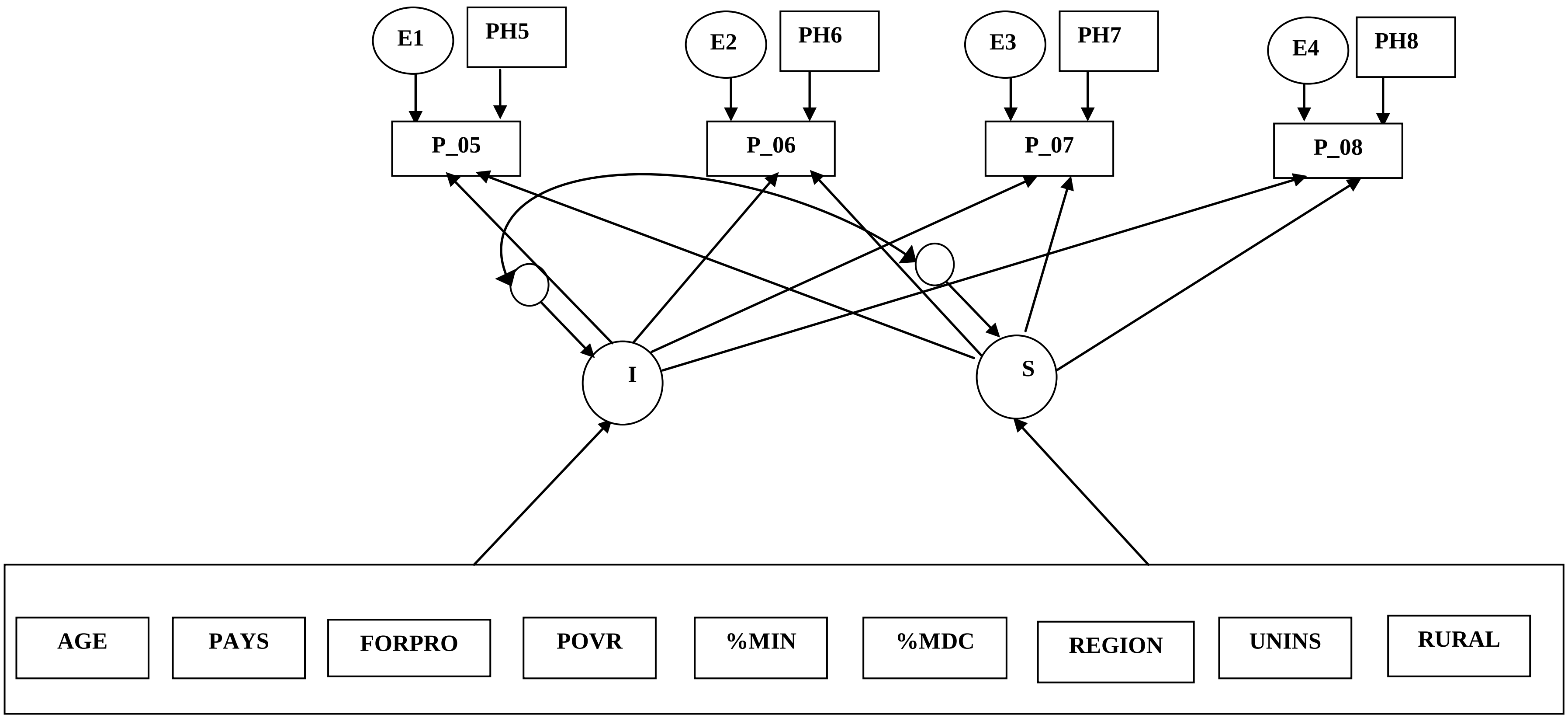


Figure 3 Growth Curve Model on Hospital-Based RHC Productivity from 2005 to 2008

P= Productivity, PH= Physician availability, I = Intercept, S = Slope, AGE= age of facility, PAYS=Payment System, FORPRO=For-profit owned, POVR=Poverty Rate, %MIN=Percentage of Minority (Non-white) population, %MDC=Percentage of Medicare-eligible residents, UNINS= Percentage of uninsured residents, RURAL=Categorization A of rural areas based on RUCA-Zip code approximation

The initial time point in consideration (the intercept) was 2005, the beginning year of the panel study. If the intercept is significant, it indicates that hospital-based RHCs in the study differ in their initial level of productivity. A significant intercept variance indicates that hospital-based RHCs show marked variation in productivity as a function of the eight time-constant predictor variables.

Slope measures changes in growth patterns and trends of productivity from 2006 to 2008 as compared to the initial time period of 2005. If the slope is significant, it indicates that individual hospital-based RHCs showed growth in productivity from 2005 to 2008. A significant slope variance indicates that individual hospital-based RHCs did not have the same growth rate in productivity, or in other words, it indicates a significant individual variation in rates of change in productivity among hospital-based RHCs.

4.5.2 Endogenous Variables

Productivity was the endogenous variable to be analyzed (Figure 4). The focus was on the following features: (1) as an endogenous variable, productivity is affected by organizational and contextual determinants of performance; (2) productivity is analyzed at an organizational level; (3) productivity is measured separately for different categories of RHCs based on rural classifications; (4) the value of productivity will range between 0 and 1.

Zero indicates the lowest level of productivity in that specific year, while a value of 1 indicates greater productivity as compared to other hospital-based RHCs in the same rural classification. Hospital-based RHCs with productivity score of 1 or 100% are considered as “leaders” that serve to “benchmark” the productivity of the remaining hospital-based RHCs within their category.

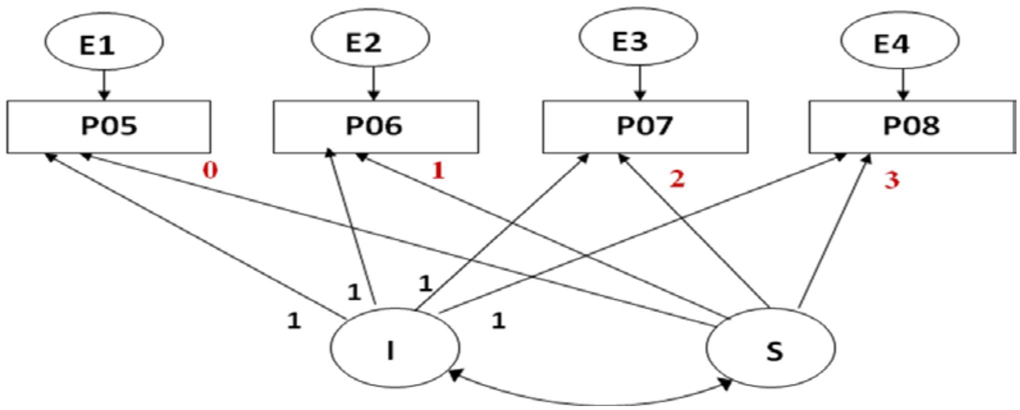


Figure 4 Unconditional Growth Curve Model for Productivity (2005-2008)

The model in Figure 4 is the initial growth model with no predictors. It is labeled as the unconditional growth curve model and is built to measure the goodness-of-fit of the growth curve measurement model. P05 to P08 represent productivity in the years 2005 to 2008, respectively. E1 to E4 represent measurement errors associated with P05 to P08, respectively.

I and S represent the intercept and slope of the latent variables, respectively. A correlation is assumed to exist between the intercept and slope growth factors. The intercept, which represents the original state of the growth curve, is assumed to have equal effect on productivity throughout the four years. Consequently, it has a fixed factor loading of 1.

The slope, on the other hand, is assumed to increase its effects in linear fashion over time; thus, its factor loadings start at 0 for 2005 and end as 3 for 2008. Since measurement of productivity is taken at equal intervals (i.e., annually), the factor loadings on the slope are also equally spaced from 0 to 3. It is good to note that the increase/decrease of productivity across time is anticipated to occur in a linear fashion. Hence, linear growth curve modeling was used in the study. Once the initial growth model attained adequate fit, then the full model (Figure 3) was tested. The full model includes time-varying and time-constant determinants of productivity.

4.6 Dynamic Slacks-Based DEA Analysis

Productivity was measured through a Data Envelopment Analysis (DEA) score. In health care research, labor FTEs are frequently used as inputs and patient visits as outputs in assessing productivity (Hollingsworth, 2008; Huang & McLaughlin, 1989; Sinay, 2001; Worthington, 2004). The literature regarding potential input and output variables in DEA analysis was discussed in Chapter 2. The current section focuses on technical aspects of DEA analysis.

Based on the seminal definition of efficiency by Farrell (1957), technical efficiency (productivity) is obtained by producing the maximum amount of output from a given amount of input or, alternatively, producing a given output with minimum input quantities, such that when a firm is technically efficient (or productive), it operates on its production frontier. This initial Farrell analysis is static. However, changes in efficiency and productivity can be measured over time.

DEA analysis can be implemented in two major ways: non-parametric and parametric DEA (Chirikos & Sear, 2000). Parametric DEA is favored by economists, since the underlying assumption is that firms always minimize costs and maximize productivity. However, managerial theories of the firm (Williamson, 1963, as cited by Bates, College, Mukherjee, & Santerre, 2006) posit that managers may strive to pursue other goals at the expense of higher profits.

This theory suggests that managers are less constrained to pursue maximum profits (and minimum costs) when property rights incentives and price competition are jointly absent or minimal, two conditions that apply well to hospitals because of the dominance of not-for-profit organizations and the lack of active price competition in some local hospital services areas (Bates et al., 2006). Consequently, non-parametric DEA is often used in health care settings to minimize strict assumptions of cost minimization, output maximization, and market pricing.

The current study chose to use non-parametric DEA for two reasons. First, a non-parametric approach allows the use of outputs and inputs even when price information is not easily available or when such information is not accurate. Second, a non-parametric method allows the specification of the production frontier based on the observed data without making arbitrary assumptions about the functional form of the production frontier, including standardized minimization of cost and output maximization.

The majority of DEA studies of productivity in the literature are cross-sectional in nature (Linna, 1998; Siciliani, 2006). DEA based on single-year data ignores the impact of time and assumes a static situation within organizations. That assumption is misleading, since dynamic settings may give rise to seemingly excessive use of resources that are intended to produce beneficial results in future periods (Cooper et al., 2007).

As stated by Kumbhakar and Lovell (2000), "Cross-sectional data provide a snapshot of producers and their efficiency [or productivity]. Panel data provide more reliable evidence on their performance, because they enable us to track the performance of each producer through a sequence of time periods" (p. 10).

There are three methods of conducting panel data analyses through DEA: Windows Analysis, Malmquist Indices, and Dynamic DEA. This study chose to use the most recent approach: Dynamic Slacks-Based DEA. Aspects that were accounted for in Dynamic DEA but that could not be replicated in Window analyses and Malmquist indices included 1) the carry-over effect of link variables such as net earnings (financial viability) on productivity scores, 2) slacks-based analyses that accounts for underutilization or overutilization of inputs, and 3) productivity optimization over a 4-year period rather than yearly optimization.

The inability of windows analyses and Malmquist indices to accommodate the aforementioned aspects biases the evaluation of productivity. For such reasons, "Single period optimization [by Windows analyses and Malmquist indices] is not suitable for performance evaluation" (Tone & Tsutsui, 2010, p. 145). Therefore, the linear growth curve modeling uses Dynamic Slacks-Based DEA analyses of productivity.

Given the relative importance of the differences among the three methods of panel data DEA analyses, further discussion is warranted. First, Dynamic DEA incorporates carry-over effects:

> Measurement of intertemporal efficiency change has long been a subject of concern in DEA. The window analysis and Malmquist index are representative methods. However, these models do not account for the effect of carry-over activities between two consecutive terms. For each term these models have inputs and outputs but the connecting activities between terms are not accounted explicitly. The dynamic DEA model proposed by Färe and Grosskopf (1996) is the first innovative scheme for dealing formally with these inter-connecting activities. (Tone, 2009, p. 67)

In essence, what distinguishes Dynamic DEA is the existence of carry-overs (Nemoto & Goto, 1996, 2003; Park & Park, 2009; Sueyoshi & Sekitani, 2005). These carry-over effects could be understood as lag effects (Emrouznejad & Thanassoulis, 2010).

Second, Dynamic DEA offers global or whole window optimization. Malmquist indices optimize by analyzing each period separately (Giuffrida 1999; Langabeer & Ozcan, 2009; Ozgen & Ozcan, 2004). The same is true for Windows analyses (Cook & Seiford, 2009; Cooper et al., 2007). In contrast, dynamic DEA accounts for long term or "global" optimization over the length of the window period (Tone, 2009; Tone & Tsutsui, 2010).

Figure 5 shows the incorporation of linking variables or carry-over effects as applied to hospital-based clinics. More often than not, capital variables (e.g., net earning) are taken as key carry-over effects or linking variables (Tone & Tsutsui, 2010). A link variable is neither an output nor an input per se. Link variables are more like quasi-inputs and quasi-outputs. Link variables are grouped into four types: desirable links, undesirable links, free links, and non-discretionary links (Tone & Tsutsui, 2010).

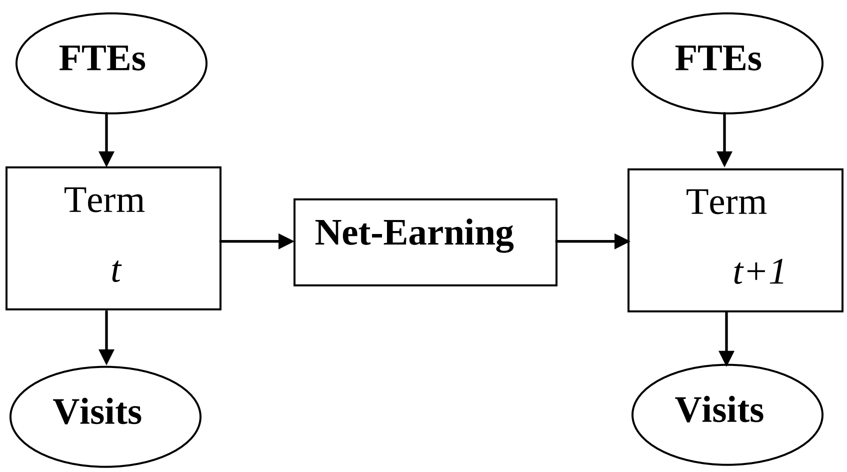


Figure 5 Dynamic DEA Structure (Adapted from Tone & Tsutsui, 2010, p.146)

Desirable links consider the comparative shortage of link variables as inefficiency while undesirable links consider the comparative excess of link variables as inefficiency. Free links assume that the observed values of link variables could be freely increased or decreased by

DMUs. Non-discretionary links compute efficiency scores while controlling for observed values of link variables.

For this study, net-earning was defined as RHC outpatient revenue minus RHC health services cost. Since net earning could take on negative values, a constant term was added to all values to ensure that the variable is non-zero positive. In addition, the net earning dollar values were divided by 100,000 to scale them into per 100,000 dollars. Such scaling of variables is recommended for DEA optimization (Ozgen & Ozcan, 2004).

In this study, net earning was used as a non-discretionary (control) link variable. In other words, net earnings (financial viability) serve as a control variable on productivity scores. Consequently, RHCs operating at a loss would not be “penalized” in the assessment of productivity and those with profit would not be “over-rated.” The other three link types require the assumption that RHC leaders can readily alter net earnings. That assumption may not be a realistic expectation on RHCs with limited leverage on revenue sources. In consideration of the above discussion, Dynamic Slacks-Based Input Oriented CRS model was used.

Key assumptions of DEA were tested before conducting the DEA analysis of productivity. They include no redundancy (inputs in the same time period should not correlate strongly with each other and outputs in the same time period should not correlated strongly with each other); inputs and outputs should be related (correlated); positivity and isotonicity should be maintained; and there should be no missing data. Although there is a practice of using small values (e.g., 0.0001) in place of missing data (Lewin, Morey, & Cook, 1982), it is generally not advisable (Huang & McLaughlin, 1989; Mukherjee, Santerre, & Zhang, 2010).

Although individual patient level quality data for outpatient visits was not available, county-level risk adjustment for four leading causes of mortality were used as a multiplier to DEA scores. Cause-specific mortality rates could be used as a proxy for health-risk differences at the population level in the absence of individual level data (Kelley & Linthicum, 2006).

CDC's WISQARS online database for leading causes of death reported that heart diseases, malignant neoplasms, cerebro-vascular disease, and chronic low respiratory disease were top cause-specific mortalities for all races, all ages, and both genders from 1999 to 2007 (CDC, 2010). The sum of mortality rates for the four leading causes of death at each county divided by the national average mortality rate for the four leading causes of death was constituted to serve as risk adjustment. Although standardized cause-specific mortality rates through logistic regression were sought, CDC vital statistics data for cause-specific mortality had no geographic identifiers (FIPS codes) as of 2005.

Data prior to 2005 provided FIPS codes for counties with more than 100,000 residents. Since RHCs are generally located in counties of fewer than 50,000 residents, those data, too, were inapplicable. Consequently, cause-specific mortality data for 2000 as reported in ARF were used (U.S. Department of Health and Human Services, Health Resources and Services Administration, Bureau of Health Professions, 2005). The ARF database offers the cause-specific mortality data for all counties regardless of population size. However, the ARF database provided neither age nor gender breakdown for cause-specific mortality rates, precluding standardization efforts.

4.7 Data Sources and Cleaning Rules

The data came from several sources. Contextual data concerning the location of RHCs were obtained from the Area Resource File (ARF) (U.S. Department of Health and Human Services, Health Resources and Services Administration, Bureau of Health Professions, 2005) and U.S. Census Bureau American Fact Finder system (U.S. Census Bureau, 2010). Organizational characteristic data, including labor and office-visit data, were obtained from CMS Medicare Cost Reports for Hospitals (CMS, 2005–2008). The Medicare cost reports for hospitals are administrative datasets annually assembled by CMS that include information on hospitals and their sub-providers.

The merging of the databases was done as follows. First, lists of hospitals that own hospital-based RHCs were extracted from Medicare Cost Report for 2005 and 2008. Therefore, hospital-based RHCs that existed in both 2005 and 2008 framed the panel study. Report record number is the only common key provided by CMS Medicare Cost Reports to navigate the various databases within the Medicare Cost Reports.

Since that was not always unique, a combination of hospital provider number and report record number was used. Since some hospitals might have more than one RHC associated with them, a second composite key made of hospital provider number, rural health clinic provider number, and report record number of cost reports was also used.

When merging datasets from 2005 and 2008, only RHCs with complete data for 1) total FTEs and visits, and 2) total health services cost and total outpatient revenue were included. Before conducting multiple imputations for missing values in a panel data set, it was necessary to ensure that valid values were available for the initial and final years of the panel data.

Second, the data set for years 2006 and 2007 were merged and subsequently joined to the already merged dataset of 2005 and 2008. If RHCs had missing values for 2006 and 2008, data imputation was performed. Third, the four-year merged dataset was supplemented with contextual data from the ARF database and U.S. Census Bureau using county FIPS codes.

Finally, data from RUCA-Zipcode version 2.0 classifications of rural areas were merged into the final dataset using RHC zip-codes as key variables. Up-to-date zip-codes of RHCs were obtained from the CMS publication on the total list of RHCs in the U.S. (CMS, 2011).

4.8 Methodological Limitations

SEM and GCM have several known limitations (Sivo & Fan, 2008; Sivo et al., 2005; Wall & Amemiya, 2000). First, SEM and linear GCM anticipate linear relationships. However, research in contingency theory has indicated that quadratic and polynomial relationships are more prevalent than previously thought (Meilich, 2006).

Second, results can be generalized only to the type of sample that was used to estimate and test SEM models (Ullman, 2007). Therefore, cross-validation of results on a newer sample is necessary. Third, hospital-based RHCs with no data for 2005 and 2008 were excluded. Hence, the generalizability of the study will be limited.

DEA methodology used for productivity has a number of limitations. With DEA analysis, it is not possible to know if there is a statistically significant difference between the maximum score of 1 and, say, 0.9 (i.e., DEA is a non-parametric and exploratory procedure). Second, productivity scores of DEA ignore non-physical inputs such as experience, information, or supervision (by definition the scores examine only physical relationships).

Third, DEA values quantity of outputs (e.g., patient visits) rather than quality of outputs. In the study, however, it is difficult to implement quality adjustments to outpatient visits made by physicians and non-physician providers. In other words, individual-level visit data were not available within data sources in use for the study. Fourth, DEA is only a relative and indirect measure of productivity.

4.9 Summary

A non-experimental design was applied on four-year panel data in order to understand the relationships between contextual and organizational variables in relation to growth trends and patterns of productivity. The unit of analysis was at the organization level. Univariate and multivariate data cleaning rules were applied to account for extreme outliers, missing values, and duplicates. Since the most recent data from the facilities were used within the context of a panel study, the impacts of threats to internal validity were anticipated to be minimal. However, external validity could be limited given the exclusion of some hospital-based RHCs.

CHAPTER FIVE: FINDINGS

For the years 2005 to 2008, this study investigated 1) growth patterns and trends of productivity, and 2) determinants of productivity in U.S hospital-based RHCs. In this chapter, the analytic results are presented in four sections. The first section presents descriptive analyses. The following section deals with unconditional growth curve modeling. This model focuses on growth patterns and trends of productivity without the influence of explanatory variables. The third section discusses conditional growth curve modeling. This model examines how time-varying and time-constant determinants of productivity relate to growth patterns and trends of productivity. The last section summarizes the hypothesis testing results.

5.1 Descriptive Analyses

Table 4 presents the descriptive statistics related to variables used in growth curve modeling. Mean productivity scores had an approximately linear increase from 0.24 in 2005 to 0.29 in 2008. There was a slight peak in the productivity scores of 2007 over what would be expected by a linear trajectory. Ninety percent of the hospital-based RHCs in the study were non-profit owned while 81% received uncapped cost-reimbursements. The average clinic in 2005 was roughly 9 years old. For the years 2005 to 2008, over 65% of the clinics had physician FTEs.

Table 4 Descriptive Statistics for Variables in Growth Curve Modeling (N = 708)

Variables	Mean	Std Dev	Min	Max	Skewness	Kurtosis
P05 (Productivity scores in 2005)	0.24	0.10	0.03	0.60	1.00	1.33
P06 (Productivity scores in 2006)	0.25	0.12	0.01	0.67	0.93	0.60
P07 (Productivity scores in 2007)	0.30	0.11	0.07	0.68	0.79	0.24
P08 (Productivity scores in 2008)	0.29	0.12	0.05	0.68	0.85	0.22
%MIN (Minority population)	12.11	14.14	10.0	76.00	1.98	4.35
%MDC (Medicare-eligible population)	19.56	4.72	7.60	43.64	0.53	1.65
%UNIN (Uninsured population)	16.05	4.91	5.40	37.90	0.48	0.65
POV (Poverty rate)	14.54	4.99	3.80	39.00	1.22	2.66
AGE (Age of clinic)	9.11	4.39	1.00	29.00	0.10	-0.12
PH_05						
0 = without Physicians in 2005	33.2% (N = 235)					
1 = with Physicians in 2005	66.8 % (N = 473)					
PH_06						
0 = without Physicians in 2006	34.6% (N = 245)					
1 = with Physicians in 2006	65.4% (N = 463)					
PH_07						
0 = without Physicians in 2007	32.9% (N = 233)					
1 = with Physicians in 2007	67.1% (N = 475)					
PH_08						
0 = without Physicians in 2008	22.2% (N = 157)					
1 = with Physicians in 2008	77.8% (N = 551)					
FORPRO (for profit ownership)						
0 = non-profit ownership	90.0% (N = 637)					
1 = for profit ownership	10.0% (N = 71)					
PAYS (payment system)						
0 = uncapped payment	81.1% (N = 574)					
1 = prospective payment	18.9% (N = 134)					
RURAL						
1 = isolated rural areas	47.7% (N = 338)					
2 = small rural towns	29.0% (N = 205)					
3 = large rural towns	15.0% (N = 106)					
4 = urban focused areas	8.3% (N = 59)					
REGION						
1 = North East	2.7% (N = 19)					
2 = West	23.2% (N = 164)					
3 = Mid West	44.4% (N = 314)					
4 = South	29.8% (N = 211)					

The average hospital-based RHC in the study was located in a county with 1) 12% of population identifying as non-white, 2) 20% Medicare-eligible population rate, 3) 16% uninsured population rate, 4) 15% poverty rate, 5) 48% in isolated rural areas, and 6) 44% in the Midwest.

Table 5 presents the correlation statistics related to variables used in growth curve modeling. In general, productivity scores for the four-year period of 2005 to 2008 were positively related to each other with moderate strength (0.47 to 0.62). Age of facility was negatively correlated with productivity scores, while rural classification was positively correlated with productivity scores.

Table 5 Correlation Statistics for Variables in Growth Curve Modeling

No	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	P_05	1.00																
2	P_06	.60**	1.00															
3	P_07	.47**	.61**	1.00														
4	P_08	.43**	.52**	.62**	1.00													
5	AGE	-.09*	-.12**	-.11**	-.07	1.00												
6	%MDC	-.12**	-.15**	-.12**	-.16**	-.01	1.00											
7	%MIN	.07	.11**	.02	.06	.04	-.46**	1.00										
8	%UNIN	-.04	-.02	-.03	.01	.02	-.26**	.63**	1.00									
9	POV	-.03	-.02	-.05	-.04	.04	-.16**	.62**	.77**	1.00								
10	PAYS	.11**	.03	.01	.01	.15**	.15**	-.12*	.08*	.10**	1.00							
11	FORPRO	-.02	-.03	-.02	.02	.10*	-.09*	.08*	.03	.08**	.015**	1.00						
12	PH5	.01	-.01	-.04	-.06	-.12**	.13**	-.17*	-.20**	-.17*	-.11**	.01	1.00					
13	PH6	-.01	-.02	-.03	-.04	-.13**	.10**	-.16*	-.18**	-.16*	-.07	.06	.85**	1.00				
14	PH7	-.03	-.05	-.02	-.05	-.04	.09*	-.13*	-.14**	-.12*	-.04	.01	.74**	.82**	1.00			
15	PH8	-.01	-.03	-.03	-.02	-.01	.02	-.08*	-.07	-.07*	-.12**	-.01	.51**	.57**	.69**	1.00		
16	REGION	-.05	-.06	-.05	-.08*	.13**	.01	.16**	.10**	.34**	.10**	.02	-.24**	-.22**	-.15**	-.06	1.00	
17	RURAL	.29**	.31**	.21**	.25**	-.03	-.44**	.25**	.08*	.06	.35**	.12**	-.12**	-.08*	-.08*	-.08*	-.03	1.00

P_05: Productivity score in 2005; P_06: Productivity score in 2006; P_07: Productivity score in 2007; P_08: Productivity score in 2008; AGE: age of clinic; %MDC: percentage of Medicare-eligible population; %MIN: percentage of minority (non-white) population; %UNIN: percentage of uninsured population; POV: poverty rate; PAYS: Payment system; FORPRO: For-profit ownership; PH5: Physician availability in 2005; PH6: Physician availability in 2006; PH7: Physician availability in 2007; PH8: Physician availability in 2008;REGION: US Census Bureau 4 Region Classification; RURAL: RUCA-Zipcode approximation classification of rural areas.

** Correlation is significant at the .01 level (two-tailed)

* Correlation is significant at the .05 level (two-tailed)

Table 6 presents the descriptive statistics related to variables used to estimate productivity scores using dynamic slacks-based DEA analyses. The input variables exhibited a mean linear increase from 2.1 total FTEs in 2005 to 2.5 total FTEs in 2008. The output variables demonstrated a mean linear increase from 7,686 visits per annum in 2005 to 9,253 visits per annum in 2008. The non-discretionary (control) link variables had a linear increase in mean net earnings from 129,924 U.S. dollars in 2005 to 157,248 US dollars in 2008. The correlation matrix for inputs, outputs, and control link variables in DEA analysis are presented in Appendix A.

Table 6 Descriptive Statistics for Variables in Data Envelopment Analyses (N = 708)

Function	Variables	Mean	Std Dev	Min	Max
Input	TOFT_05 (Total FTEs in 2005)	2.11	2.17	0.01	30.16
Input	TOFT_06 (Total FTEs in 2006)	2.20	2.20	0.03	29.71
Input	TOFT_07 (Total FTEs in 2007)	2.26	2.36	0.04	32.74
Input	TOFT_08 (Total FTEs in 2008)	2.50	2.49	0.04	32.64
Output	TOVI_05 (Total visits in 2005)	7686	9431	27	128447
Output	TOVI_06 (Total visits in 2006)	7901	9329	137	121626
Output	TOVI_07 (Total visits in 2007)	8233	9979	64	131689
Output	TOVI_08 (Total visits in 2008)	9253	10545	52	127824
Link	NETE _05 (Net earnings in 2005)	129924	758107	-8964888	5764517
Link	NETE _06 (Net earnings in 2006)	139420	806803	-8606273	5824941
Link	NETE _07 (Net earnings in 2007)	152631	888388	-9573781	7061215
Link	NETE _08 (Net earnings in 2008)	157248	976375	-10082440	8411745
DEA score	rP_05* (raw productivity score in 2005)	0.44	0.18	0.07	1.00
DEA score	rP_06* (raw productivity score in 2006)	0.46	0.22	0.03	1.00
DEA score	rP_07* (raw productivity score in 2007)	0.54	0.21	0.14	1.00
DEA score	rP_08* (raw productivity score in 2008)	0.53	0.21	0.09	1.00
Adjuster	CMR (cause-specific mortality rate)	0.55	0.05	0.39	0.82

* Raw DEA scores are productivity measures without the CMR multiplier for population-level risk adjustment (cause specific mortality rates for four leading causes of death at the county level divided by U.S. average rate for the four leading causes of death).

Assumptions of linearity, normality, and outliers were explored for the endogenous variables (productivity scores from 2005 to 2008). As Figure 6 shows, a scatter matrix of productivity scores of 2005 to 2008 exhibited linear relationships. In addition, the line plot of productivity scores versus time also showed an approximately linear relationship.

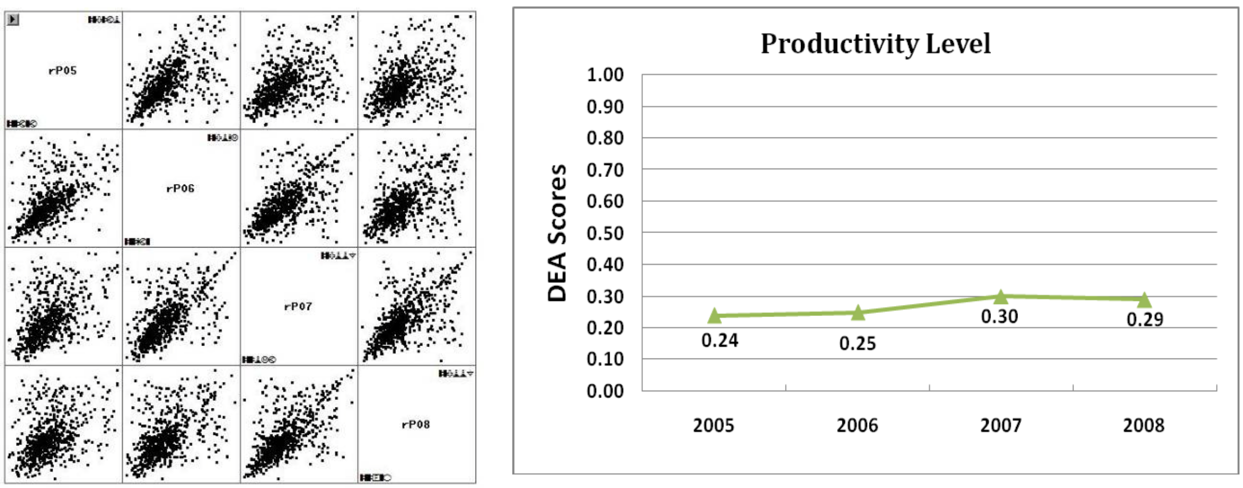


Figure 6 Scatter Matrix and Line Plot of Dynamic DEA Scores (2005 to 2008)

Univariate normality was assessed through Q-Q plots, histograms, normality Z-scores and a Kolmogorov-Smirnov test of normality. Appendix B presents the Q-Q plots and histograms for productivity scores as well as for other continuous variables used in growth curve modeling. Using normality Z-scores (ratio of skewness / standard deviation of skewness or ratio of kurtosis/ standard deviation of kurtosis) cut-off value of 3 (Mertler & Vannatta, 2005), productivity scores of 2005 to 2008 were marginally non-normal.

Given a sample size of 2,832 (708 hospital-based RHCs times 4 years), the Kolmogorov-Smirnov test of normality was another option to assess univariate normality. Non-significant *p*-

values are taken as a sign of normality (Mertler & Vannatta, 2005). Accordingly, productivity scores from 2005 to 2008 were found to be non-normal ($p < .01$).

Multivariate normality was assessed through Mardia's tests on skewness and kurtosis through SAS PROC MODEL. Mardia's normalized coefficient for skewness ($p < .001$) and kurtosis ($p < .001$) were both significant. Due to the violation of multivariate normality in productivity scores, growth-curve modeling was estimated through Satorra-Bentler maximum likelihood parameter estimates (Ullman, 2007). Satorra-Bentler MLM estimator in Mplus adjusts standard errors to the extent of non-normality observed in variables (Muthen & Muthen, 2010).

For continuous variables, univariate outliers were sought through SAS PROC STANDARD. Standardized Z-scores of 3.29 and above were taken as potential signs of univariate outliers (Tabachnik & Fidell, 2007). Among the productivity scores, which are endogenous variables, there were no univariate outliers. Amongst the exogenous variables, 24 univariate outliers were spotted. For categorical variables, frequency splits of more than 90-10 were taken as univariate outliers (Tabachnik & Fidell, 2007). There were no univariate outliers among categorical variables.

Multivariate outliers were sought through SAS PROC REG leverage values. In assessing multivariate outliers, productivity scores (P_05 to P_08) were taken as dependent variables, while all exogenous variables were taken as independent variables. In all, 14 multivariate outliers that were not already identified as univariate outliers were detected. In total there were 38 univariate and multivariate outliers. The outliers were verified to be accurate values.

Given the very large sample size of 2,832, a few outliers (about 1%) are to be expected (Tabachnik & Fidell, 2007). In addition, removing or replacing outliers in a data set that includes DEA scores could bias the analyses. Therefore, identified outliers were retained.

Before conducting multivariate modeling, the representativeness of the 708 hospital-based RHCs needed to be assessed. In the 2008 Medicare Cost Reports for Hospitals, 1,713 hospital-based RHCs were reported. In the 2005 Medicare Cost Reports for Hospitals, 1,596 hospital-based RHCs were reported. Although 1,423 hospital-based RHCs reported in 2005 were also present in 2008, the study included half of them (N = 708, 50%). In all, 715 hospital-based RHCs were excluded for the following reasons.

First, only hospital-based RHCs with non-missing values on total visits, total FTEs, health services cost, and outpatient revenue for both 2005 and 2008 were retained. These variables were needed for DEA and thus could not be missing. Consequently, 693 hospital-based RHCs were excluded. All other variables had valid values for both 2005 and 2008. In a panel data analysis, it is more valid to require starting and ending years to have non-missing values and impute any other missing values for the intervening years. Second, 22 hospital-based RHCs were excluded for lack of matching RUCA Zip-code when merging the data.

All hospital-based RHCs that had valid values for all variables for the year 2005 and 2008 were retained and merged. For the intervening years of 2006 and 2007, all variables with or without missing values were added to the merged data of 2005 and 2008. The frequencies of missing data on all variables from 2006 and 2007 were all below 3% (See Appendix C).

SAS PROC MI and PROC GLM in conjunction with PROC MIANALYZE were used to conduct multiple imputation of missing data. Multiple imputation was the method of choice, since 1) it requires no assumptions about whether the data are randomly missing, 2) it retains sampling variability, and 3) it is well suited to panel data (Tabachnick & Fidell, 2007). The multiple imputations generated 15 data points for each missing value. For variables that were normally distributed, the mean of the 15 data points was used to replace missing values. For variables that were not normally distributed, the median of the 15 data points was used to replace missing values.

Statistical tests were conducted between included and excluded hospital-based RHCs with regard to study variables (Table 7). For continuous variables that were normally distributed, t-tests were used; non-normally distributed continuous variables had Wilcoxon non-parametric tests. Categorical variables were contrasted through a chi-square test of difference.

Table 7 Comparisons of Included and Excluded Hospital-Based Rural Health Clinics

Variables	Included RHCs (N = 708) Mean	Excluded RHCs (N= 715) N	Mean	Test Results p-value	Remark
AGE† (age of hospital-based clinic)	9.11	679	8.81	.615	
%MDC† (percentage of Medicare eligible)	19.56	647	18.95	.013***	
%UNIN† (percentage of uninsured)	16.05	647	16.10	.846	
POV* (poverty rate)	14.54	647	15.69	.001***	
%MIN* (percentage of minority population)	12.11	647	16.70	.001***	
TOFT_05*(total clinical FTEs in 2005)	2.11	272	1.99	.834	
TOFT_06* (total clinical FTEs in 2006)	2.20	404	2.01	.866	
TOFT_07* (total clinical FTEs in 2007)	2.26	466	2.01	.823	
TOFT_08* (total clinical FTEs in 2008)	2.50	369	2.13	.080	
TOVI_05* (total clinical visits in 2005)	7686	273	6915	.931	
TOVI_06* (total clinical visits in 2006)	7901	406	7128	.674	
TOVI_07* (total clinical visits in 2007)	8233	467	7306	.990	
TOVI_08* (total clinical visits in 2008)	9253	373	7861	.371	
NETE _05* (net earnings in 2005)	129924	177	67957	.016***	
NETE _06* (net earnings in 2006)	139420	294	102525	< .001***	
NETE _07* (net earnings in 2007)	152631	379	55735	< .001***	
NETE _08* (net earnings in 2008)	157248	290	106206	.001***	
CMR* (cause-specific mortality rate)	0.55	647	.55	.831	
PH_05** (physician presence in 2005)	66.8 %	715	27.8%	< .001***	0.390 Phi
PH_06** (physician presence in 2006)	65.4%	715	38.3%	< .001***	0.390 Phi
PH_07** (physician presence in 2007)	67.1%	715	42.4%	< .001***	0.248 Phi
PH_08** (physician presence in 2008)	77.8%	715	37.3%	< .001***	0. 409Phi
FORPRO** (for-profit ownership)	10.0%	679	10.9%	.597	
PAYS** (capped payment system)	18.9%	636	23.7%	.031***	-0.059 Phi
RURAL** (More rural to less rural)	8.3%	631	11.7%	.169	
REGION** (Northeast to the South)	29.8%	647	38.6%	.001***	0.122 Cramer's V

† Independent samples t-test, alpha = .05, two-tailed, for normally distributed variables
* Wilcoxon non-parametric test, alpha = .05, two-tailed, for non normally distributed variables
** Chi-square test of difference, alpha = .05, two-tailed, for categorical variables
*** Significant differences

From organizational variables, there were significant differences in physician availability, net earnings, and payment system. From environmental variables, significant differences were observed in regional location, percentage of minority population, percentage of Medicare-eligible beneficiaries, and poverty rate. Taking into account effect sizes, the significant differences in payment system (-0.06 Phi coefficients) and regional location (0.1 Cramer's V) were trivial. Phi coefficients and Cramer's V close to zero indicate trivial effect sizes (in other words, differences of little importance).

The implications of significant differences are as follows. The findings of this study are least applicable to those hospital-based RHCs with lower net-earnings and fewer physicians as compared to included hospital-based RHCs. In addition, the generalizability of this study is least applicable to hospital-based RHCs located in counties with lower percentage of Medicare-eligible residents, higher percentage of minorities, and higher levels of poverty rate as compared to the counties of included hospital-based RHCs.

5.2 Unconditional Linear Growth Curve Model Results

Prior to assessing the determinants of growth changes in an endogenous variable, it is useful to assess growth trends and patterns without any conditioning explanatory variables (Duncan, Duncan, Strycker, Li, & Alpert, 1999). Growth models without explanatory variables are termed unconditional models. Figure 7 presents the unconditional growth curve model for productivity in U.S. hospital-based RHCs for the years 2005 to 2008.

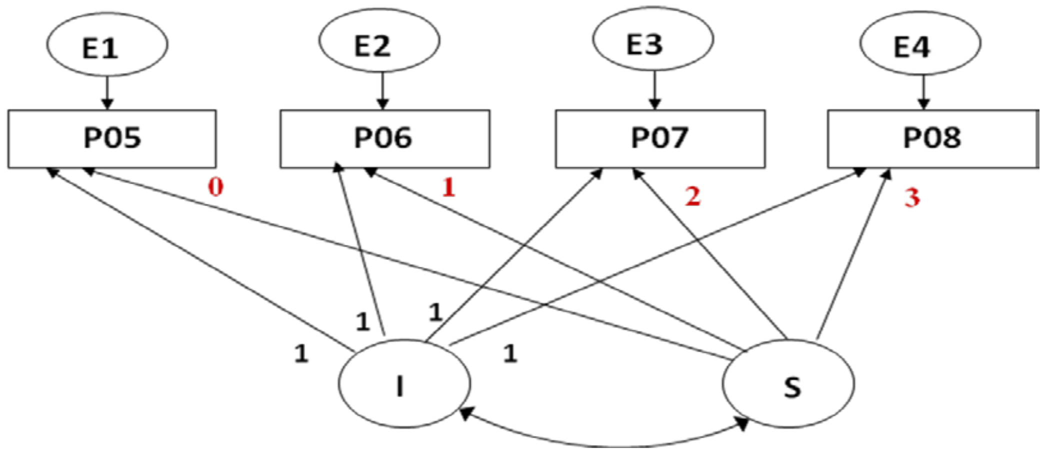


Figure 7 Proposed Unconditional Growth Curve Model for Productivity (2005-2008)

Intercept (I) is a latent measure of productivity that assesses initial differences in productivity for the baseline year of 2005. Slope (S) is a latent measure of productivity that estimates differential rate of changes in growth trends and patterns from 2006 to 2008.

The unconditional growth curve model shown in Figure 7 was fitted to raw data on 708 hospital-based RHCs for the years 2005 to 2008. Satorra-Bentler rescaled chi-square with robust standard errors for non-normality or maximum likelihood mean-adjusted (MLM) estimation was used to estimate all models. The fit of models was tested through goodness-of-fit indices using Mplus version 6 software.

The unconditional growth curve model with no post-hoc modifications is called the generic model. The generic model was fitted to data with no errors and warnings. The extent of non-normality adjustment in data was acceptable (Scaling Correction Factor for MLM = 1.258). A scaling correction factor of 1 is a sign of total absence of non-normality indicating no need for non-normality adjustment. Values close to 1 are desirable (Muthen & Muthen, 1998–2010).

As Table 8 shows, the generic model had poor fit (Chi-square [5, N = 708] = 81.786, $p < .001$, RMSEA = .147, SRMR = .073, CFI = .893, TLI = .871, WRMR = 2.413). Post hoc model modifications were performed in an attempt to develop a better fitting and possibly more parsimonious model. On the basis of modification indices and logical relevance, one new path and two co-variances were added one at a time. Productivity scores in 2006 had a direct effect on productivity scores for 2007.

Table 8 Unconditional Linear Growth Curve Model Fit Results

Index	Generic Model	Revised Model	Remarks
Chi-Square	81.786	4.656	
Degrees of freedom	5	2	
Chi-square/ Degrees of freedom	16.357	2.328	Good Fit
P-value	< .001	0.098	Good Fit
RMSEA (Root Mean Square Error Of Approximation)	0.147	0.043	Good Fit
SRMR (Standardized Root Mean Square Residual)	0.073	0.017	Good Fit
CFI (Bentler's Comparative Fit Index)	0.893	0.996	Good Fit
TLI (Tucker-Lewis Index)	0.871	0.989	Good Fit
WRMR (Weighted Root Mean Square Residual)	2.413	0.640	Good Fit

The direct effect (autoregressive effect) of 2006 and 2007 had some logical relevance since productivity scores of 2007 were slightly higher than would be expected by the linear trajectory. Figure 8 presents the mean productivity scores from 2005 to 2008, with the dashed line representing the expected linear trajectory.

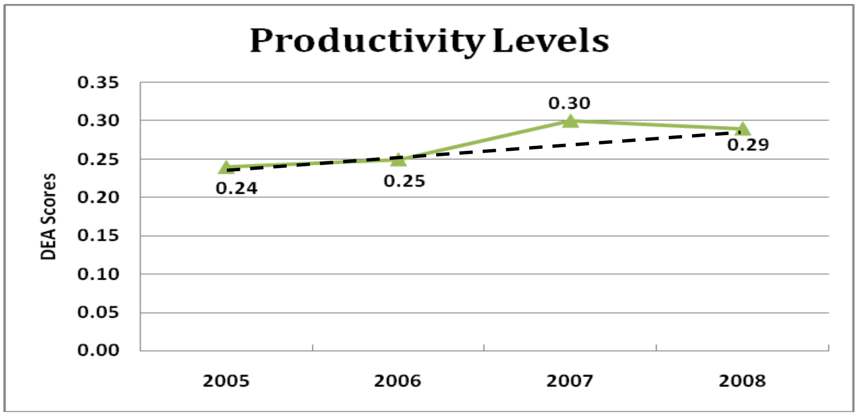


Figure 8 Mean Dynamic DEA Productivity Scores from 2005 to 2008

The new path between productivity scores of 2006 and 2007 indicates that the higher peak in productivity observed in 2007 was related to the productivity level of the previous year. Two residual co-variances were estimated. The revised model, which incorporated the aforementioned modifications, is shown in Figure 9. The revised model was significantly improved with the addition of a new path and two residual co-variances (Chi-square [2, N = 708] = 4.656, p = .10, RMSEA = .04, SRMR = .02, CFI = .996, TLI = .989). The revised model had good fit and support from data.

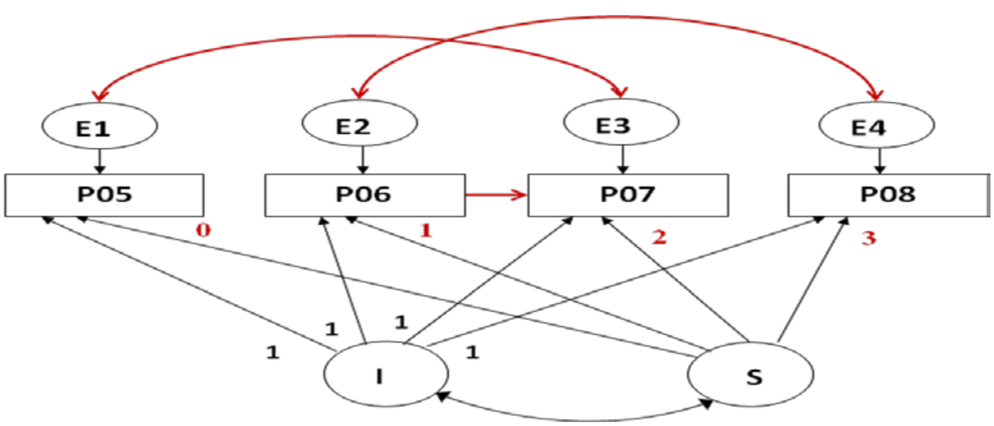


Figure 9 Revised Unconditional Growth Curve Model for Productivity (2005-2008)

Parameter estimates for the revised unconditional growth curve model are shown in Table 9. The intercept was statistically significant (p < .001). Therefore, hospital-based RHCs differed from each other in their baseline level of productivity. The intercept variance was also statistically significant (p < .001). Consequently, range of differences in productivity for the year 2005 showed marked variability from one hospital-based RHC to another.

Table 9 Parameter Estimates for Revised Unconditional Linear Growth Curve Model

Parameters	Unstandardized	S.E.	C.R.	*P*-value	Standardized
Intercept Mean *	0.244	0.004	63.144	< .001	
Intercept Variance	0.009	0.001	10.569	< .001	1.00
Slope Mean	0.015	0.002	10.107	< .001	0.55
Slope Variance	0.001	0.000	5.189	< .001	1.00
Intercept Slope Covariance	-0.001	0.000	-4.234	< .001	-0.416
P_06 → P_07	0.110	0.013	8.671	< .001	0.110
Error3 Error1 Covariance	-0.002	0.000	-4.660	< .001	-0.002
Error4 Error2 Covariance	0.001	0.000	2.649	.008	0.001
	Squared Multiple Correlations				
P_05	0.819	0.055	14.944	< .001	
P_06	0.474	0.030	15.693	< .001	
P_07	0.678	0.033	20.551	< .001	
P_08	0.611	0.051	11.930	< .001	

P_05: Productivity score in 2005; P_06: Productivity score in 2006; P_07: Productivity score in 2007; P_08: Productivity score in 2008; S.E. Standard Error; C.R. Critical Ratio.
* The intercept mean parameter is about mean of productivity score in 2005. Intercept mean is not about the relationship between two variables. As such, standardization of parameters is not meaningful for mean intercept. In contrast mean of slope is about the moderating relationship between rate of change in productivity and determinants of productivity.

The slope was statistically significant (p < .001). Hence, hospital-based RHCs did attain growth in productivity from 2005 to 2008. In addition, the mean of slope (standardized estimate = 0.55) was not zero, indicating the presence of approximate linear change in productivity. The slope variance was also statistically significant ($p < .001$). In other words, hospital-based RHCs did not share the same productivity growth rate.

Intercept and Slope covariance was statistically significant and negative ($p < .001$). Hospital-based RHCs with high levels of initial productivity in 2005 had a slower rate of growth in productivity in subsequent years (from 2006 to 2008).

The squared multiple correlations indicate how much of the variability in productivity scores for each year was accounted for by the revised unconditional growth curve model. The revised model explained a statistically significant amount of variation for each year from 2005 to 2008 ($p < .001$). In addition, the revised model explained 60% or more of the variation of productivity scores for each year except 2006. For 2006, only 47.4% of the variation was explained by the model.

5.3 Conditional Linear Growth Curve Model

Conditional growth curve modeling was conducted by introducing time-varying and time-constant determinants of productivity to the unconditional growth curve model. Conditional growth curve modeling tests whether determinants of productivity had a conditioning influence on growth patterns and trends of productivity (Intercept and Slope). Figure 10 depicts the conditional growth curve model in U.S. hospital-based RHCs for the years 2005 to 2008.

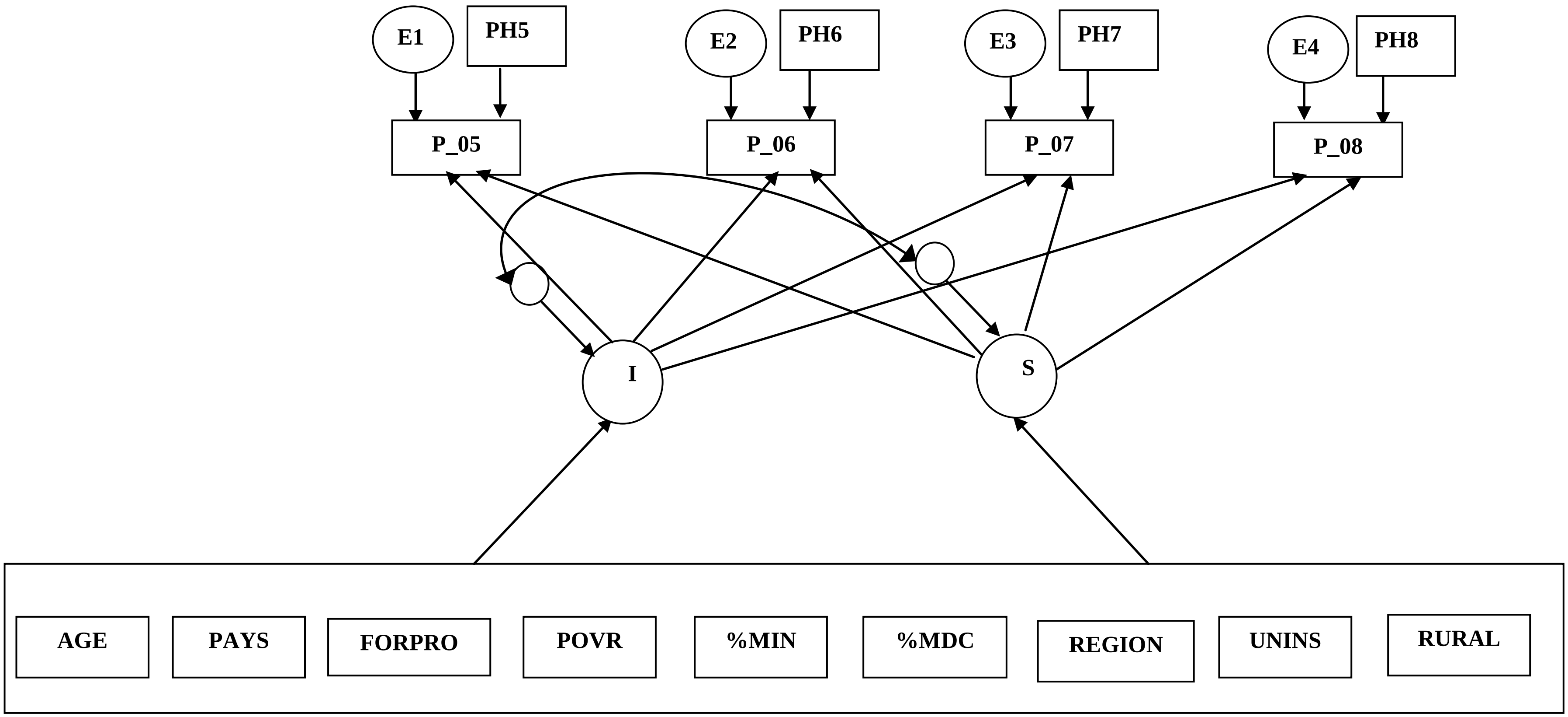


Figure 10 Proposed Conditional Growth Curve Model for Productivity (2005 to 2008)

P= Productivity, PH= Physician availability, I = Intercept, S = Slope, AGE= age of facility, PAYS=Payment System, FORPRO=For-profit owned, POVR=Poverty Rate, %MIN=Percentage of Minority (Non-white) population, %MDC=Percentage of Medicare-eligible residents, UNINS= Percentage of uninsured residents, RURAL=Categorization A of rural areas based on RUCA-Zip code approximation

Productivity DEA scores (P_05-P_08) were time-varying endogenous variables that served as indicators for the two latent measures of productivity—Intercept (I) and Slope (S). Physician availability (PH5-PH8) was the time-varying explanatory variables. There were nine time-constant explanatory variables. Three time-constant variables were organizational: age of facility, payment system, and for-profit ownership. Six time-constant variables were environmental: poverty rate, percentage of minority population, percentage of Medicare-eligible population, region, percentage of uninsured population, and rural classification.

The conditional growth curve model shown in Figure 10 was fitted to raw data on 708 hospital-based RHCs for the years 2005 to 2008. Satorra-Bentler MLM estimation was used to estimate all models. The fit of models was tested through goodness-of-fit indices. The extent of non-normality adjustment in data was acceptable (Scaling Correction Factor = 1.115).

The conditional growth curve model with no modifications is called the generic model. Since the unconditional growth curve model is already tested, there is no need to report the results of the generic model for conditional growth curve modeling. Therefore, the results of the revised conditional growth curve model were presented.

The revised conditional growth model is shown in Figure 11. From the model shown in Figure 10, non-significant relationships were dropped one at a time. On the basis of modification indices, one residual covariance was estimated between 2006 (E2) and 2007 (E3). As Table 10 shows, the revised model was significantly improved with the addition of one covariance (Chi-square [16, N = 708] = 44.998, p = .001, RMSEA = .05, SRMR = .03, CFI = .97, TLI = .96, WRMR = 1.1). The revised model had good fit and support from data.

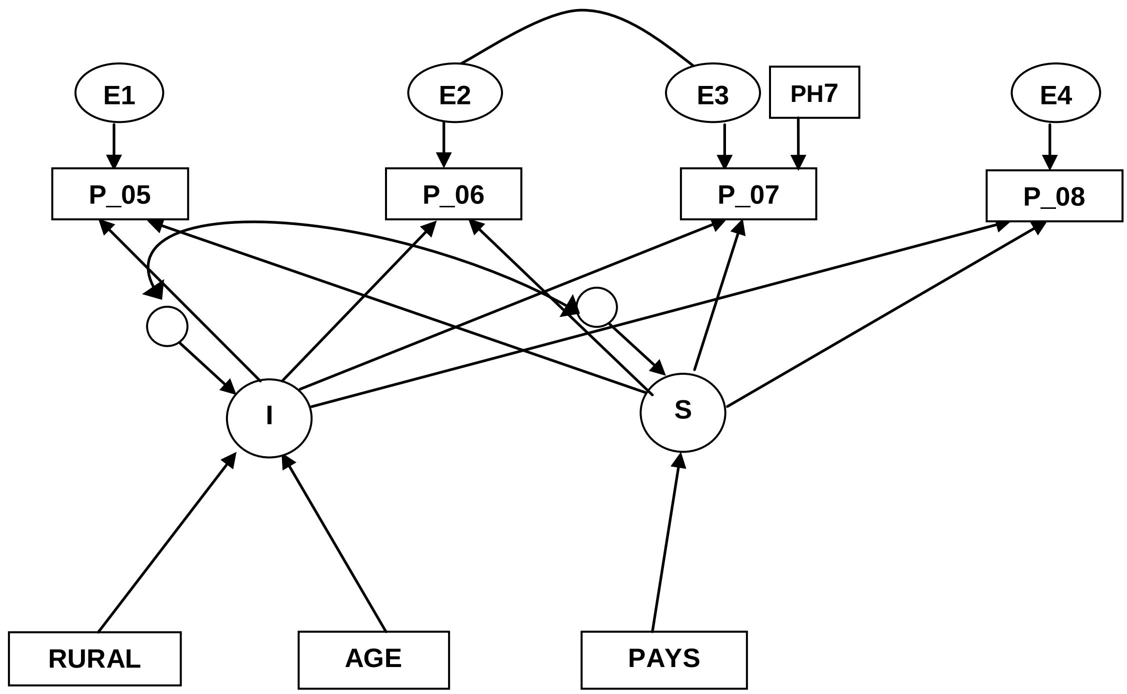


Figure 11 Revised Conditional Growth Curve Model for Productivity (2005-2008)

Table 10 Revised Conditional Linear Growth Curve Model Fit Results

Index	Revised Model	Remarks on Revised Model
Chi-Square	44.998	
Degrees of freedom	16	
Chi-square/ Degrees of freedom	2.812	Good fit
P-value	.001	Poor fit
RMSEA (Root Mean Square Error Of Approximation)	0.051	Good fit
SRMR (Standardized Root Mean Square Residual)	0.034	Good fit
CFI (Bentler's Comparative Fit Index)	0.969	Good fit
TLI (Tucker-Lewis Index)	0.958	Good fit
WRMR (Weighted Root Mean Square Residual)	1.09	Good fit

Parameter estimates for the revised conditional linear growth curve model are shown in Table 11. When explanatory variables are included, "the interpretation of intercept and slope growth factors slightly changes from that of the unconditional growth curve model" (Duncan et al., 1999, p. 39). The intercept was statistically significant ($p < .001$). Therefore, after controlling for the significant effect of age of hospital-based RHC and rural classification on intercept, hospital-based RHCs still differed from each other in their baseline level of productivity.

Table 11 Parameter Estimates for Conditional Linear Growth Curve Model

Parameters	Unstandardized	S.E.	C.R.	*P*-value	*Standardized*
Intercept mean	0.201	0.010	19.974	< .001	
Intercept variance	0.007	0.001	9.242	< .001	0.861
Slope mean	0.026	0.004	6.035	< .001	0.869
Slope variance	0.001	0.000	6.230	< .001	0.987
Intercept Slope Covariance	-0.001	0.000	-3.529	< .001	-0.348
RURAL → Intercept	0.033	0.004	8.911	< .001	0.368
AGE → Intercept	-0.002	0.001	-2.775	.006	-0.023
PAYSYS → Slope	-0.009	0.004	-2.505	.012	-0.290
PH7 → P_07	0.029	0.003	8.419	< .001	0.029
Error3 Error2 Covariance	0.001	0.000	3.643	< .001	0.001
Squared Multiple Correlations					
Intercept	0.139	0.029	4.825	< .001	
Slope	0.016	0.010	1.256	.209	
P_05	0.754	0.054	13.909	< .001	
P_06	0.496	0.033	15.260	< .001	
P_07	0.562	0.030	18.925	< .001	
P_08	0.742	0.051	14.693	< .001	

RURAL: RUCA-Zipcode classification of rural areas; AGE: Age of hospital-based RHC; PAYSYS: payment system; PH7: Physician presence for 2007; P_05: Productivity score in 2005; P_06: Productivity score in 2006; P_07: Productivity score in 2007; P_08: Productivity score in 2008; S.E. Standard Error; C.R. Critical Ratio.

In the unconditional growth curve model, the mean of intercept was the same as the mean of productivity scores for 2005 (0.24). (See Tables 4 and 9.) In Table 11, the mean of the intercept (0.20) is the portion of the mean not accounted for by age and rural classification. The difference between a mean of 0.24 and 0.20 (i.e., 0.04) is the part of the mean intercept attributable to age and rural classification. Therefore, the maximum possible variance explained in the intercept by age and rural classification was 17% (0.04/0.24).

The intercept variance was also statistically significant ($p < .001$). Consequently, after controlling for the significant effect of age of hospital-based RHC and rural classification on intercept variance, hospital-based RHCs still differed from each other in the extent of unexplained variation of productivity.

Slope measures the relationship between two variables: rate of change in productivity and time. As such, a variable associated with slope would have a moderating effect on rate of change in productivity. Therefore, the statistical significance of slope constitutes the test of fit as moderation SCT framework. The slope was statistically significant ($p < .001$). Hence, after controlling for the significant moderating effect of payment system on slope, hospital-based RHCs still showed growth in productivity from 2005 to 2008. The slope variance was also statistically significant ($p < .001$). In other words, after controlling for the significant moderating effect of payment system on slope, hospital-based RHCs still differed in productivity growth rates.

Intercept and Slope covariance was statistically significant and negative ($p < .001$). Hospital-based RHCs with a high level of initial productivity in 2005 had a slower rate of growth in productivity in subsequent years (from 2006 to 2008).

The revised conditional growth curve model explained 13.9% of the variation in the initial level of productivity in 2005. The explained variation in 2005 was statistically significant ($p < .001$). The revised conditional growth curve model was not able to explain the variation in growth trends and patterns of productivity. The explained variation in rate of change of productivity from 2006 to 2008 was not statistically significant ($p = .21$).

The squared multiple correlations indicate how much of the variability in productivity scores for each year was accounted for by the revised conditional growth curve model. The revised model explained a statistically significant amount of variation for each year from 2005 to 2008 ($p < .001$). In addition, the revised model explained 75% of the variation in productivity scores for 2005, 50% of the variation in productivity scores for 2006, 56% of the variation in productivity scores for 2007, and 74% of the variation in productivity scores for 2008.

Table 11 presents the significant relationships in the conditional growth curve model. Concerning the initial level of productivity in 2005 (intercept), hospital-based RHCs located in less rural areas (or urban focused areas) were positively related with intercept (standardized estimate = 0.37).

In other words, facilities located in urban focused areas tended to have the highest levels of initial productivity in 2005, while facilities located in isolated rural areas tended to have the lowest levels of initial productivity in 2005. It is good to recall that rural classification was coded as a categorical variable, with 1 being "isolated rural areas" and 4 being "urban focused areas."

Older facilities were negatively related with initial levels of productivity in 2005 ($p = .006$). Therefore, newer facilities tended to have relatively higher productivity scores for the initial year of 2005. Age of facility, although significant, had little relative importance (standardized estimate = -0.02).

Hospital-based RHCs under the capped prospective payment system had a negative association with changes in productivity growth (slope) from 2005 to 2008 (standardized estimate = -0.29). The productivity growth of hospital-based RHCs under a cost reimbursement system was faster as compared to those under a prospective payment system. It is good to recall that payment system was a binary variable, coded with 0 being “Uncapped cost reimbursement” and 1 being “Capped prospective reimbursement.”

For time-varying variables, the presence of physicians in hospital-based RHCs in 2007 was positively related to the productivity levels of 2007. However, the relative importance of this positive association is weak (standardized estimate = 0.03).

5.4 Hypotheses Testing Results

This last section presents the research hypotheses and the findings from the revised conditional growth curve model for hospital-based RHCs from 2005 to 2008. The three research hypotheses focus on the growth parameters: mean and variance of intercept, mean and variance of slope, and the co-variance of intercept and slope. The first two hypotheses also indicate the relationship between explanatory variables and productivity.

1. For the baseline year of 2005, is there a significant variation in the initial/starting levels of productivity among hospital-based RHCs? In other words, do hospital-based RHCs have similar baseline productivity levels?

Hypothesis 1A: Hospital-based RHCs will differ in the levels of productivity for the year 2005.

Supported: Differences in baseline productivity levels in 2005, as measured through intercept, was statistically significant (*P* < .001). Therefore, after controlling for the significant effect of age and rural classification on intercept, hospital-based RHCs still differed from each other in their baseline levels of productivity. Therefore, any attempt to study whether productivity showed growth from 2006 to 2008 would need to control for the baseline differences. Growth curve modeling is designed to account for baseline differences when testing the significance of growth and growth rates over time.

Hypothesis 1B: Hospital-based RHCs will show significant variability in starting levels of productivity for the year 2005.

Supported: The intercept variance was statistically significant ($P < .001$). Consequently, after controlling for the significant effect of age and rural classification on intercept, hospital-based RHCs still differed from each other in the extent of unexplained variation of productivity. The variability around the initial levels of productivity differed from one hospital-based RHC to another.

Rural classification and age of facility were the only variables significantly related with baseline levels of productivity in 2005. In general, rural classification and age of facilities explained 13.9% of the variation in initial level of productivity. The explained variation was significant. Facilities in urban focused areas had the highest levels of productivity in 2005 while facilities in isolated rural areas had the lowest levels of productivity in 2005. Older facilities had lower levels of productivity in 2005 while newer facilities had higher levels of productivity in 2005.

2. For the years 2006 to 2008, is there a significant variation in the growth trajectory of productivity among hospital-based RHCs? In other words, taking into account any

differences in baseline levels of productivity, is there a substantial growth in productivity from 2005 to 2008? If there is a growth in productivity, is productivity increasing, decreasing or remaining stable from 2005 to 2008? If productivity is increasing or decreasing over the study period, is the rate of increase or decrease in productivity similar across hospital-based RHCs?

Hypothesis 2A: Hospital-based RHCs will differ in the average rate of change of productivity for the years 2006 to 2008. In other words, there will be an average growth in productivity (either decreasing or increasing).

Supported: The slope was statistically significant ($P < .001$). Hence, after controlling for the significant moderating effect of payment system on slope, hospital-based RHCs still showed growth in productivity from 2006 to 2008. In addition, the mean of slope was not zero, indicating the presence of an approximate linear change in productivity. Moreover, the positive slope indicated an average increase (improvement) in productivity from 2005 to 2008.

Hypothesis 2B: Hospital-based RHCs will show significant variability in the rate of change of productivity for the years 2006 to 2008. In other words, the rate of increase or decrease in productivity is not similar across hospital-based RHCs.

Supported: The variance of slope was statistically significant ($P < .001$). In other words, after controlling for the significant moderating effect of payment system on slope, hospital-based RHCs still differed in productivity growth rate. It appears that hospital-based RHCs did not have the same productivity growth rates. Alternatively, not all increases or decreases in productivity are of the same rate.

For the time-varying variable (physician availability), a significant relationship was found for 2007. Hospital-based RHCs with physicians in 2007 were positively related to the productivity levels of 2007. In other words, facilities with physicians had higher productivity levels. Hospital-based RHCs under prospective payment systems had a slower rate of change in productivity for the years 2006 to 2008 while hospital-based RHCs under cost-reimbursement system had a faster rate of change in productivity. However, physician availability and payment system were not able to explain the significant variation in change of productivity from 2005 to 2008.

3. For the years 2005 to 2008, is there a relationship between hospital-based RHC's initial levels of productivity in 2005 and their rate of change in productivity from 2006 to 2008?

Hypothesis 3: Initial levels of productivity in hospital-based RHCs will be negatively related to rate of change in productivity.

Supported: Intercept and Slope covariance was statistically significant ($P < .001$) and negative. Hospital-based RHCs with a high level of initial productivity in 2005 had a slower rate of growth in productivity in subsequent years (from 2006 to 2008).

5.5 Summary

For the baseline year of 2005, the 708 hospital-based RHCs in the study significantly differed from each other in their mean levels of productivity. The significant baseline differences in productivity indicate that simple trend analyses (e.g. plotting average productivity levels from 2005 to 2008) will not be a valid indication of an increasing or decreasing trend in productivity. Growth curve modeling will be able to test the significant of increasing or decreasing trends accounting for baseline differences in productivity.

Since there is no productivity standard imposed on hospital-based RHCs, it would not be that surprising to observe significant differences in baseline productivity. Hospital-based RHCs also significantly differed from each other in their variability around the mean levels of productivity. Rural classification and age of facility explained 14% of variation in initial levels of productivity.

For the years 2006 to 2008, the same group of facilities differed in their mean rate of change in productivity. Therefore, hospital-based RHCs were improving their productivity from 2005 to 2008. In other words, the 4 year period from 2005 to 2008 witnessed an average productivity growth. This refutes concerns that there is no improvement in productivity for hospital-based RHCs. They also significantly differed in the variance around the mean rate of change.

Hence, although the 708 hospital-based RHCs showed an average growth in productivity, they did not have the same rate of productivity growth. Prospective payment system was associated with slower productivity growth rates. However, determinants of productivity in this study were not able to explain the significant variation in the rate of change of productivity (productivity growth rates).

CHAPTER SIX: DISCUSSIONS AND CONCLUSIONS

This study investigated the growth patterns and trends of productivity in U.S. hospital-based RHCs for the years 2005 to 2008. In this chapter, the results of the research are discussed in four sections. The first section provides discussions of findings. The following section focuses on the theoretical, practical and policy implications of the findings. The third section discusses the conceptual, methodological, and practical limitations of the study. The final section identifies areas in need of future research.

6.1 Discussions of Findings

To date, no study had examined the growth patterns and trends of hospital-based RHCs. In addition, how determinants of productivity related to the growth patterns and trends of productivity over time had not been investigated. For the years 2005 to 2008, this study investigated 1) growth pattern and trends of productivity, and 2) determinants of productivity in U.S hospital-based RHCs. The findings of the study were discussed in reference to the four research questions.

1. For the baseline year of 2005, is there a significant variation in the initial levels of productivity among hospital-based RHCs? In other words, do hospital-based RHCs have similar baseline productivity levels?

As measured through dynamic, input oriented, slacks-based, and constant rate of return data envelopment analyses, hospital-based RHCs exhibited significant differences in the mean and variance of productivity scores for the baseline year of 2005. Among the determinants of productivity included in this study, rural classification was the most important variable in explaining baseline differences in productivity (standardized estimate = 0.37).

On average, rural classification was positively related to productivity. As proximity of rural areas to urban areas increases on average, productivity increases. Age of facility was significantly related to baseline differences in productivity. However, age of facility had minimal relative importance (standardized estimate = -0.02). On average, age of facility is negatively related to productivity. As facilities get older on average, their productivity declines on average. Rural classification and age of facility explained 14% of the variation in initial levels of productivity.

While standardized estimates indicate the relative importance of variables, unstandardized estimates represent the degree of change in an endogenous variable for each unit change in exogenous variable. As one moves from isolated rural areas to small rural towns, or from small rural towns to large rural towns, or from large rural towns to urban focused areas, initial levels of productivity scores increased by an average of 0.033 units (unstandardized estimate = 0.033). As age of facilities increases by a year, productivity scores drop by -0.002 units (unstandardized estimate = -0.002).

Although productivity DEA scores are iota (unitless) measures scaled between 0 and 1, they could be converted to percentages. Therefore, roughly speaking, each level of progression in rural classification was accompanied by a 3.3% average increase in productivity. In contrast, as age of facilities increases by a year, the drop in productivity was minimal (-0.2%).

The relative importance of rural classification could be further examined by breaking down productivity scores over the four levels of rural classification: isolated rural areas, small rural towns, large rural towns and urban focused areas. As shown in Figure 12, hospital-based RHCs in urban focused areas had consistently higher productivity levels, while hospital-based RHCs in isolated rural areas (frontiers) had consistently lower productivity levels.

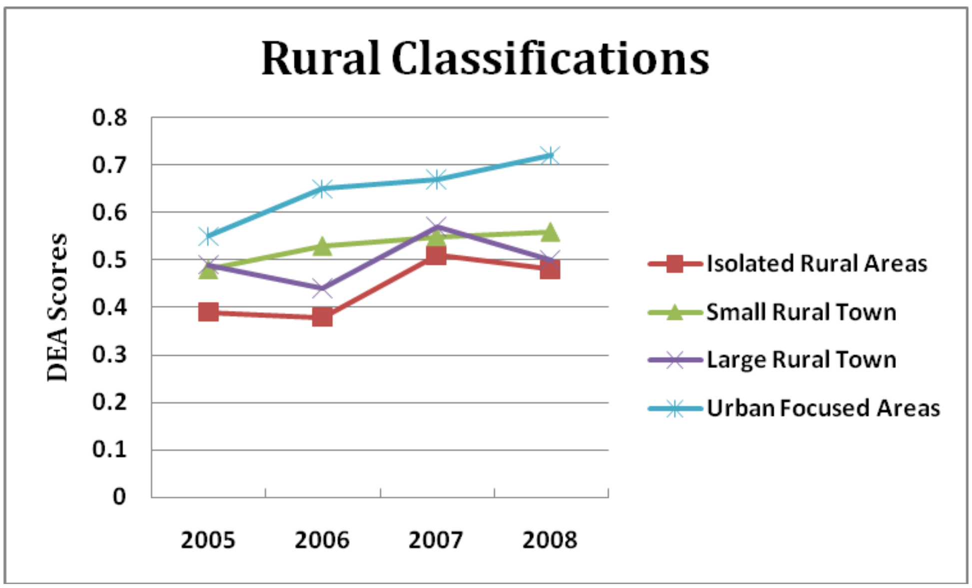


Figure 12 Line Plot of Dynamic DEA Scores for Hospital-based RHCs from 2005 to 2008

In terms of the linearity of productivity growth, hospital-based RHCs in urban focused areas and small rural towns had a clear linear trajectory. In contrast, hospital-based RHCs in isolated rural areas and large rural towns had a more staggered trajectory. The exploration of productivity levels of hospital-based RHCs through rural classification was a new area ventured by this study. As such, the possible explanations for the varying patterns of productivity trajectories would be a matter of speculation.

We speculated that hospital-based RHCs in large rural towns, by virtue of their proximity to hospitals in urban areas, might face a net out-migration of patients. Such out-migration, in part, might be caused by “outshopping”—a situation in which local residents systematically bypass local hospital-based RHCs (Taylor, 1997). Therefore, for hospital-based RHCs located in large rural towns, the volume of visits (a measure of output in productivity analyses) could show much fluctuation.

In another line, hospital-based RHCs in small rural towns appear to benefit from regular visits by specialist physicians from urban areas (Drew, Cashman, Savageau, & Stenger 2006). If that is so, the similar linear trajectory of productivity growth in hospital-based RHCs in small rural towns and urban focused areas would be less of a surprise. The availability of visiting physicians in small rural towns might encourage a flow of visits with similar linear pattern as was observed in urban focused hospital-based RHCs.

In contrast to the relatively smooth linear increase in productivity for hospital-based RHCs in urban focused areas and small rural towns, hospital-based RHCs in isolated rural areas exhibited a staggered trajectory of productivity that mirrors hospital-based RHCs in large rural towns. Unlike hospital-based RHCs in large rural towns, RHCs located in frontier areas are further away from urban areas.

Hence, the variability of productivity in hospital-based RHCs located in frontier areas might be less a factor of residents out-shopping them but more a reflection of scarcity of demand for care. RHCs in remote locations have difficulty sustaining a stream of patient visits (Gale & Coburn, 2003).

From a contingency theory perspective, variables that show greater variability tend to be contingency factors. In that regard, rural areas showed marked variations from place to place as compared to urban areas (Rosenblatt & Hart, 1999). Consequently, the finding that rural classification is a significant factor in explaining differences in productivity is theoretically plausible. However, specific aspects of rural areas (e.g. percentage of minority residents, percentage of Medicare beneficiaries, poverty rate) were not significantly related to differences in productivity.

2. For the years 2006 to 2008, is there a significant variation in the growth trajectory of productivity among hospital-based RHCs? In other words, taking into account any differences in baseline levels of productivity, was there a substantial growth in productivity from 2005 to 2008? If there is a growth in productivity, is productivity increasing or decreasing from 2005 to 2008? If productivity is increasing or decreasing over the study period, is the rate of increase or decrease in productivity similar across hospital-based RHCs?

As measured through dynamic, input oriented, slacks-based, and constant rate of return data envelopment analyses, hospital-based RHCs exhibited significant differences in the mean and variance of rate of change in productivity scores for the years 2006 to 2008. Hospital-based RHCs in the study did show a growth in productivity. In fact, they did show an average increase or improvement in productivity from 2006 to 2008 as compared to baseline year of 2005.

However, the rate of increase in productivity was not similar across all hospital-based RHCs. Among the determinants of productivity included in this study, payment system was the only variable significantly related to slope (standardized estimate = -0.30). Hospital-based RHCs under cost-reimbursement system showed faster productivity growth rates as compared to hospital-based RHCs under prospective system that showed slower productivity growth rates. However, payment system alone was not able to account for the significant variation in productivity growth rates.

As one moves from hospital-based RHCs under uncapped cost-reimbursement systems to hospital-based RHCs under prospective payment systems, the average rate of change in productivity decreases by 0.01 units (unstandardized estimate = -0.01). Therefore, roughly speaking, the mean rate of change in productivity for the years 2006 and 2008 were 1% lower year to year for hospital-based RHCs under prospective payment systems as compared to those under uncapped cost-reimbursement systems.

Figure 13 shows that hospital-based RHCs under cost-reimbursement systems had lower productivity scores for the baseline year of 2005 as compared to those under prospective payment systems. However, hospital-based RHCs under cost-reimbursement systems had slightly higher productivity scores for the years 2007 and 2008 as compared to those under prospective payment systems. Therefore, as compared to cost-reimbursement system, prospective payment system appeared to be negatively related with productivity growth.

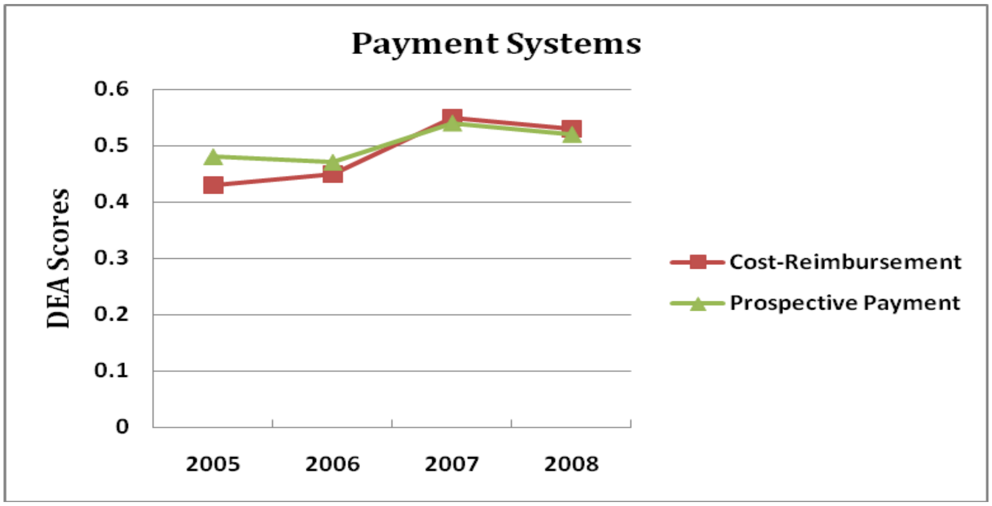


Figure 13 Dynamic DEA scores of Productivity by Payment System (2005 to 2008)

The finding that payment system was negatively related to productivity growth adds to the limited literature on RHCs. McAtee and Beverly (2005) reported that hospital-based RHCs under prospective systems struggled for financial viability. McBride and Mueller (2002) indicated that RHCs are much more dependent on CMS payments as compared to urban providers. Since the influence of payment system on rural providers is a complex issue, the negative association between payment system and rate of change in productivity should be taken with caution.

From an organizational performance perspective, payment system is part and parcel of financial resources that impact performance. Small rural hospitals (those with fewer than 50 beds), among other things, tend to be at disadvantage in terms of economies of scale. Consequently, the cost-reimbursement payment system for small hospitals is a means to compensate diseconomies of scale.

3. For the years 2005 to 2008, is there a relationship between hospital-based RHC's initial levels of productivity in 2005 and their rate of change in productivity from 2006 to 2008?

Hospital-based RHCs with high levels of baseline productivity in 2005 had a slower rate of growth in productivity from 2006 to 2008. In other words, hospital-based RHCs with higher intercepts in the baseline year of 2005 were associated with smaller slopes for the years 2006 to 2008.

Consequently, on average, facilities that had already attained higher level of productivity in 2005 were not able to increase their productivity at a faster rate in subsequent years. The relative importance of the association between initial levels of productivity in 2005 and rate of change in productivity was moderate (standardized estimate = -0.35).

According to organizational performance theories, productivity in health care facilities could not increase indefinitely without having a performance trade-off in other measures of performance, such as quality of care, financial viability, cost-efficiency and patient satisfaction (Flood et al., 2006). Therefore, hospital-based RHCs with higher productivity levels in 2005 might focus on the improvement of other dimensions of performance.

In contrast, hospital-based RHCs with lower productivity levels in 2005 might need to focus more on boosting productivity for 2006 to 2008 to be operationally active. Rather than waiting for patients to visit their facilities, facilities with lower productivity might venture out to provide more community-based visits to boost their productivity and revenue. Consequently, initial levels of productivity in the baseline year of 2005 could reasonably be negatively related to rate of change in productivity for the years 2006 to 2008.

The negative association between intercept and slope growth parameters could be examined spatially. The spatial exploration of intercept and slope was done at the county level. The FSCORE option in Mplus software was used to generate individual facility-level intercept and slope parameters. Using a natural break algorithm in GIS (Gatrell et al., 2003), intercept and slope values were grouped into three categories.

The 708 hospital-based RHCs in the study were located in 497 counties. Ninety-eight counties (19.7%) had more than one hospital-based RHC. For these counties, the means of intercepts and slopes of facilities within the county were used. As shown in Figure 14, counties with hospital-based RHCs with lower mean intercepts were coded as black while those with near average intercepts were coded as gray. Counties with hospital-based RHCs with higher mean intercepts were coded as light blue.

In like manner, counties with hospital-based RHCs with declining slopes (negative growth) were coded as black while those with approximately stable slopes (minimal growth) were coded as gray. Counties with hospital-based RHCs with higher mean slopes (strong growth) were coded as light blue. In general, hospital-based RHCs with lower intercepts in 2005 tended to have stable or higher slopes from 2006 to 2008 and vice versa. This spatial pattern was readily discernable in the West (e.g., in the states of California, Oregon, Washington, Idaho, and Montana).

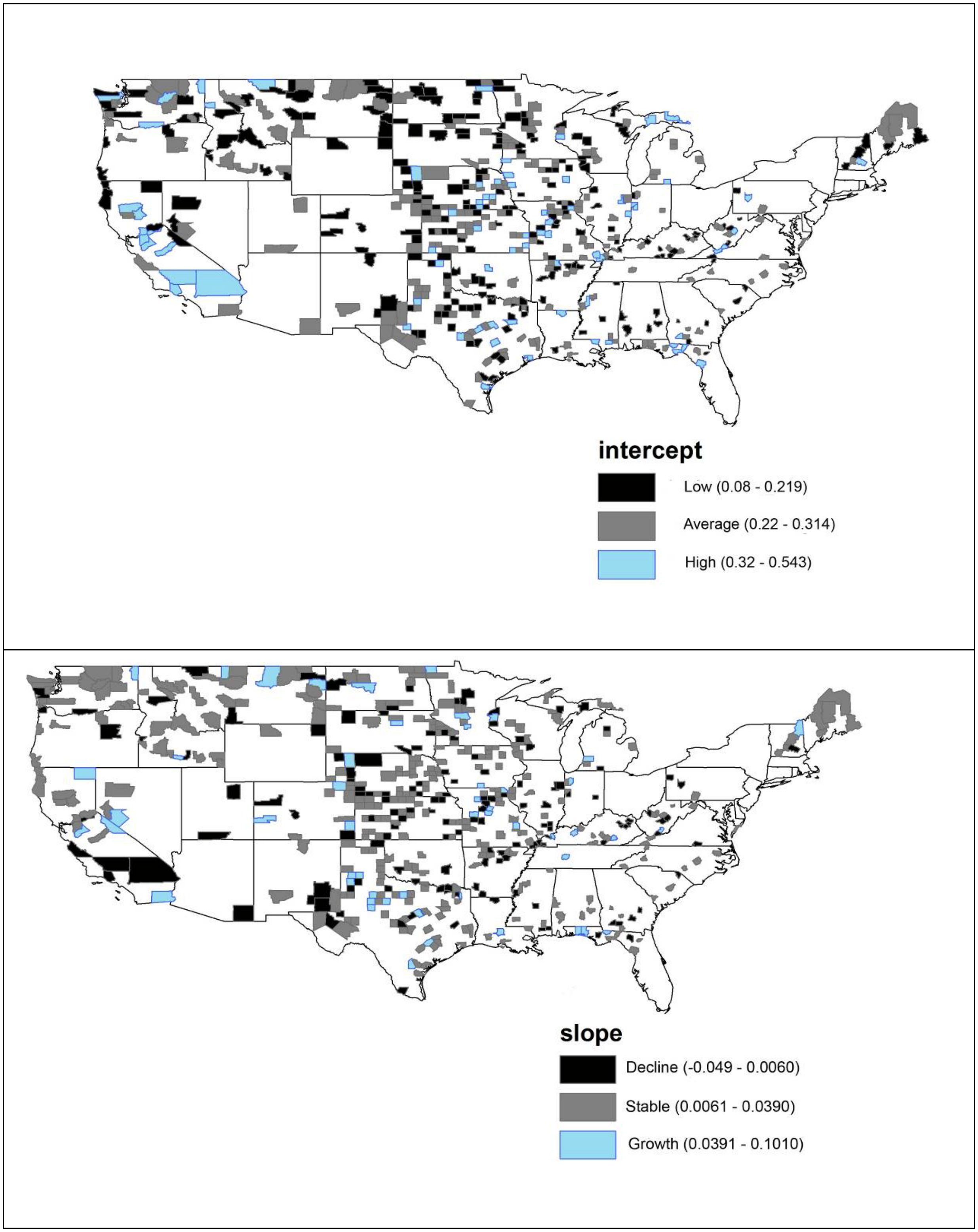


Figure 14 Plot of Intercepts and Slopes for Hospital-Based RHCs from 2005 to 2008

From an organizational performance theories point of view, human and material resources often tend to be key determinants of performance. However, both resources are finite and submit to the law of diminishing returns. In economic theory, the marginal utility of performance improvements decreases once higher level of performance is already attained.

In simpler terms, each unit of increase in human and material resources only yields a marginal increase in performance for facilities that had already attained relatively high performance. In such a light, the negative relationship between baseline levels of productivity and productivity growth over time are in line with theoretical expectations of organizational performance and the economic law of diminishing returns.

4. Can the change trajectories in productivity be explained by time-varying (physician availability) and time-constant (age, ownership, payment system, poverty rate, minority population, Medicare-eligible population, uninsured population, rural classification, and geographic location) determinants of productivity for the years 2005 to 2008? In other words, if hospital-based RHCs did show growth in productivity from 2005 to 2008, which set of determinants explained the growth in productivity? If hospital-based RHCs significantly differed in productivity growth rates, which set of determinants explained the differences in productivity growth rates?

Statistically significant relationships were found for four of the ten determinants of productivity. Although the four variables significantly explained baseline differences in productivity, they were not able to explain changes in productivity growth trajectories (both the growth in productivity and the rate of growth in productivity). Physician availability in hospital-based RHCs for the year 2007 was positively related with productivity scores of 2007. Hence, hospital-based RHCs with physicians had higher productivity. In a descriptive study of RHCs, Sinay (2001) reported that productive RHCs had more physicians. The finding of this study adds support to Sinay's results through inferential statistics.

However, physician availability in hospital-based RHCs was not related to productivity scores for the years 2005, 2006 and 2008. Consequently, physician availability in hospital-based RHCs was not able to account for productivity growth for the years 2005 to 2008. Several aspects might have contributed to absence of association between physician availability in hospital-based RHCs and productivity growth rates.

First, the 708 hospital-based RHCs in this study were more homogenous in terms of physician availability. For the years 2005 to 2008, 65% or more of the hospital-based RHCs in the study had access to physicians. Consequently, the physician availability variable showed little variation from year to year. Second, a binary variable measures in kind not in degrees (extent). Third, the measurement of productivity did not account for case mix of visits. Physician visits would have differing qualitative aspects as compared to non-physician visits. However, the data sources in the study limited the inclusion of quality aspects of productivity.

Age of facility and productivity were negatively related. In other words, newer facilities appeared to have higher productivity. In a study that focused on cost-efficiency, Ortiz et al (2009) also reported a negative association between age of provider-based RHCs and cost efficiency. In an in-depth study of RHCs, Cheh and Thompson (1997) reported that newer RHCs were associated with reduced number of emergency room visits. In a panel study of relative efficiency of rural primary care facilities, Huang and McLaughlin (1989) indicated that newer facilities tended to have different and more aggressive management strategies. In a sense, the higher levels of productivity for newer hospital-based RHCs in the study could be a reflection of the dynamism of newer facilities.

Figure 15 depicts age of facilities and productivity scores over time. Since age of hospital-based RHCs was a normally distributed variable, the 25th and 75th percentiles were used to categorize RHCs into three groups. Age of facilities was measured as the difference of time in years from 2005 till initial date of Medicare certification as an RHC.

Hospital-based RHCs with age of 0 to 5 years were considered to be “newer” facilities, while those over 12 years were considered to be “older” facilities. Hospital-based RHCs with ages of 6 to 11 years constituted the average group. Using these three groups, productivity scores for 2005 and 2008 were plotted over time (Figure 15).

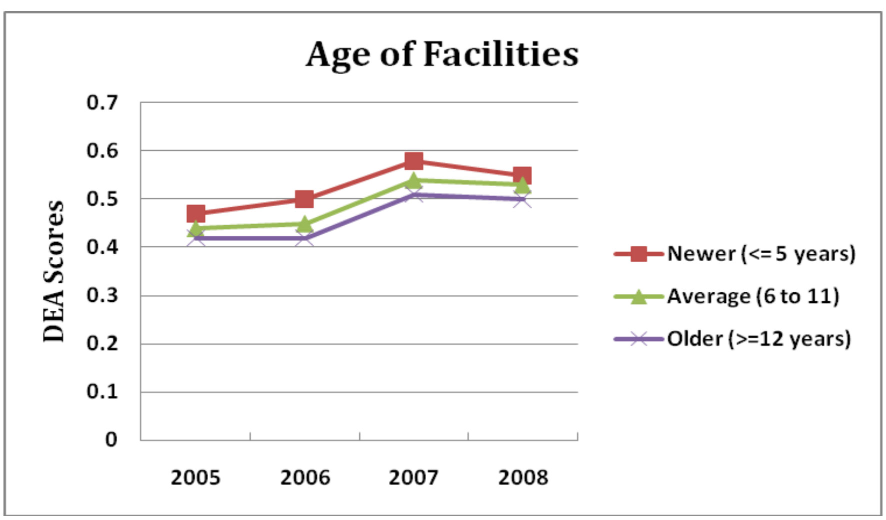


Figure 15 Dynamic DEA Productivity Scores by Age of Hospital-Based RHCs

As Figure 15 shows, “newer” hospital-based RHCs had consistently higher productivity levels from 2005 to 2008. In contrast, “older” hospital-based RHCs had consistently lower productivity levels from 2005 to 2008. In addition to differences in management style that could account for these differences (Huang and McLaughlin, 1989), there is also the aspect of needs assessment. Newer hospital-based RHCs are opened after a more recent assessment of needs. Consequently, they could attain and improve productivity quickly.

In contrast, the needs assessment that supported the inception of older hospital-based RHCs might be outdated. The rapid shifts and changes that engulf rural areas (e.g. continued graying of rural population, the inflow of immigrants, etc) might affect the relevance of older hospital-based RHCs. In the absence of periodic recertification requirements, there might be less of an incentive for older hospital-based RHCs to adjust their situation to meet more current needs.

6.2 Implications of Findings

This section discusses some of the theoretical, practical, and policy-related implications of the findings. The context-design-performance model of organizational performance and structural contingency theories was applied to investigate determinants of productivity growth and trends in hospital-based RHCs. Within the growth curve methodology, determinants of productivity were taken as moderating (conditioning) variables on slope of productivity (i.e. productivity growth rates).

Although determinants of productivity accounted for 14% of variation in initial levels of productivity (intercept), they were not able to account for the variation in rate of growth (slope) of productivity. Consequently, determinants of productivity did not have a moderating effect over time. Meilich (2006) reported that the application of contingency theory models over time often yielded non-significant results.

In SCT, the fit between organizational and contextual variables is anticipated to affect organizational performance. Fit as moderation, which is used in this study, is one approach to estimate the fit or alignment of organizational and contextual factors. For instance, if a variable or set of variables are associated with productivity, testing the fit as moderation requires the assumption that the same variable or set of variables also affect the rate of change in productivity (or productivity growth rates). Although four of the nine organizational and contextual variables in this study were related to productivity, they were not able to account for productivity growth rates. Thus the inability of SCT to account for performance growth over time (Meilich, 2006) also applies to the group of hospital-based RHCs in this study.

Several implication to SCT include: 1) there is a need to examine other frameworks of fit such as fit as mediation, fit as gestalt and fit as co-variation; 2) SCT is less relevant to the study of small scale organization whenever such organization exhibit more homogeneity in terms of their organizational aspects. There is smaller chance to alter the limited human, material and financial resources available in small organizations in a way to affect organizational performance; and 3) there is a need to focus more on variables related to strategies. Thus instead of just utilizing structural contingency theory (SCT), it would be useful to employ strategic contingency theory. For instance organizational strategies (e.g., the use of disease-management programs) and organizational culture (e.g., the use of interdisciplinary teams) are examples of strategic contingency measures.

OPT assumes that the main intent of organizations is to maximize performance. However, maximizing productivity may not be the only objective of RHCs. Hence not all determinants of performance are compatible, leading to the possibility of performance trade-offs (Cameron, 1986; Campbell, 1977). In other words, determinants of productivity could relate differently to other measures of performance such as quality of care, patient satisfaction, and cost-efficiency.

Therefore productivity in health care facilities could not increase indefinitely without having a performance trade-off in other measures, such as quality, financial viability, and patient satisfaction (Flood et al., 2006). Not surprisingly then, the findings of this study showed that hospital-based RHCs with higher productivity levels in 2005 had a slower productivity growth rates from 2006 to 2008. It was not possible for facilities with relatively higher productivity to continue growing faster in productivity.

Several implications to OPT include: 1) due to the potential presence of performance trade-off, it would be more fruitful to examine determinants of productivity in the presence of other performance measures such as quality of care and cost efficiency; 2) applying OPT to the study of organizational performance needs to take into account the law of diminishing returns (i.e. pertinent economic theories). Since the marginal utility of increased performance decreases with each attainment of higher performance levels, health care facilities could not increase productivity indefinitely even if no concomitant performance trade-off occurs. Therefore, OPT needs to be supplemented with such economic rationale; and 3) determinants of organizational performance may not necessarily be determinants of rate of change in organizational performance. Since identifying determinants that relate to changes in organizational performance are more desirable, OPT needs to be continually tested through longitudinal analyses.

In terms of practical significance, the findings of the study contributed in several ways. The first practical significance indicates that hospital-based RHCs with physicians had higher productivity levels. Physician services generate more visits and net-earnings for RHCs. Consequently, there is a strong need to attract and retain physician providers to rural areas. The Patient Protection and Affordable Care Act (PPACA) of 2010 promised to extend and increase benefits to rural physicians (Sections 5101, 5303, 3102–3107).

Section 5101 authorized the creation of "A National Health Care Workforce Commission" by September 30, 2010. Among other things, the commission is tasked to develop ways to address geographic distribution of health care providers including physicians as compared to need. The recommendations are due by the end of 2011. In the mean time, the Act already indicated some actions. Section 5303 provided new federal grants and loan repayments programs for institutions that are willing to partner with Federally Qualified Health Centers and RHCs to provide physician residency programs at these facilities. Pending on the outcome of the national commission on Section 5101, enhanced payments to rural physicians will be extended till the end of 2011 as documented in Sections 3102–3107.

The Act could include the following additional recommendations: 1) since physicians who grew up in rural areas are more likely to embark upon rural careers (WWAMI, 2009), more encouragement needs to target those students raised in rural areas to pursue a career in medicine. That may require medical school curriculum and admission policies to focus more on students from rural backgrounds, provide attractive financial support, and prioritize the preparation and placement of rural providers; 2) since rural physician practice requires a broad range of skills than the average urban physician may need to field (WWAMI, 2009), there needs to be a support to residency training programs that expose physicians to rural practice and impart the skills needed in rural practice settings. The Act already took a step in the right direction as evidenced by Section 5303. However, the first recommendation needs to accompany such measures; and 3) the first two recommendations will not suffice in tandem. There needs to be more financial and lifestyle incentives to make rural practice attractive. That may include increased reimbursement to rural services, subsidies targeting rural practice development including electronic health records, tax credits for rural practice and locum tenens support (WWAMI, 2009). In addition, there needs to be reimbursement for telemedicine and some form of malpractice immunity for physician services provided free of charge (WWAMI, 2009).

Second practical significance relates to the fact that hospital-based RHCs significantly differed from each other in initial levels of productivity for the baseline year of 2005. Moreover, hospital-based RHCs significantly differed from each other in the productivity growth rates from 2006 to 2008. After controlling for significant effects of rural classification, age of facility, physician availability and payment system differences, hospital-based RHCs still showed an increasing growth in productivity levels from 2005 to 2008.

Although CMS places productivity standards on independent RHCs, hospital-based RHCs are exempt (Gale & Coburn, 2003). In the absence of uniform productivity standards, it was no surprise that the productivity growth and trends significantly differed from one clinic to another. Such variation means that hospital-based RHCs could design a variety of strategies to improve their productivity.

For instance, hospital-based RHCs with higher levels of productivity could focus more on improving the quality aspect of their visits rather than maximizing the raw number of visits. In contrast, hospital-based RHCs with lower levels of productivity would probably focus more on generating more visits to sustain their operations. That might require RHC managers in less-productive facilities to implement more community-based visits and outreaches.

In spite of the assumptions that rural areas in America face a net out ward migration, hospital-based RHCs in this study exhibited an average annual growth of productivity by 3.3% from 2005 to 2008. A possible reason could be the compensatory effect of immigration to rural areas from Latin America particularly Mexico (Martin and Taylor, 2003). The large movement of immigrants to rural areas is not only changing the face of many rural communities for the first time in centuries, but it is also generating high demand of care from relatively younger and larger family units.

Such dramatic changes affect RHCs substantially. Cases in point are RHCs in Family Healthcare Network in Tulare County; CA (Family Healthcare Network, 2010). Tulare County is located in rural San Joaquin Valley. With increased Mexican migrant population, providers in the area are now facing patients with prevalence of some type of mental health or psycho-social issue 70 percent of the time. However, RHCs are not allowed to primarily render mental health services (CMS, 2009). Consequently, providers struggled with the inability to bill both medical and behavioral health visits that occur on the same day and receive reimbursement for both. At the time of reporting, the family healthcare network was working with state authorities to design an integrated health care delivery system.

Third practical significance relates to the significant differences in productivity growth rate also bring to light more issues. For instance, hospital-based RHCs engage in a variety of primary care activities through a diverse group of providers. Some facilities have a geriatric focus while others have a family medicine focus. Some facilities might be staffed with certified nurse midwives, while others might have access to physician assistants or nurse practitioners. Therefore, the strategies to enhance productivity will be different. For example, those RHCs without physicians might seek to establish or expand visiting physician programs.

Older hospital-based RHCs had consistently lower productivity levels from 2005 to 2008 as compared to newer hospital-based RHCs. Perhaps, the outdated nature of needs assessment by older hospital-based RHCs could be a factor. Therefore, there is a need to introduce recertification requirements for hospital-based RHCs. At least, updated needs assessments might be requested every 5 years or so to assess the relevance of the facility in a particular context.

Continued needs assessment is no small issue for rural health services. Cases in point are mobile (rural) health clinics established by St Joseph Health System in Sonoma County; CA (Ficco, 2010). Faced with the continued mobility of migrant farm workers from Mexico, the health system revised its approach and instituted mobile health clinic services. Migrant farm workers get care that is sporadic and fragmented as the workers move from farm to farm; community to community; all the while leaving their medical records, lab test results and medical care plans behind, resulting in unnecessary duplication of services (Ficco, 2010). By enabling mobile health clinics to have access to electronic health records and locating the clinics to where care is needed, there was an attempt to provide services to those who needed it most.

In terms of policy significance, the findings of the study contribute in several ways. First, rural location was a relatively important factor in explaining growth trends and patterns of productivity. Consequently, policy formulations with regard to RHC productivity may need to minimize uniform approaches. Hospital-based RHCs in isolated rural areas and large rural towns exhibited strong fluctuations in productivity growth.

In contrast, hospital-based RHCs in urban focused areas and small rural towns had a steady linear increase. Hospital-based RHCs located in urban focused areas had significantly higher productivity as compared to other hospital-based RHCs. Hospital-based RHCs in isolated rural areas had significant lower productivity levels as compared to the rest of hospital-based RHCs. Since rural classification was a key determinant of productivity, productivity standards that disregard rural classification will be heavy handed.

Therefore, if productivity standards were to be extended to hospital-based RHCs, different levels of standards might need to be set depending on rural classification. It is neither sensible nor equitable to impose the same level of productivity standards on all RHCs (as is currently done to free-standing RHCs). The PPACA Act of 2010 is bringing increased accountability of health care organizations and providers. Hence, it is probable that the exemption from any productivity standards by hospital-based RHCs might come into question.

If indeed a productivity standard is to be introduced, then rural classification would be one of the key factors to be taken into account. The productivity levels of hospital based RHCs needs to be separately benchmarked on the bases of rural classification. The benchmarked minimum productivity levels for each category of rural classification could be updated periodically based on recent data. As was done in this study, the assessment of productivity level should control for the financial viability of the facilities.

Dynamic slacks-based DEA scores could be used to estimate productivity standards values which then could be converted to minimum visits per FTE values. For instance, if a productivity score of 0.6 is considered to be acceptable, then the minimum productivity standard would be 40% lower than what was attained by most productive facilities in a particular rural classification. Then 40% of the average annual visits per FTE at the most productivity facilities identified by DEA could be used to benchmark minimum productivity levels (number of visits per FTE). The DEA analysis could be conducted every 3 to 5 years to adjust for changes in productivity levels.

Second, the capped prospective payment system was associated with slower growth in productivity rates. Hospital-based RHCs whose parent hospital has fewer than 50 beds continue to receive the uncapped cost-reimbursement payment system. In spite of CMS's role as the single payer that most influences rural health provisions, little empirical research focused on payment system effects on RHCs (McBride & Mueller, 2002). Although the finding of this study was far from being conclusive, payment system appeared to significantly affect rate of change in productivity.

Third, the spatial exploration of rate of growth in productivity (slope) revealed distinct regional variations. Although the overall trend was an increasing improvement in productivity from 2005 to 2008, there is a need to focus on those facilities which had declining productivity growth rates (those not following the overall trend). Figure 16 shows a map where counties with hospital-based RHCs facing a decline in productivity for the years 2006 to 2008 were indicated with vertical bars.

The height of bar columns was proportional to the extent of drop in slope parameter estimate. The reference bar column for decline in slope was -0.025 or a 2.5% drop in productivity (see legend in Figure 16). Counties with hospital-based RHCs included in the study were colored in light blue.

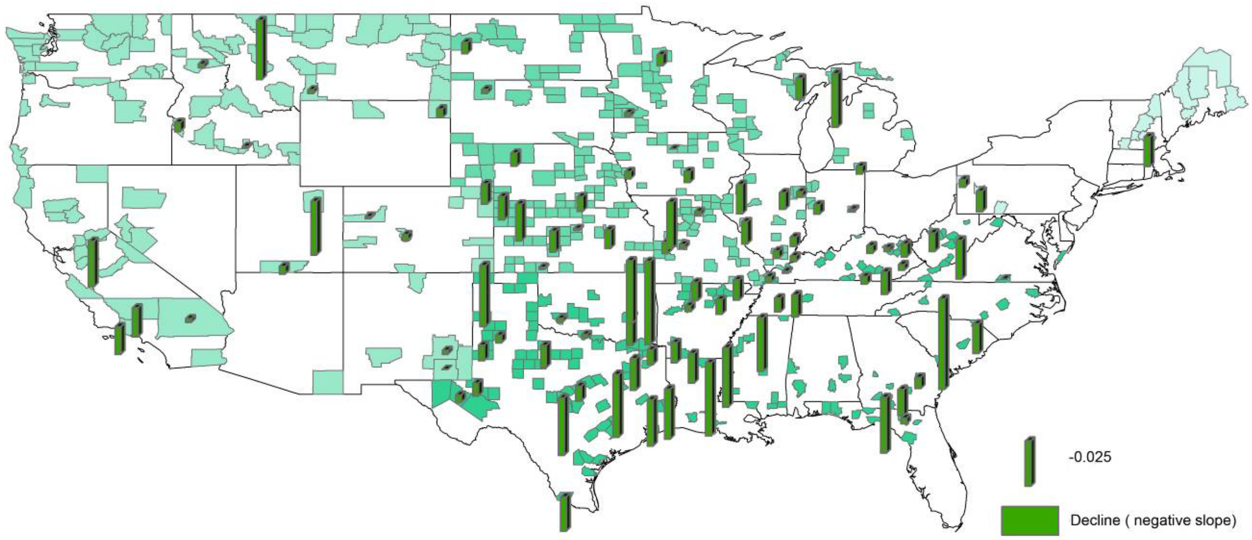


Figure 16 Map of Hospital-Based RHCs with Declining Productivity Growth Rates

Hospital-based RHCs in the South tended to have more hospital-based RHCs with steeper declines in rate of change in productivity. In particular, the state of Texas seemed to have more hospital-based RHCs with steeper declines in productivity growth rates. In contrast, hospital-based RHCs in the West, which generally have more isolated rural areas or "frontier" counties, had fewer hospital-based RHCs with declining rates of productivity growth.

This is an example of a potential use of GIS in rural health planning and practice. Although the average trend was an increasing productivity growth from 2005 to 2008, and although regional classification was not statistically significant, it was insightful to identify locations which had more concentration of facilities that buckle the overall trend (e.g. in this case those with steeper decline in productivity growth rates from 2005 to 2008).

6.3 Limitations of the Study

The theoretical, research design, and methodological limitations of the study are discussed in this section. From a theoretical perspective, contingency and organizational performance theories indicate additional determinants of productivity that were not included in this study due to data limitations. For instance, the use of technology (e.g., Electronic Medical Records, Telemedicine), organizational strategies (e.g., the use of disease-management programs), organizational culture (e.g., the use of interdisciplinary teams), and the disincentive of working in rural areas (e.g., because of professional and social isolation) are potential determinants of productivity.

Another conceptual limitation relates to the definition of productivity. In general, organizational performance considers the objective of productivity to be the maximization of outputs while minimizing inputs (Flood et al., 2006). In the particular case of this study, the outputs were visits while the inputs were FTEs. However, maximizing visits is not the only objective of health care facilities. In fact, it may not even be the most desirable one. The quality of those visits is crucial. However, in the absence of individual-level data, it was not possible to employ case-mix adjustment of productivity measures.

An attempt was made to incorporate population-level risk differences. Hence, hospital-based RHCs in counties with less at-risk populations have a lower multiplier on their productivity scores than those that are located in counties with higher at-risk populations. Nevertheless, population-level adjustments are not adequate substitutes for quality-adjusted visits at the individual level.

Theorists in structural contingency and organizational performance do indicate that the various aspects of performance (productivity, quality, financial viability, etc.) have performance trade-offs (Flood et al., 2006). Therefore, determinants of productivity could relate differently to other measures of performance not included in the study, such as quality of care, patient satisfaction, and cost efficiency.

From a research design perspective, two limitations stand out. A correlational research design cannot rule out alternative explanations. For instance, the productivity of hospital-based RHCs in more remote areas was lower than those found in urban-focused areas. However, that might be a reflection of the various degrees of patient volume rather than a lack of productivity. In other words, hospital-based RHCs in urban focused areas might appear to be more productive as a function of their larger population base rather than their intrinsic superior productivity.

Another research design limitation relates to the non-random nature of missing data in panel designs. Since the panel design was not randomly assigned, dropping some hospital-based RHCs due to missing values limits generalizability. Hospital-based RHCs that have missing data for all years from 2005 to 2008 are of the particular concern. Given the Medicare Cost Report data source, it was not possible to verify whether these clinics were in operation or not. In order to minimize the loss of generalizability, the panel window was reduced to four years from the initial five year period.

However, growth curve methodology requires a minimum of 4 years for adequate model testing. Therefore, it was not possible to narrow the panel data to three years. In effect the 4-year panel yielded 708 hospital-based RHCs as compared to the 519 hospital-based RHCs that would have been included with a 5-year panel (2004 to 2008). For the sake of internal validity, it was necessary to retain hospital-based RHCs with non-missing values on the initial year of panel window (2005) as well as the final year (2008). Any missing values for the intermediate years (2006 and 2007) were imputed.

The potential impact of missing data in the intervening years of 2006 and 2007 is minimal. As Appendix C clearly shows, the frequency of missing values for all variables were well below 3%. However, the impact of missing data on 2005 and 2008 affected the results of the study as follows:

1) the findings of this study are least applicable to those hospital-based RHCs with lower net-earnings (about < $130,000 per annum) and fewer physicians (about < 65% physician availability) as compared to hospital-based RHCs in this study. Hospital-based RHCs in this study were similar to other hospital-based RHCs in terms of ownership, age of facility, and payment system;

2) the generalizability of this study is least applicable to hospital-based RHCs located in counties with lower percentage of Medicare-eligible residents (< 19.6%), higher percentage of minorities (> 12.1%), and higher levels of poverty rate (> 14.5%) as compared to the counties of hospital-based RHCs included in this study. Counties of hospital-based RHCs in this study were similar to counties of other hospital-based RHCs in terms of rural classification, regional location, and percentage of uninsured population.

From a research method perspective, two limitations were at the forefront. For growth curve modeling, two key aspects are noteworthy. First, the methodology assumes that the initial period of the study is like the "beginning year of the facility." In that sense, the slope parameter for the initial year is often constrained to be zero ("no growth" year). The need to constrain the initial year in order to estimate growth for subsequent years means that the selection of the initial year will affect the observed pattern of productivity growth. Hence, the observed linear pattern of productivity growth for the years 2005 to 2008 might be different if a different baseline year was selected.

Second, growth curve modeling nearly always requires post-hoc modification of models to attain adequate fit. Such was the case in this study. Since the result of structural equation modeling or growth curve models can be generalized only to the type of sample that was used to estimate and test SEM models (Ullman, 2007), the results of the study need to be cross-validated on a newer panel of hospital-based RHCs.

For data envelopment analyses, several limitations were of importance. First, by design, DEA scores are constrained between 0 and 1. Hence the distributions of DEA scores are censored. Truncated distributions violate both univariate and multivariate normality. Although estimation procedures designed for non-normal data were used, such procedures are incapable of remedying truncation. Truncation leads to over estimated standard errors especially when facilities with higher productivity (scores of 1) and low productivity (scores of 0) show marked variation among each other (Zhang et al., 2008). Therefore, potentially significant relationships might be rendered non-significant due to inflated standard errors.

Second, DEA is a relative ranking tool. Since all facilities are compared to the same group of top-ranked facilities, DEA scores tend to be highly correlated with each other. That could in turn bias the parameter estimates. The serial high correlation among all facilities underestimates standard errors. Therefore, potentially non-significant relationships might be rendered significant due to underestimated standard errors.

Third, productivity scores of DEA ignore non-physical inputs such as experience, information, or supervision (by definition the scores examine only physical relationships). In addition, DEA scores vary depending on the set of output, input, and control variables used. Consequently, the findings pertaining to productivity depend on the specification of similar inputs, outputs, and control variables as noted in this study.

6.4 Future Research

A number of aspects of this study could be enhanced through future research endeavors. In terms of DEA analyses, this study would be one of the first applications of dynamic DEA methodology in health services research. Dynamic DEA methodology, one of the most recent DEA methods, appeared to provide improvements over the traditional methods of panel data DEA analyses: Windows analyses and Malmquist indices.

However, a systematic comparison of these three methods of longitudinal DEA analysis is necessary (Tone & Tsutsui, 2010). Moreover, the biasing effects of DEA scores on parameter estimates could be remedied by more sophisticated models that utilize Monte Carlo simulation

(Zhang et al., 2008). On top of that, the truncated nature of DEA scores could be accommodated through truncated panel data regression in lieu of growth curve modeling (Zhang et al., 2008).

In terms of growth curve modeling, this study tested the basic model of growth trajectory. This model will not be the only one that could fit the data. At least three alternative growth curve models could be investigated. The lag effect of productivity could be examined through autoregressive (AR) growth curve models. In addition, since the error residuals were correlated, moving average (MA) growth curve models are another option. On top of that, both lag effects and moving average processes could co-exist. Therefore, autoregressive moving average (ARMA) growth curve modeling is a third alternative.

In terms of conceptual approaches, future research could explore other measures of performance closely related to productivity. For example, the inclusion of net earnings (financial viability) as a control variable in productivity measures affected the dynamic DEA scores. Therefore, it might be fruitful to study financial viability as a dependent variable. Then one could examine the growth patterns and trends of financial viability for the same panel of hospital-based RHCs. In particular, a parallel process growth curve model might examine whether profitable clinics are also productive.

6.5 Summary

Through unconditional growth curve models, this study found out that: 1) hospital-based rural clinics did show an average growth in productivity from 2005 to 2008; and 2) hospital-based rural clinics did not have the same productivity growth rate from 2005 to 2008. In order to examine what factors were related to productivity and productivity growth rates, conditional growth curve models were tested. Conditional growth models introduced explanatory variables to understand where the significant differences in productivity and productivity growth rates lie.

Accordingly, the findings of the conditional growth models revealed that: 1) hospital-based clinics with higher baseline levels of productivity in 2005 had a slower rate of growth in productivity for the years 2006 to 2008; 2) hospital-based clinics with physicians had significantly higher productivity; 3) hospital-based clinics in urban focused areas had significantly higher productivity; 4) newer hospital-based clinics had significantly higher productivity; and 5) prospective payment system was negatively related to productivity growth rates.

Organizational and contextual factors included in this study significantly explained baseline differences in productivity. However, they were unable to explain productivity growth rates. Consequently, future research could improve the study by, 1) including additional explanatory variables, such as the use of technology and disease management programs; 2) adjusting productivity measures by case mix measures, and 3) conducting truncated panel data regression with Monte Carlo simulation. These improvements could enhance the prospect of identifying explanatory variables that could explain productivity growth rates.

This study made contributions in the areas of theory, methodology, and policy implications. The study applied the context-design-performance model of organizational performance and structural contingency theories over a four-year time period (2005 to 2008). Given the limited literature of testing such models over time, this study would be of some value.

This study introduced growth curve methodology to rural health services research. In addition, it is one of the few studies that applied dynamic slacks-based DEA methodology.

Several policy implications of the research merit attention. Physician availability was related to higher productivity. The promises of the Patient Protection and Affordable Care Act (PPACA) of 2010 to attract and retain physicians to rural areas need to be implemented sooner rather than later. In that regard, several recommendations were outlined. In the absence of productivity standards on hospital-based RHCs, growth patterns and trends of productivity were significantly varied from 2005 to 2008. With the prospect of introducing productivity standards on the horizon, the results of the study indicated the need to avoid uniform productivity standards. A possible scenario of setting productivity standards, if need be, was noted. Last but not least, prospective payment systems were associated with a slower rate of growth in productivity. Therefore, a much closer investigation of payment system effects on productivity is warranted.

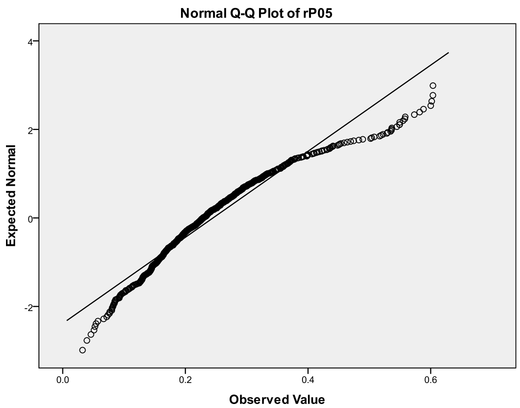
APPENDIX A: CORRELATION MATRIX FOR DEA VARIABLES

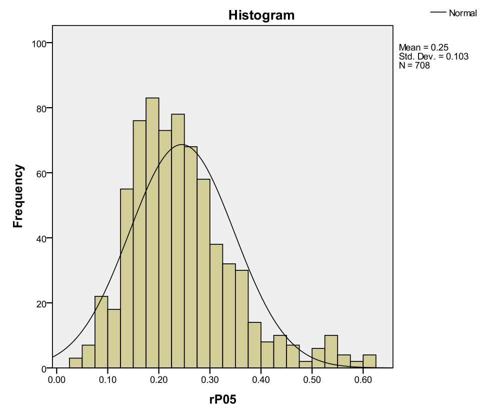
No	Variables	1	2	3	4	5	6	7	8	9	10	11	12
1	TOFT_05	1.00											
2	TOFT_06	.94	1.00										
3	TOFT_07	.91	.94	1.00									
4	TOFT_08	.86	.89	.92	1.00								
5	TOVI_05	.93	.90	.88	.84	1.00							
6	TOVI_06	.89	.93	.90	.86	.96	1.00						
7	TOVI_07	.85	.88	.93	.87	.92	.95	1.00					
8	TOVI_08	.80	.83	.87	.92	.87	.91	.93	1.00				
9	NETE_05	-.27	-.26	-.26	-.28	-.26	-.25	-.24	-.26	1.00			
10	NETE_06	-.24	-.23	-.25	-.26	-.23	-.20	-.21	-.22	.93	1.00		
11	NETE_07	-.25	-.24	-.25	-.27	-.24	-.21	-.21	-.22	.90	.92	1.00	
12	NETE_08	-.25	-.23	-.23	-.28	-.24	-.20	-.20	-.21	.87	.89	.93	1.00

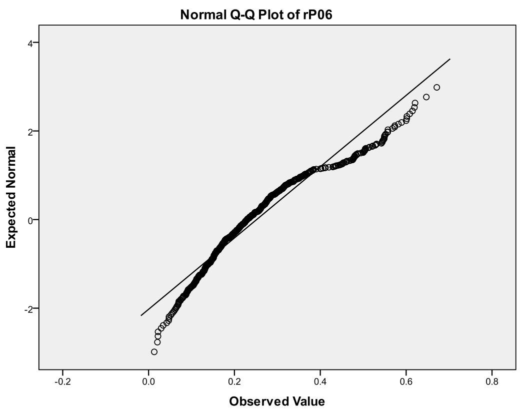
TOFT_05: Total FTEs in 2005; TOFT_06: Total FTEs in 2006; TOFT_07: Total FTEs in 2007; TOFT_08: Total FTEs in 2008; TOVI_05: Total Visits in 2005; TOVI_06: Total Visits in 2006; TOVI_07: Total Visits in 2007; TOVI_08: Total Visits in 2008; NETE_05: Net Earnings in 2005; NETE_05: Net Earnings in 2005; NETE_06: Net Earnings in 2006; NETE_07: Net Earnings in 2007; NETE_08: Net Earnings in 2008.
All correlation is significant at the .01 level (two-tailed)

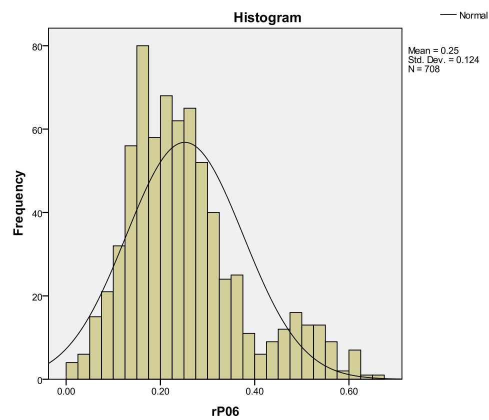
APPENDIX B: Q-Q PLOTS AND HISTOGRAMS

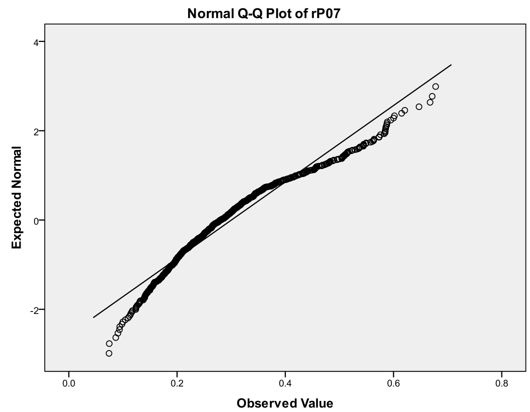
Productivity DEA Scores Normality Plots (P05 - P08)	
Normal Q-Q Plots	**Hisgograms**

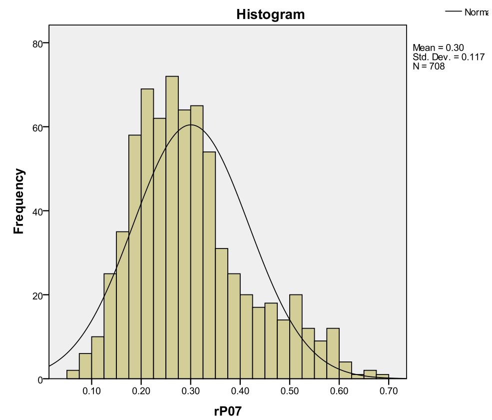


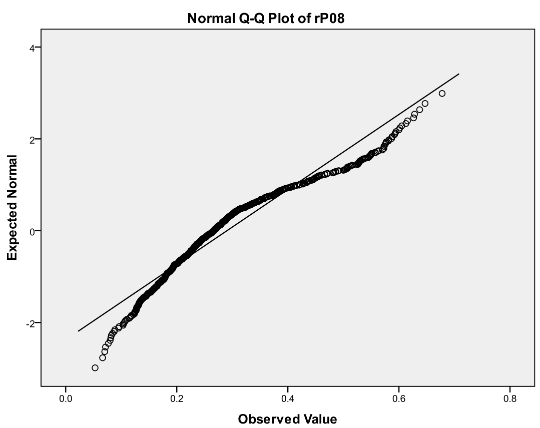


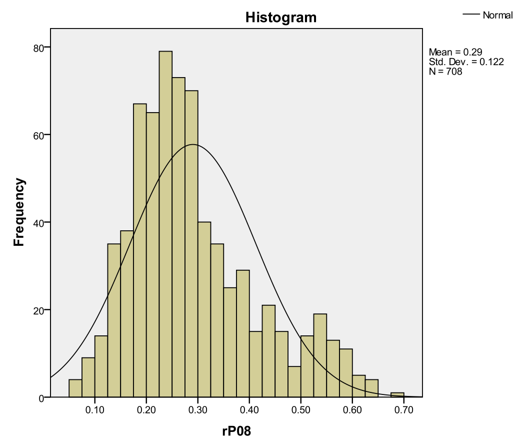




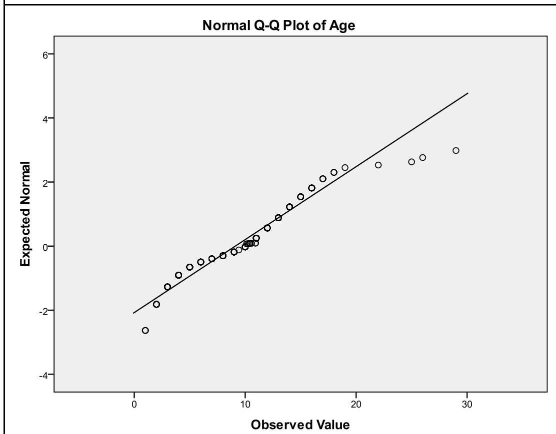


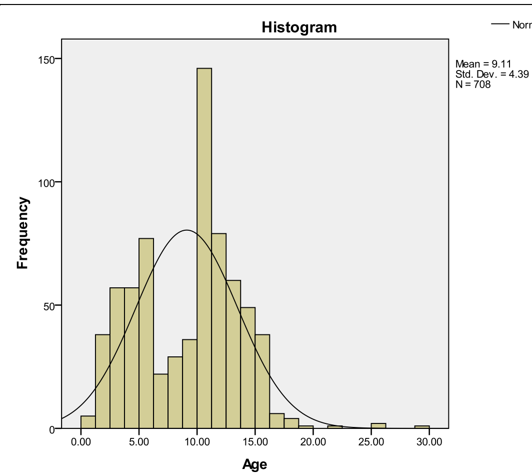


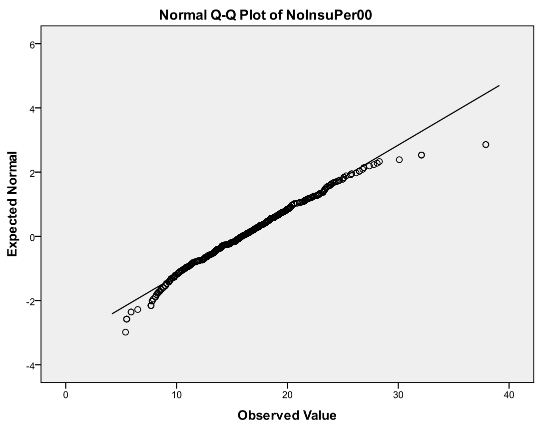


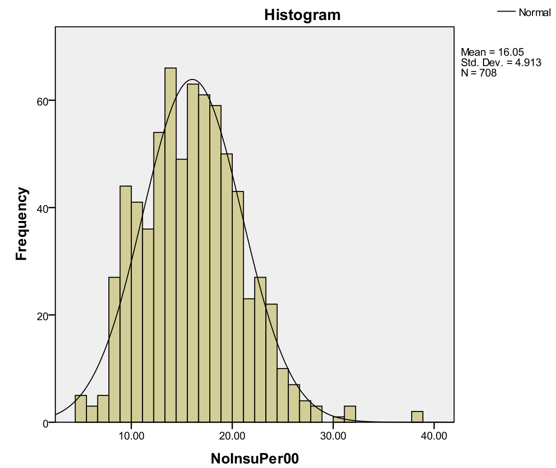


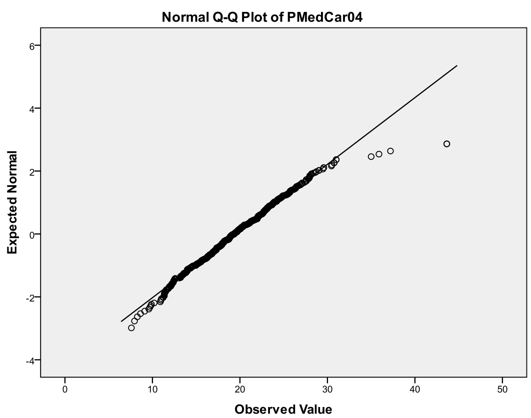
Exogenous Variables

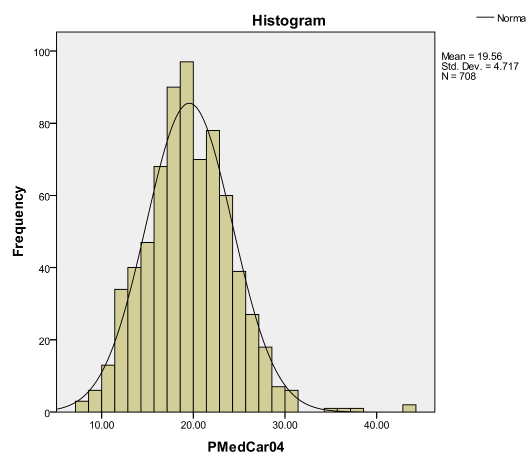


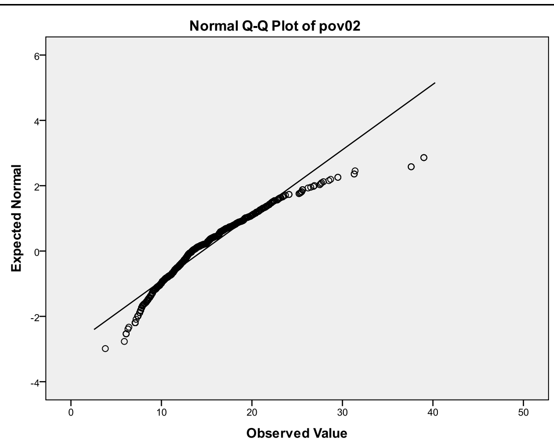


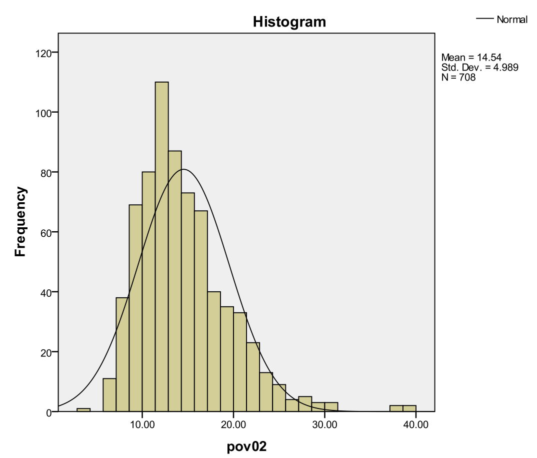

Normal Q-Q Plot of NoInsuPer00
Expected Normal
Observed Value
6
4
2
0
-2
-4
0
10
20
30
40

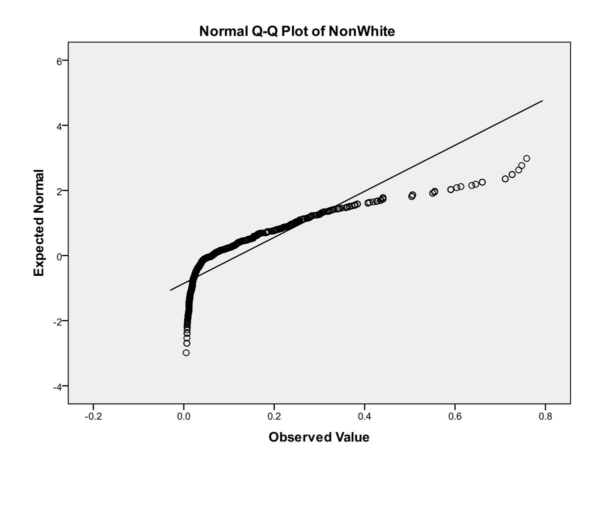

Histogram
Normal
Mean = 16.05
Std. Dev. = 4.913
N = 708
Frequency
NoInsuPer00
60
40
20
0
10.00
20.00
30.00
40.00

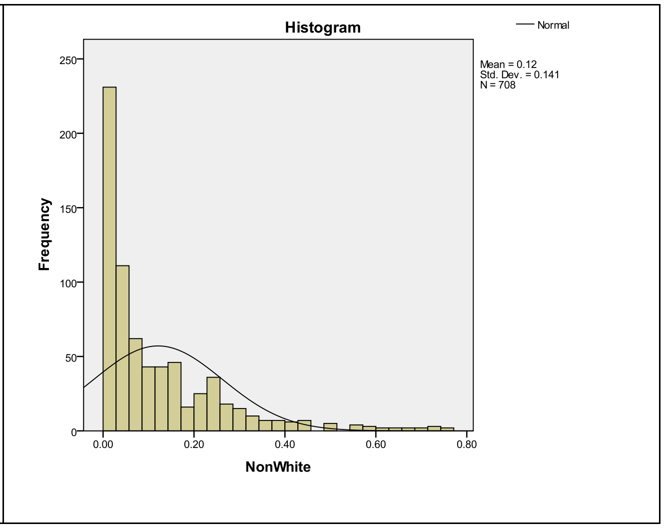

Normal Q-Q Plot of PMedCar04
Expected Normal
Observed Value
6
4
2
0
-2
-4
0
10
20
30
40
50


Histogram
Norma
Mean = 19.56
Std. Dev. = 4.717
N = 708
Frequency
PMedCar04
100
80
60
40
20
0
10.00
20.00
30.00
40.00


Normal Q-Q Plot of pov02
Expected Normal
Observed Value
6
4
2
0
-2
-4
0
10
20
30
40
50


Histogram
Normal
Mean = 14.54
Std. Dev. = 4.989
N = 708
Frequency
pov02
120
100
80
60
40
20
0
10.00
20.00
30.00
40.00


Normal Q-Q Plot of NonWhite
Expected Normal
Observed Value
6
4
2
0
-2
-4
-0.2
0.0
0.2
0.4
0.6
0.8


Histogram
Normal
Mean = 0.12
Std. Dev. = 0.141
N = 708
Frequency
NonWhite
250
200
150
100
50
0
0.00
0.20
0.40
0.60
0.80

APPENDIX C: MISSING VALUE ANALYSIS

Missing Value Analysis for Included Hospital-based RHCs (N=708)

	Missing Value Frequency Counts	
Variables	N (708)	Percentage (%)
TOFT_05 (total clinical FTEs in 2005)	0	0
TOFT_06 (total clinical FTEs in 2006)	13	1.83
TOFT_07 (total clinical FTEs in 2007)	8	1.13
TOFT_08 (total clinical FTEs in 2008)	0	0
TOVI_05 (total clinical visits in 2005)	0	0
TOVI_06 (total clinical visits in 2006)	13	1.83
TOVI_07 (total clinical visits in 2007)	8	1.13
TOVI_08 (total clinical visits in 2008)	0	0
NETE _05 (net earnings in 2005)	0	0
NETE _06 (net earnings in 2006)	16	1.84
NETE _07 (net earnings in 2007)	13	1.83
NETE _08 (net earnings in 2008)	0	0
PH5(Physician availability in 2005)	0	0
PH6(Physician availability in 2006)	0	0
PH7(Physician availability in 2007)	0	0
PH8(Physician availability in 2008)	0	0
AGE (age of hospital-based rural health clinic)	15	2.11
FORPRO (for-profit ownership)	15	1.83
PAYS (payment system)	2	0.30
CMR (cause-specific mortality rate)	0	0
RURAL (RUCA-Zip code Categorization of Rural Areas)	0	0
REGION (US Census Bureau Classification)	0	0
%MDC (percentage of Medicare eligible population)	0	0
%UNIN (percentage of uninsured population)	0	0
%MIN (percentage of minority population)	0	0
POV (poverty rate)	0	0

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