THE EFFECTS OF GOVERNMENT-FUNDED MANAGED CARE ON UNCOMPENSATED CARE IN TEXAS HOSPITALS

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Abstract

This study examined the effects of government-funded managed care on hospitals' provision of uncompensated care using a panel data set of Texas Metropolitan Statistical Area hospitals for the period 2000 through 2005. The level of uncompensated care provided by hospitals is considered a measure of access to care for the low-income, uninsured, and under-insured populations. Texas hospitals are of particular interest given that the state has the highest rate of uninsurance in the nation; more than one-fourth of the state's population is uninsured. Additionally, Texas has the most stringent prescriptive charity care law for not-for-profit hospitals among all states. These uncompensated care demand factors, when combined with the revenue reduction and cost pressure effects of managed care, represent challenges to Texas hospitals' ability to continue providing uncompensated care. The objective of this study was to examine the effects of Medicare and Medicaid managed care on Texas hospitals' uncompensated care provision, controlling for other managed care provision, profit, mission, demand for uncompensated care, other hospitals' supply of uncompensated care, market characteristics, and hospital characteristics. This study was limited to non-federal, non-state, short-term acute care medical-surgical hospitals with at least 25 beds located in counties within the Metropolitan Statistical Areas of Texas $(N = 750)$. The unit of analysis was the hospital. This study used a one-way fixed-effects panel regression model with robust standard errors. The significance criterion used was $p \leq .10$. For the key variables, this study found that Medicare managed care was negatively associated with hospitals' uncompensated care provision. Among the other variables, the study results show that profit net of uncompensated care expense, physician-owned specialty hospital outpatient

surgeries, outpatient mix, total expenses as a percent of net revenue, and risk-adjusted mortality for acute stroke were positively associated with hospitals' provision of uncompensated care. The study results also show that commercial managed care, for-profit hospitals, teaching intensity, rural health centers, number of beds, severity of illness, births per admission, and the years 2000 through 2003, compared to 2004, were negatively associated with hospitals' uncompensated care provision. This study's main results suggest that Texas Metropolitan Statistical Area hospitals should consider their uncompensated care provision when negotiating Medicare managed care payments. This study expands and diversifies the pool of existing state-level hospital uncompensated care studies in two significant ways. First, it broadens existing literature concerning the effects of managed care with its examination of the specific effects of government-funded managed care on hospitals' uncompensated care provision. Second, it diversifies the present physician-owned specialty hospital literature with its findings on the effects of these hospitals' outpatient surgeries on general hospitals' uncompensated care provision. The study's findings will benefit hospital administrators, trustees, industry leadership, policy makers, regulators, advocacy groups, and others at the local, state, and national levels that are interested in and concerned about managed care and other factors that influence hospitals' provision of uncompensated care at the state level.

Dedications

I dedicate this work to my late parents,

Harris Frank Hipp and Emma Guenther Hipp,

who each independently instilled in me

a work ethic and the desire to continue learning.

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There are many I want to thank for helping me sustain and complete this dissertation. Each belongs to one of four spheres – committee, family, work, and university.

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List of Abbreviations

AHA	American Hospital Association
AHRQ	Agency for Healthcare Research and Quality
AP-DRG	All Patient Diagnosis Related Groups
APR-DRG	All Patient Refined Diagnosis Related Groups
ARF	Area Research File
ASC	Ambulatory Surgery Center
CMS	Centers for Medicare and Medicaid Services
CMS-DRG	Centers for Medicare and Medicaid Services Diagnosis Related Groups
COTH	Council of Teaching Hospitals
DRA	Deficit Reduction Act of 2005
DSH	Medicaid Disproportionate Share Hospital Program
EMTALA	Emergency Medical Treatment and Active Labor Act
FE	Fixed-Effects
FEM	Fixed-Effects Model
FGLS	Feasible Generalized Least Squares
FP	For-Profit
FQHC	Federally Qualified Health Center
GLS	Generalized Least Squares
HCRIS	Healthcare Cost Report Information System
HMO	Health Maintenance Organization
ICD-9-CM	International Classification of Diseases, 9th Clinical Modification
i.i.d.	Independent and Identically Distributed
IQI	Inpatient Quality Indicator
LM	Lagrange Multiplier
LGOVT	Local Government
LSDV	Least Squares Dummy Variable
MSA	Metropolitan Statistical Area
MSE	Mean Square Error
NFP	Not-For-Profit
OLS	Ordinary Least Squares
PPO	Preferred Provider Organization
RE	Random-Effects
REM	Random-Effects Model
RHC	Rural Health Center
SMSA	Standard Metropolitan Statistical Area
TDSHS	Texas Department of State Health Services
THA	Texas Hospital Association
THCIC	Texas Health Care Information Council
UPL	Medicaid Upper Payment Limit Program
U.S.	United States

Chapter 1 – Introduction

1.1 Introduction

Hospital provision of uncompensated care continues to be the critical feature of our national health care system that lacks universal health insurance coverage. Uncompensated care is service provided by a hospital for which no payment is received from the patient or from third-party payers. The number of uninsured continues to grow in the United States ("U.S.") and likewise does the level of uncompensated hospital care. Hospitals' uncompensated care expenses were $31.2 billion in 2006, up from $28.8 billion in 2005 and $26.9 billion in 2004 (Evans, 2005).

This is a study about uncompensated hospital care and how government-funded managed care influences its supply. Texas offers a unique setting for studying the effect of uncompensated care. Costs for such care in the state exceeded the national rate in 2000. Then, hospitals in Texas were responsible for more than one-tenth of the nation's total uncompensated care costs. Texas has the highest rate of health care uninsured in the nation. In 2007, more than one-fourth of the state's population was uninsured. Using a three-year average from 2005 to 2007, Texas was responsible for 12.4 percent of the nations' total uninsured. Texas has had a strong prescriptive charity care law for not-for-profit hospitals since 1993. The law has national status and is a benchmark for other states. Finally, hospitals in Texas provide more than three times as much charity care as states to which it has been compared. The confluence of these factors creates financial burdens on Texas hospitals, potentially jeopardizing their supply of uncompensated care when the financial pressures brought on by managed care are additionally considered.

1.2 Background

The concept of uncompensated hospital care has been a fundamental feature of our health care system for many decades. The federal Hill-Burton Act led to uncompensated care being established as an element of hospital financing in the U.S. (Blumstein, 1986; Coleman, 2005). Uncompensated care has a critical role in our system, which is to assure the availability of care to the sick and needy inhabitants of our country. Uncompensated care is the safety net for last resort hospital care in the U.S. (Melnick, Mann, & Bamezai, 2000; Weissman, 2005). An implicit understanding within our nation's health care system is that when low-income, uninsured, or under-insured persons become ill or injured and require hospital care, they can receive it at little or no charge (Weissman, 2005). Throughout most of the recorded history of medicine, and within the varied organizational contexts of our medical care delivery, hospitals in the U.S. have delivered care to those who could not pay for it (Hadley & Holahan, 2003, February 12; Melnick, Mann, & Bamezai, 2000). However, over recent decades provision of uncompensated care has become a major dilemma for hospitals (Duncan, 1992).

Hospitals are not the sole providers of care to the low-income, uninsured, or under-insured persons, though they are considered the critical provider of care to the U.S. population (Hogeland, 1988; L. S. Lewin, Eckels, & Miller, 1988; Zollinger et al., 1991). Nationally, 63 percent of uncompensated care provided to the uninsured occurs in hospitals, for both inpatient and outpatient care (Hadley & Holahan, 2004).

Charity care, a component of uncompensated care, is essentially an unfunded governmental mandate on hospitals (PricewaterhouseCoopers, 2005). However, in certain cases, hospitals receive financial benefit from their tax status as charitable organizations.

Reasons that hospitals may provide charity care vary, but generally include mission, federal emergency treatment laws, federal construction funds obligations, tax-exemption, and state regulation. Hospitals with a religious or community-focused mission provide charity care as a core value. These values are typically delineated in their charters, covenants, and mission statements or directed by the hospital's board and executive management. Mission-based organizations view serving the community as an obligation regardless of a patient's ability to pay, regulations, or mandates. Uncompensated care is provided by hospitals, particularly in life-threatening situations. One reason is their legal duty to treat under the common law and the federal Emergency Medical Treatment and Labor Act ("EMTALA") (P.L. 99-272 and P.L. 101-239), the patient anti-dumping law, which requires hospital personnel to evaluate and stabilize patients with an emergency medical condition regardless of their ability to pay (U.S. Department of Health & Human Services, 2009c). Some hospitals have a specific obligation to provide uncompensated care as a condition of having received federal construction funds through the Hill-Burton program. In 1946, the U.S. Congress passed the Hospital Survey and Construction Act (P.L. 79-725), commonly known as the Hill-Burton Act, in part, to encourage hospital construction. Hospitals received federal funds in exchange for providing care to the low-income (U.S. Department of Health & Human Services, 2009a). Currently, four Texas hospitals still have Hill-Burton Act-related obligations (U.S. Department of Health & Human Services, 2009b). For not-for-profit hospitals, a powerful incentive is preservation of their not-for-profit, tax-exempt status. Not-for-profit hospitals may qualify for exemptions from federal income tax as well as certain state and local taxes, including income, franchise, sales and use, and property taxes. The criteria for receiving a tax exemption can vary based on applicable federal, state, and/or local standards and may include factors relating to the hospital's provision of charity care. For example, the Internal Revenue Service has set forth the "community benefit standard" for determining whether a hospital is entitled to exemption from federal income tax as described in the Internal Revenue Code, Section 501(c)(3). Some states have laws requiring not-for-profit hospitals to provide charity care at specific levels, usually a percentage of net patient revenue. Some states also have community benefit reporting requirements. For example, Texas' law mandates that not-for-profit hospitals provide either [1] charity care services or government-sponsored unreimbursed care in an amount reasonable in relation to community needs, the hospital's financial resources, and tax exempt benefits; [2] charity and government-sponsored unreimbursed care in an amount equal to or greater than the benefits that the provider obtains through its tax exempt status; or [3] charity care and community benefits make up at least 5 percent of the hospital's net patient revenue, provided that at least 4 percent of net patient revenue is provided in charity and government-sponsored unreimbursed care (Texas Legislative Council, 1993).

Across all states, Texas has the highest percentage of people without health insurance coverage. Using a three-year average from 2005 to 2007, the proportion of people without health insurance coverage in Texas was 24.4 percent, followed by New Mexico at 21.9 percent, Florida at 20.5 percent, Arizona at 19.6 percent, and Louisiana at 19.4 percent (U.S. Census Bureau, 2008b). During that time, Texas was responsible for 12.4 percent of the nations' total uninsured.[1] As Figure 1-1 indicates, the rate of uninsured in Texas has consistently exceeded that of the nation (U.S. Census Bureau, 2008a) and the difference is large.

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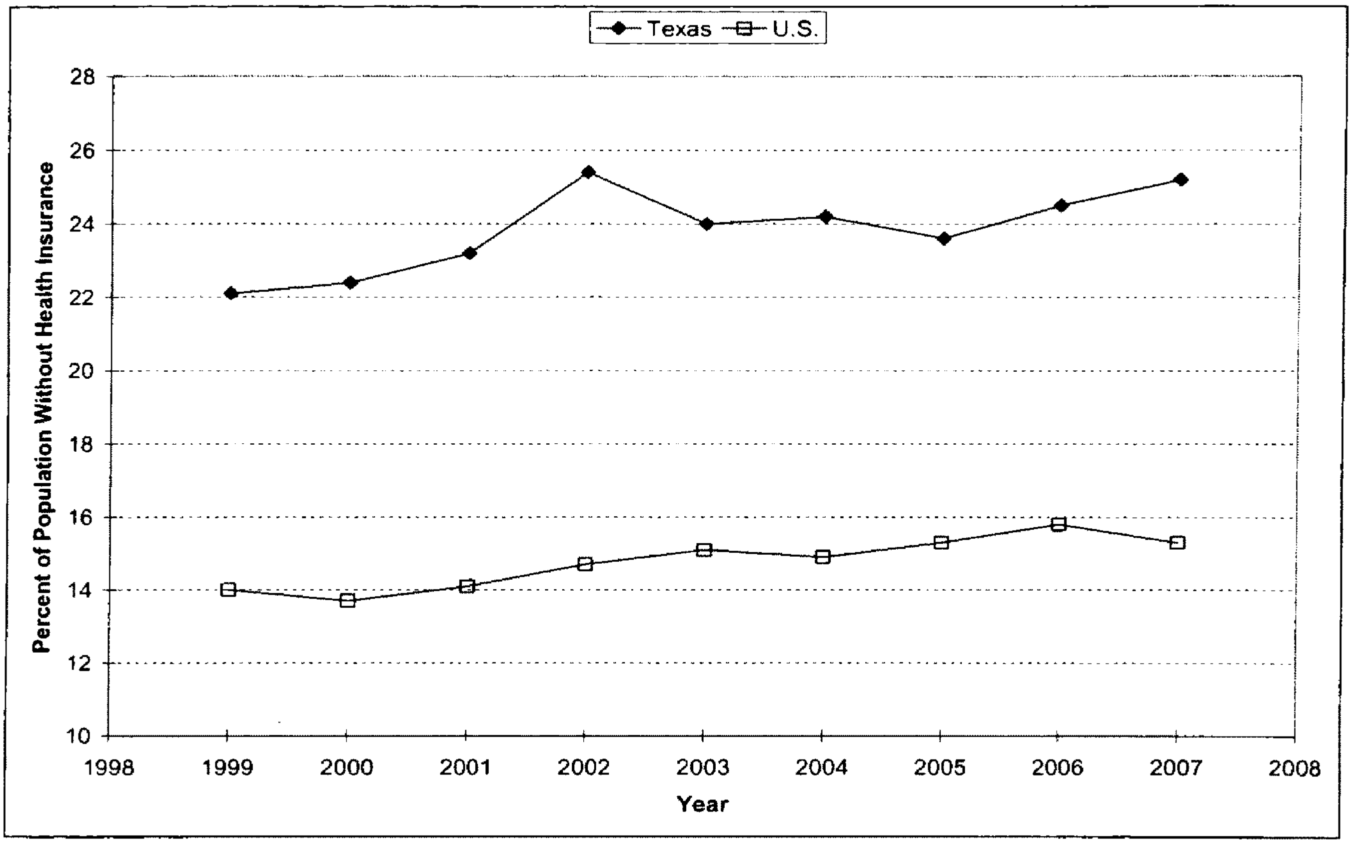
[1] Author's calculations using Census Bureau health insurance data (U.S. Census Bureau, 2008b).

Figure 1-1. Historical uninsured rates for Texas and United States, 1999-2007



Texas has had a strong prescriptive charity care law for not-for-profit hospitals. In 1990, the State of Texas legally challenged one of its largest not-for-profit hospitals alleging that it was not providing its share of charity healthcare (Bain, Blankley, & Forgione, 1999, 2001; Blankley & Forgione, 1996; Burda, 1990; Lutz, 1990). In 1991, the U.S. Internal Revenue Service warned Texas' not-for-profit hospitals that they should be prepared to justify their tax-exempt status (Lutz, 1991). In 1993, the state became the first to pass legislation requiring not-for-profit hospitals to provide a minimum specific percentage of patient revenues for charity care, indigent health care, and community benefits (Lutz, 1993;

Texas Legislative Council, 1993; Wood, 2001). The resulting laws are referred to nationally as the "Texas Standard". Charity care, the major component of uncompensated care, is in effect an unfunded governmental mandate on hospitals (PricewaterhouseCoopers, 2005).

Hospitals in Texas incur and provide higher amounts of uncompensated care. In a recent charity care study (Sutton & Stensland, 2004) comparing California, Texas, and Washington State hospitals between 1996 and 1998 found that two times as much of Texas' hospitals uncompensated care was charity, and that Texas' hospitals incurred more than two times as much uncompensated care as California's hospitals. Their study also found that Texas hospitals provided more than three times as much charity care as California hospitals, and provided almost two times as much charity care as Washington State hospitals.

Uncompensated care is a widespread problem among hospitals in the U.S. and the costs of providing it are not trivial. In 2000, uncompensated care costs for acute care hospitals totaled $21.6 billion (American Hospital Association, 2002), representing 6.1 percent of total costs for such hospitals (Ashby, 2002). Hospitals in Texas are responsible for a sizable fraction of national hospital uncompensated care costs. In 2000, uncompensated care costs in Texas' acute care hospitals totaled $2.6 billion, representing 11.3 percent of total expenses.[2] Then, Texas' acute care hospitals accounted for more than 12 percent of national uncompensated care hospital costs. More recently, hospitals' uncompensated care expenses nationally were about $31.2 billion in 2006, up from $28.8 billion in 2005. Since 2000, the amount of uncompensated care provided by hospitals nationally has increased by $9.6 billion, or 44 percent (Rubenstein, 2007).

[2] Author's analysis of 2000-2005 *TDSHS-AHA-THA Annual Survey of Hospitals* data (Texas Department of State Health Services, 2000-2005).

At the national level, there is increasing concern about the ability of hospitals that provide considerable amounts of uncompensated care to continue to do so (Campbell & Ahern, 1993; Dunn & Chen, 1994; Gaskin, 1997; Weissman, 1996). In 2004, federal funds[3] constituted 67.9 percent of the total funds available to providers for support uncompensated care of the uninsured (Hadley & Holahan, 2004, p. 10). Between 2001 and 2004, safety net federal spending increased by 15.4 percent, while total federal health care spending increased by 23 percent (Hadley, Cravens, Coughlin, & Holahan, 2005). While the number of uninsured increased by about 5 million persons during the same period, safety net federal spending per uninsured person decreased by 8.9 percent across the period (Hadley et al., 2005). Not surprisingly, the political and economic climate in the U.S. places constraints on the manner in which the problem of hospital uncompensated care can be solved (Bookheimer, 1989).

Hospitals fund uncompensated care through a delicate balance of internal and external cross-subsidies (Hadley & Feder, 1985). Largely, this balance depends on hospitals' ability to receive reimbursement from paying patients that exceeds the costs of treating uncompensated care patients, a "cost shifting" subsidy (Clement, 1997; Friesner & Rosenman, 2004; Komisar, 1993; Morrisey, 1993; Zwanziger & Bamezai, 2006). Cost shifting occurs in Texas' hospitals (Custer, 1989). In 2005, health insurance premiums in Texas for a family with private, employer-sponsored coverage were $1,551 higher due the unpaid cost of health care for the uninsured, in contrast to $922 higher for the nation (Stoll, 2005).

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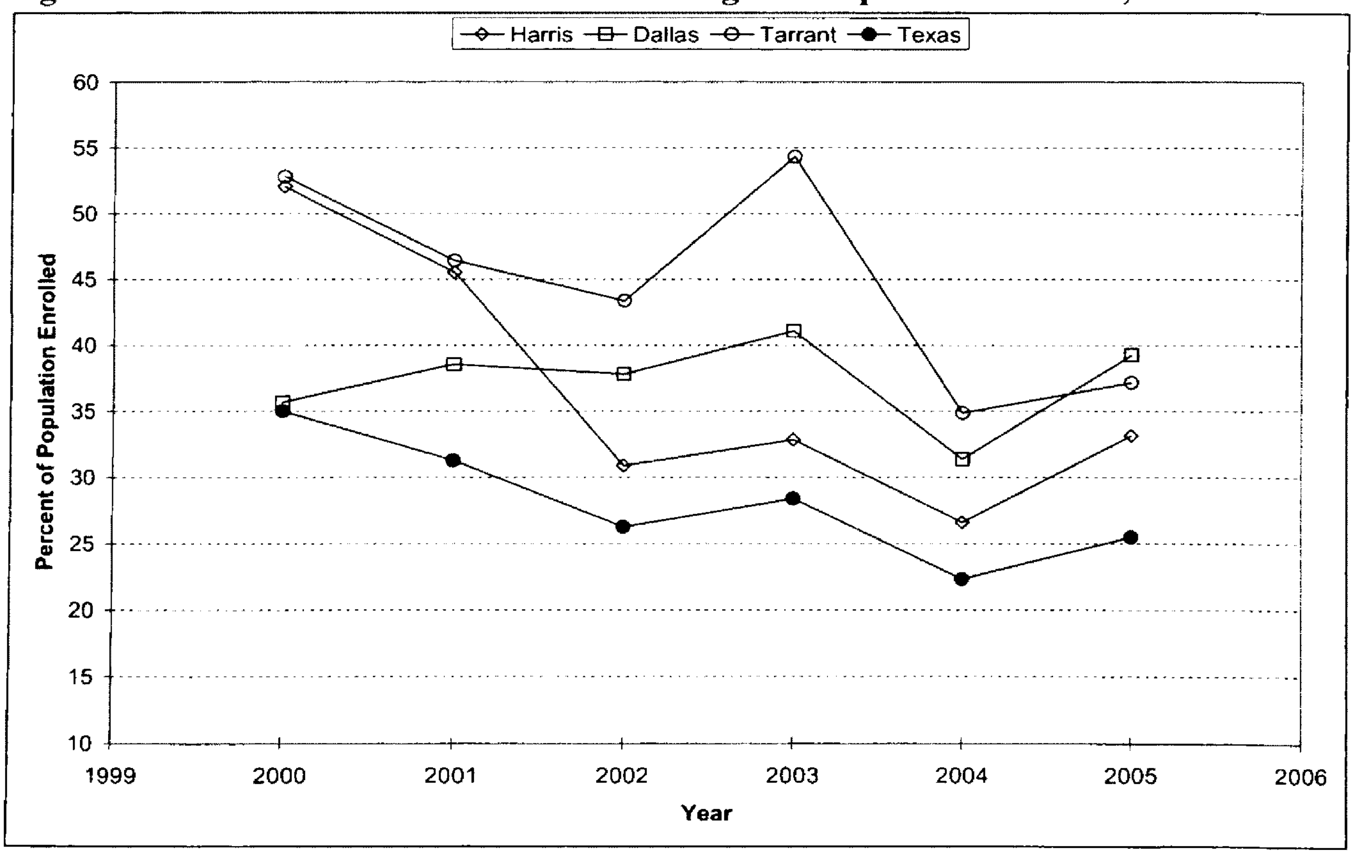
[3] Federal funds are comprised of Medicare and Medicaid Disproportionate Share Hospital Program payments, indirect medical education payments, supplemental provider payments, and other federal programs, including Bureau of Primary Care Programs, National Health Service Corps, Maternal and Child Health, Indian Health Service, and Veterans Affairs Programs.

There is concern that this system of subsidies that has preserved the hospital safety net is eroding due to managed care growth and price competition, tightening of fiscal pressures begun under Medicare's fixed-price payment system, Medicaid disproportionate share spending limits, and growth in the number of uninsured persons (Melnick, Mann, & Bamezai, 2000; Rosenbaum & Darnell, 1997). Studies indicate that hospitals facing the fiscal pressure from government and private payers reduce their uncompensated care loads (Atkinson, Helms, & Needleman, 1997; Bazzoli, Lindrooth, Kang, & Hasnain-Wynia, 2006; Cunningham & Tu, 1997; Gruber, 1992, 1994; Mann, Melnick, Bamezai, & Zwanziger, 1997; Prospective Payment Assessment Commission, 1996). Hospitals can be expected to respond to reimbursement changes (i.e., managed care discounting) along multiple dimensions. These changes could lead hospitals to respond by reducing the quality of their care, increasing their efficiency, changing their service mix, increasing prices to the privately insured, accepting lower profitability, or reducing uncompensated care provision (Bazzoli et al., 2006; Zwanziger & Bamezai, 2006).

Managed care threatens hospitals' provision of charity care (Preston, 1996). Studies have demonstrated that increased health maintenance organization ("HMO") penetration is related to decreased hospital uncompensated care provision (Davidoff, LoSasso, Bazzoli, & Zuckerman, 2000; Gaskin, 1997; Rosko, 2004; Thorpe, Seiber, & Florence, 2001) and decreased total margins (Thorpe et al., 2001). Smaller Medicare and Medicaid payments were associated with reductions in the supply of uncompensated care (Campbell & Ahern, 1993; Mann et al., 1997). Research also shows that higher proportions of Commercial managed care-funded patients treated at the hospital-level are related to decreased hospital provision of uncompensated care (McKay & Meng, 2007).

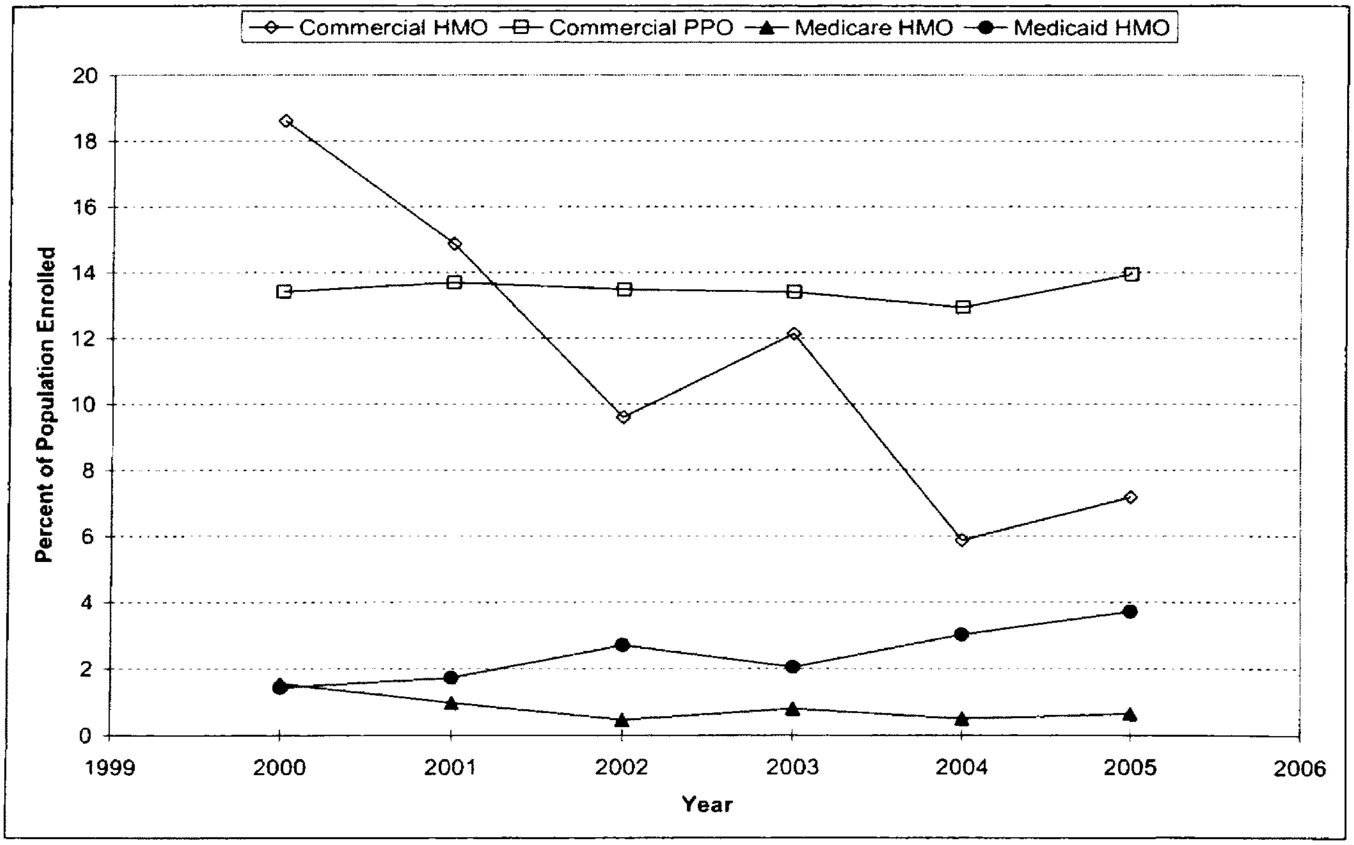
As shown in Figure 1-2, the managed care penetration rate for Texas declined between 2000 and 2005, although it began to increase in 2005. In Texas' three most populated counties (major city), Harris (Houston), Dallas (Dallas), and Tarrant (Fort Worth) the penetration rate also declined, but has begun to increase. However, the most notable attribute of Figure 1-2 is that for the three most populated counties, where many low-income, uninsured, and under-insured reside and related uncompensated care demand is high, the counties' managed care penetration rates were consistently higher than that of the state overall throughout the six-year period 2000 to 2005.

Figure 1-2. Texas and selected counties' managed care penetration rates, 2000-2005



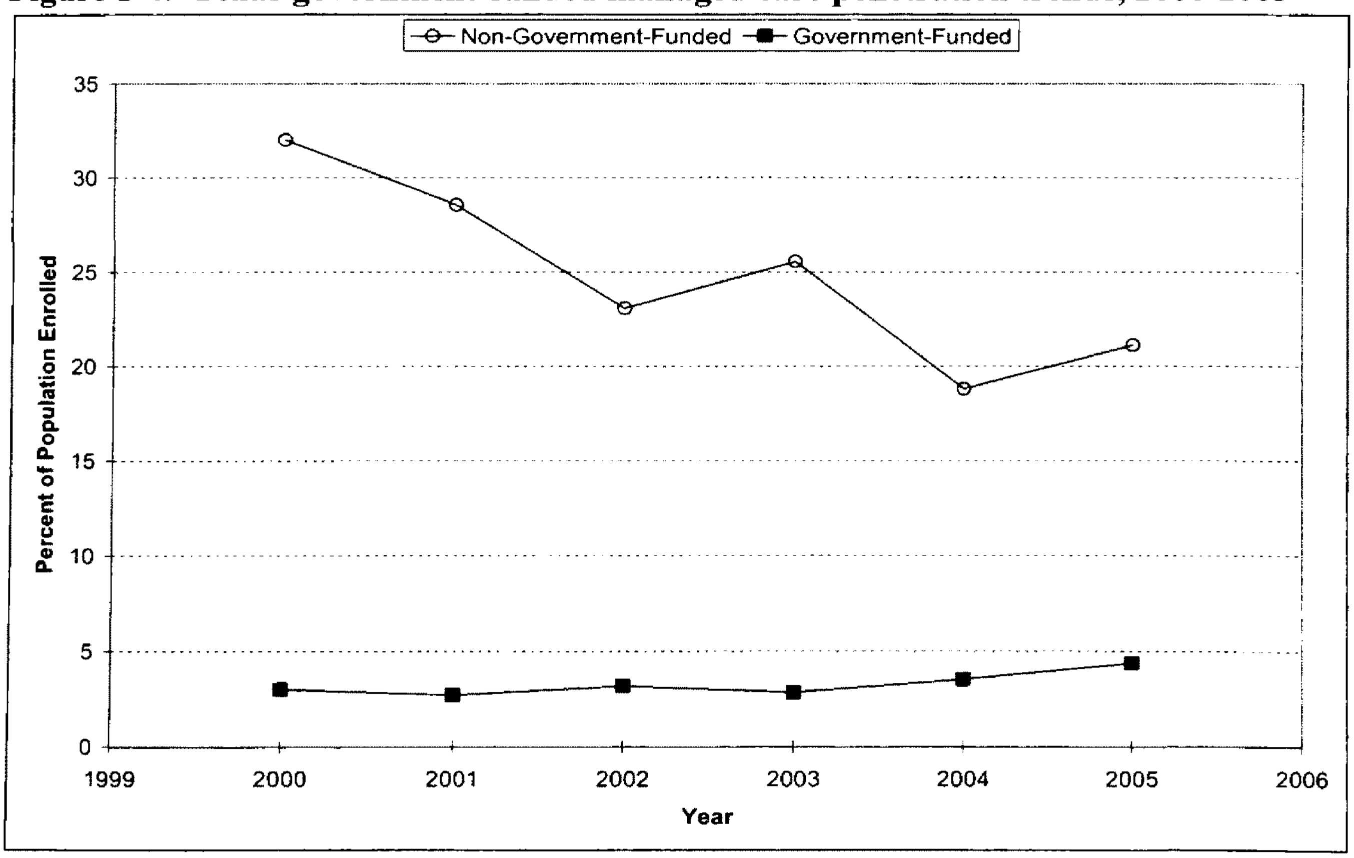
Certain types of managed care continued to make it in Texas between 2000 and 2005. The important feature of Figure 1-3 is the quick and dramatic decline of commercial HMO penetration rate during that timeframe. This decline is consistent with national trends during that period (Marquis, Rogowski, & Escarce, 2004). Other prominent features of Figure 1-3 are the relative stability of commercial PPO penetration and the growth of Medicaid HMO penetration during the last two years of the six-year period. Less noticeable are the slight fluctuations in Medicare HMO penetration.

Figure 1-3. Texas managed care penetration trends by payer type, 2000-2005



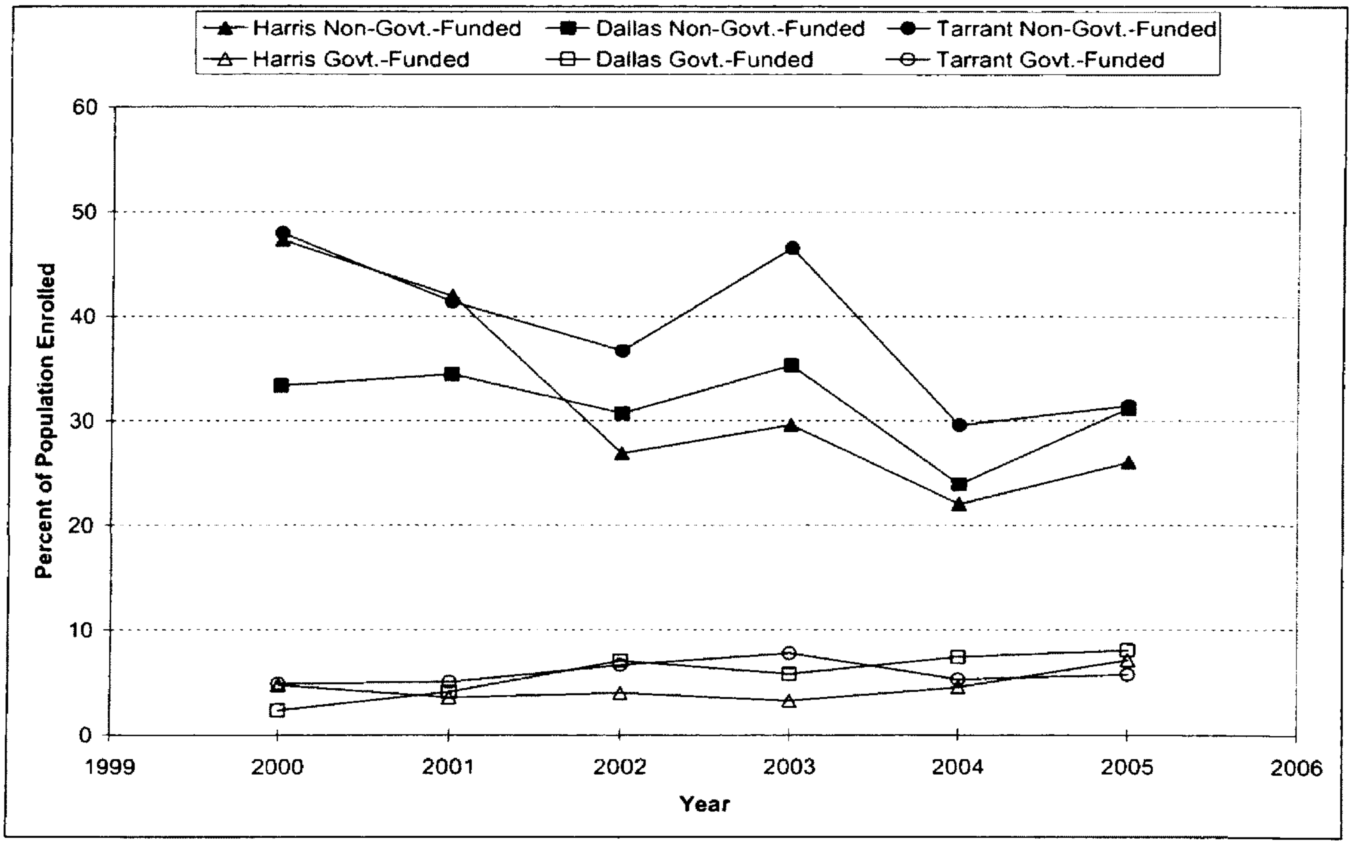
Non-government-funded managed care penetration steadily decreased in Texas between 2000 and 2005. As shown in Figure 1-4, whenever commercial HMO and PPO managed care penetration rates are collapsed into a "non-government-funded" measure, that rate decreased during the period 2000 to 2004 by about 15 percentage points and began to rise thereafter. Referring back to Figure 1-3, this decline can be attributed to the decreased commercial HMO penetration rate. Similarly, whenever the Medicare and Medicaid HMO managed care penetration rates are consolidated into a "government-funded" measure, it shows relative stability during the six-year period and growth during the last two years. Again referring back to Figure 1-3, the stability and later growth can be attributed to the counter-balancing effects of Medicaid HMO managed care penetration against that of Medicare HMO penetration. Figure 1-4 suggests that government-funded managed care has been constant in Texas.

Figure 1-4. Texas government-funded managed care penetration trends, 2000-2005



As illustrated in Figure 1-5, for the three most populated Texas counties again, their non-government-funded managed care penetration rates declined noticeably during the period between 2000 and 2005. Figure 1-5 also indicates that the government-funded penetration rate was relatively steady and increased somewhat toward the end the six-year period.[4]

Figure 1-5. Selected Texas counties' managed care penetration trends, 2000-2005



The managed care industry had a period of rapid growth in the early 1990s, motivated by concerns of rising health care costs (Marquis et al., 2004). Since the industry's peak enrollment in 1999, managed care plans (particularly HMOs) in the private sector have

[4] Author's analysis of special Texas data extract obtained from HealthLeaders-InterStudy (HealthLeaders-InterStudy, 2008).

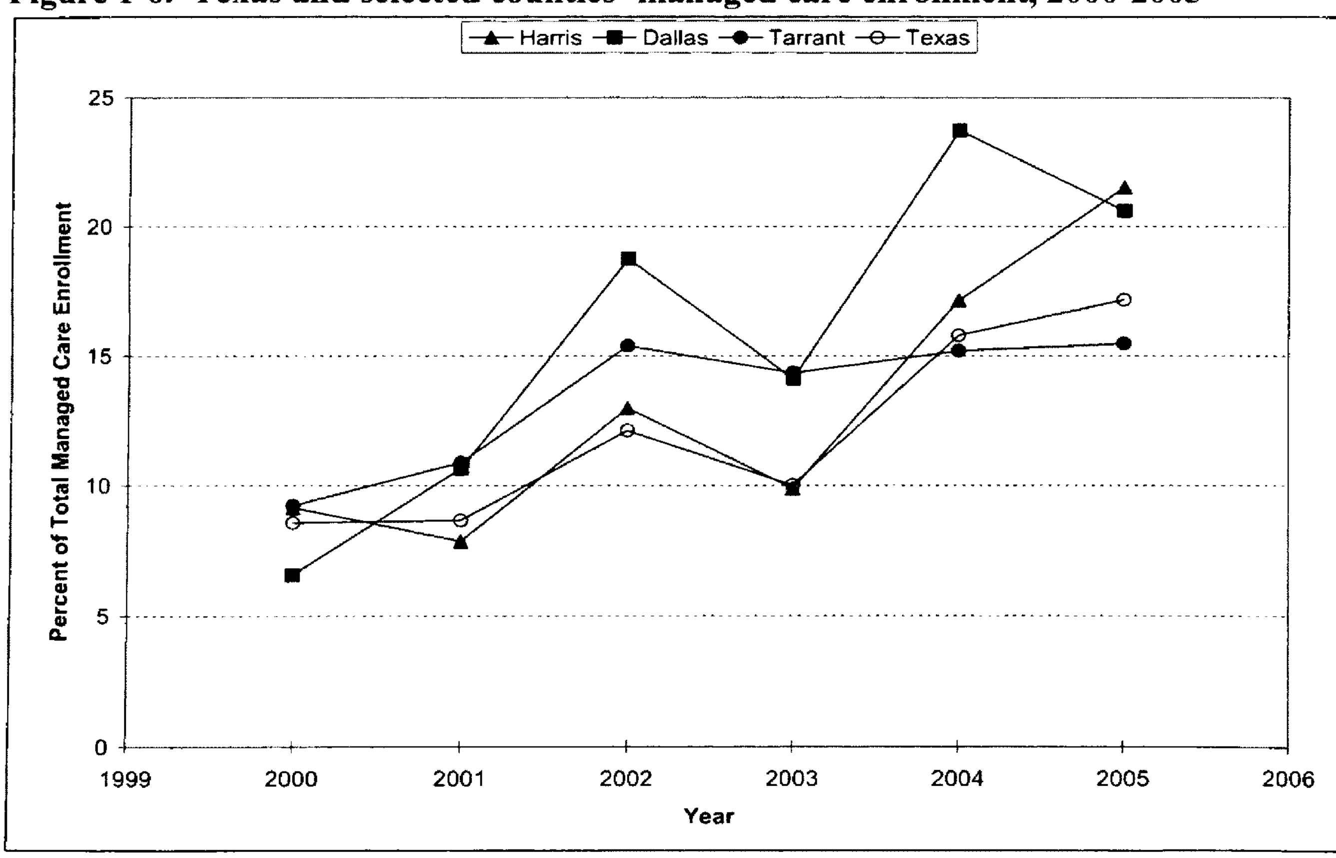
experienced a slow, steady decline in enrollment. During the same period, the Medicare+Choice (Medicare managed care) program also had difficulty with retaining enrollees after a healthy expansion during most of the 1990's (Gold, 2003, April 2), although the federal government still relied on managed care as a means to control Medicare costs (Shen & Melnick, 2006). Contrary to the decline in private and Medicare enrollment, state and local governments, with hopes of easing program costs, increasingly placed their Medicaid enrollees into managed care plans (Marquis et al., 2004). States are attracted to Medicaid managed care (Hurley & Somers, 2003).

Medicaid is an important portion of hospitals' revenues (Quinn, 2008). However, managed care plans reduce hospitals' revenues (Shen, Wu, & Melnick, 2008) because managed care plans typically negotiate deep discounts on hospitals' rates (Bamezai, Zwanziger, Melnick, & Mann, 1999; D. A. Draper, Hurley, Lesser, & Strunk, 2002). However, large managed care buyers, such as government programs (i.e., Medicare and Medicaid), can extract even larger discounts off hospitals' established rates due to their patient-channeling ability (Wu, 2009). In Texas, county-owned (i.e., local government) hospitals may be disproportionately affected by Medicaid managed care (Holahan, Zuckerman, Evans, & Rangarajan, 1998).

Texas has one of the least generous Medicaid programs in the nation. For federal fiscal year 2006, the state ranked 48th of 51 (including the District of Columbia) in Medicaid payments per enrollee (Kaiser Family Foundation, 2006).

As shown in Figure 1-6, the government-funded fraction of the total number of people enrolled in managed care in Texas increased rapidly between 2000 and 2005. Referring back to Figure 1-3 again, this growth conveys three central trends within the overall managed care environment in Texas: [1] the diminished impact of commercial HMO enrollments; [2] the stability of commercial PPO enrollment; and [3] the overall growth trend in Medicaid HMO enrollment. Figure 1-6 also conveys for two of the three most populated Texas counties (i.e., Harris and Dallas), the government-funded portion of total managed care enrollment steadily increased and was larger than that of the state overall. For the third county (Tarrant), its portion was less than that of Harris and Dallas counties, but it approximated the Texas percentage enough as to be a negligible difference.[5] The sole overall growth shown in Figure 1-3 is that of Medicaid HMO enrollment.

Figure 1-6. Texas and selected counties' managed care enrollment, 2000-2005



[5] Ibid.

The single most important message from Figure 1-6 is that the government-funded fraction of total managed care enrollment progressively increased between 2000 and 2005. This trend has implications to hospitals recalling that large managed care buyers, such as government programs (i.e., Medicare and Medicaid), can obtain even larger discounts than commercial managed care products due to their patient-channeling ability (Wu, 2009).

1.3 Research Problem

Uncompensated care costs in Texas' acute care hospitals totaled $2.6 billion in 2000, representing more than 11 percent of total hospital expenses. These costs exceeded the national percentage. Hospitals in Texas are responsible for a sizable fraction of national uncompensated care hospital costs. Texas has the highest state percentage of health care uninsured and a prominent prescriptive charity care law for not-for-profit hospitals. Thus, hospitals in Texas operate in an atypical uninsured environment and the resulting demand for uncompensated care is universal and resolute. Many Texas residents are dependent on their local hospital's supply of uncompensated care.

Texas has a not so insignificant level of managed care penetration; particularly in larger counties where many low-income, uninsured, and under-insured reside and the related demand for uncompensated care provision is high. Although Texas' overall managed care penetration declined from 35 percent in 2000 to 25.5 percent in 2005 (see Figure 1-2), hospitals operating therein must nevertheless continue discounting prices and forgoing revenues to compete for managed care business. Managed care plans typically negotiate deep discounts on hospitals' rates. The government-funded fraction of the total number of people enrolled in managed care in Texas is steadily increasing (see Figure 1-4). The reason for growth of managed care in Medicare and Medicaid is the potential for cost reduction, especially in inpatient areas. For example, Medicare inpatient days per 1,000 population average approximately 2,700 to 2,800 in traditional fee-for-service plans, but decrease to 1,200 in Medicare risk contracts. Medicaid inpatient days per 1,000 population average 1,100 in traditional programs, but decrease to 600 in managed care programs. The potential for cost reduction is enormous and government fiscal pressure is forcing the movement to managed care (Cleverley, 1997). Large managed care buyers, such as government programs, can extract even larger discounts and competitive forces make it difficult for hospitals to shift the costs of caring for low-income, uninsured, and under-insured onto paying patients. County-owned hospitals in Texas may be disproportionately affected by Medicaid managed care.

The ongoing uncompensated care demand, managed care discounts, and even bigger discounts for the expanding fraction of government-funded managed care put additional fiscal pressure on Texas hospitals. This pressure will continue increasing as government-funded managed care persists in becoming an even larger fraction of total managed care enrollment, as indicated in Figure 1-6, and additional hospital discounts are extracted. This interplay of uncompensated care demand and managed care discounts could eventually place Texas' hospitals' uncompensated care supply at risk.

1.4 Significance

This study is significant from four perspectives. First, there are no published studies, of which the author is aware, that have investigated how the extent of government-funded managed care (i.e., Medicare and Medicaid HMOs) impacts hospitals' provision of uncompensated care in a high-uncompensated care demand state such as Texas. This study creates new knowledge about the effects of government-funded managed care on hospitals' uncompensated care provision. Second, this study supports existing literature on the effects of commercial managed care on hospitals' uncompensated care provision. Third, there are no published studies, of which the author is aware, that have integrated quality outcome measures (risk-adjusted mortality) into the study of hospitals' uncompensated care provision. This study integrates quality outcome measures into the study of hospitals' uncompensated care provision. Fourth, this study expands the existing literature relating to the effects of physician-owned specialty hospitals on other hospitals' uncompensated care provision.

This study aims to generate original knowledge on the relationship between hospitals' uncompensated care provision and government-funded managed care by taking advantage of the unique uncompensated care demand environment in Texas, by introducing quality outcome measures, and by introducing physician-owned specialty hospital measures to this particular area of health services research.

The results of this study will benefit hospital administrators, trustees, industry leadership, policy makers, regulators, advocacy groups, and others at the local, state, and national levels that are interested in and concerned about factors that influence hospitals' provision of uncompensated care.

Chapter 2 – Literature Review

2.1 Terminology

This study will utilize the terms bad debt, charity care, and uncompensated care. These terms are explicated below from the perspective of a hospital located in Texas.

2.1.1 Bad Debts

Bad debts relate to amounts owed to a hospital by patients who can pay. Bad debts are income lost to a hospital due to failure of patients to pay amounts owned (AcademyHealth, 2004). Bad debt expense is the current period charge for actual or expected doubtful accounts resulting from the extension of credit (American Institute of Certified Public Accountants, 2001). For Texas hospital reporting purposes, bad debt expense is the accounting provision of actual or expected uncollectibles resulting from the extension of credit (Texas Department of State Health Services, 2000-2005). Bad debts may sometimes be recovered by increasing charges to paying patients. Some cost-based reimbursement programs reimburse certain bad debts. The impact of the loss of revenue from bad debts may be partially offset for for-profit hospitals by the fact that income tax is not payable on income not received.

2.1.2 Charity Care

Charity care relates to services provided to those who are unable to pay. Charity care generally refers to services provided by hospitals to persons who are unable to pay for the cost of services, especially those who are low-income, uninsured, and under-insured

(AcademyHealth, 2004). Charity care is the provision of health care services that were never expected to result in cash inflows and results from a hospital's policy to provide healthcare services free of charge to persons who meet certain financial criteria (American Institute of Certified Public Accountants, 2001). For Texas hospital reporting purposes, charity care results from a provider's policy to provide health care services free of charge to individuals who meet certain financial criteria (Texas Department of State Health Services, 2000-2005).

2.1.3 Uncompensated Care

When bad debts and charity care amounts are aggregated, they are referred to as uncompensated care (i.e., bad debts + charity care = uncompensated care). Thus, uncompensated care is service provided by a hospital for which no payment is received from the patient or from third-party payers (AcademyHealth, 2004). Some costs for these services may be covered through cost shifting although competitive forces make the practice difficult. (Zwanziger & Bamezai, 2006). Not all uncompensated care results from charity care. It also includes bad debts from persons who are not classified as charity cases for which no payment is expected, or no charge is made. Uncompensated care includes entire or partial bills from the uninsured, as well as unpaid co-payments and deductibles. It does not include the contractual allowances of government and private insurers, lack of Medicare or Medicaid payment for days beyond a length of stay limit, or discounts (Ashby, 2002). A contractual allowance (contractual adjustment) is the difference between what hospitals bill and what they receive in payment from third-party payers, most commonly government programs (AcademyHealth, 2004). For Texas hospitals, uncompensated care is care for which no payment is expected, or no charge is made. It is the sum of bad debt expense and charity care costs absorbed by a hospital in providing health care services for patients who are uninsured or unable to pay (Texas Department of State Health Services, 2000-2005).

Although charity care and bad debt are aggregated for purposes of this study, each component has been studied separately (Buczko, 1994) in addition to uncompensated care. Bad debt has been studied separately (Kwon, Stoeberl, Martin, & Bae, 1999; Weissman, Lukas, & Epstein, 1992; Zhang, 2005). Buczko (1994) argues that uncompensated care should be disaggregated into its respective charity care and bad debt components considering that the factors that influence each are different. However, previous research studies have aggregated charity care and bad debt because hospitals' classification of the two components has not been consistent due to the difficulty in distinguishing the difference between them (Atkinson et al., 1997; Gaskin, 1997; Kane & Magnus, 2001; Magnus, Smith, & Wheeler, 2004; Mann et al., 1997; McKay & Meng, 2007; Nicholson, Pauly, Burns, Baumritter, & Asch, 2000; Rosko, 2004; Rundall, Sofaer, & Lambert, 1988; Sloan, Blumstein, & Perrin, 1986; Thorpe, Florence, & Seiber, 2000; Thorpe et al., 2001; Weissman, 2005). For example, for-profit hospitals may be more likely to attempt collection from uninsured patients than not-for-profit hospitals and thus would be more likely to list care provided where no payment is collected as bad debt. In some observations of this study, hospitals coded all of their non-reimbursed care entirely as bad debts, or entirely as charity care. Both charity care and bad debt have been shown to be significantly related to the amount of hospital care provided to low-income patients (Weissman, Dryfoos, & London, 1999). Criteria hospitals use for classifying the two components of uncompensated care can vary in substance and specificity across states (Buczko, 1994).

2.2 *Literature Review*

2.2.1 Distribution of Uncompensated Care

Descriptive analyses have found that the distribution of uncompensated care across hospitals is disproportionate. Specifically, large urban local government hospitals provide about one-third of the total uncompensated care nationwide, and the share of total uncompensated care for urban, local government teaching hospitals is three times as large as their share of the total hospital market (Mann et al., 1997). Public hospitals and urban academic medical centers are viewed as safety-net institutions (Baxter & Mechanic, 1997; Fishman, 1997; Fishman & Bentley, 1997; National Association of Public Hospitals and Health Systems, 2006) which are important to the communities they serve (Atkinson et al., 1997; Cunningham & Tu, 1997; Fishman & Bentley, 1997; Meyer, 2004; National Association of Public Hospitals and Health Systems, 2006). Institutional theory suggests a positive association between hospital size and uncompensated care provision would occur because larger hospitals may be under pressure to conform to external pressures due to their higher visibility (Oliver, 1991).

There are certain differences between urban and rural hospitals' provision of uncompensated care. Some studies found that the impact of uncompensated care on rural hospitals was equal to or higher than that of urban hospitals (Duncan & Miller, 1989; Feder & Hadley, 1983). However, in absolute terms, large urban, mainly teaching, hospitals provide a bulk of the uncompensated care (Fishman, 1997; Mulstein, 1984). Hospitals in the South provide more uncompensated care than those elsewhere in the U.S. (Fishman, 1997; Sloan, Valvona, & Mullner, 1986). Other work found that in MSAs under 250,000 and those between 250,000 and 1,000,000 population were associated with less uncompensated care provision (Thorpe et al., 2001).

2.2.2 System/Alliance Membership and Uncompensated Care

Studies are mixed as to whether membership in a multi-hospital system is related to uncompensated care provision. Some studies found that multi-hospital system membership reduces uncompensated care provision (Buczko, 1994; Morlock, Alexander, & Hunter, 1985). Some studies found there is no effect resulting from multi-hospital membership on provision of uncompensated care (Pattison & Katz, 1983; Rosko, 2004; Sloan & Vraciu, 1983). Other work found that membership in a multi-hospital system increases hospitals' provision of uncompensated care (Young, 1996). Similarly, it has been found that there was no effect of alliance membership on provision of uncompensated care (Rosko, 2004). Interrelated work found that affiliation with a health system or health network was positively related to community responsiveness (S.-Y. D. Lee, Alexander, & Bazzoli, 2003).

2.2.3 Competition and Uncompensated Care

Studies of how competition among hospitals affects their provision of uncompensated care are varied. One study found that hospitals in more competitive markets tend to provide more uncompensated care than those in less competitive markets (Mann et al., 1997). Studies using the Herfindahl-Hirschman Index (Herfindahl, 1950; Hirschman, 1964; Rhoades, 1993; U.S. Department of Justice, 2006) as a measure to assess the effect of competition on hospitals' provision of uncompensated care were mixed. Several such studies found that increased competition among hospitals decreased the provision of uncompensated care (Frank, Salkever, & Mitchell, 1990; Gaskin, 1997; Gruber, 1992, 1994; Young, 1996).

However, one study found no competitive effect on the supply of uncompensated care (Rosko, 2004).

2.2.4 Provision of Social Goods and Uncompensated Care

Economic theories of hospital behavior suggest that hospitals trade off margins or profits against the costs of providing social goods, including uncompensated care provision (Banks, Paterson, & Wendel, 1997; Frank, Salkever, & Mitchell, 1990; Gaskin, 1997; Gruber, 1992, 1994; Hadley & Feder, 1985; Norton & Staiger, 1994; Thorpe et al., 2001). Management theory (Emerson, 1962; Pfeffer & Salancik, 1978) conveys that organizations adapt to their environments, implying that hospitals provide uncompensated care to meet their community's needs.

2.2.5 Teaching Status and Uncompensated Care

In most uncompensated care studies, teaching status is routinely associated with increased uncompensated care provision (Banks et al., 1997; Frank & Salkever, 1991; Frank, Salkever, & Mitchell, 1990; Mann et al., 1997; McKay & Meng, 2007; Reuter & Gaskin, 1997; Rosko, 2001a; Thorpe et al., 2001; Young, 1996). Although one study (Rosko, 2004) indicated no association between the ratio of residents-to-beds and uncompensated care provision. Two descriptive studies associated teaching status with increased uncompensated care (Frank, Salkever, & Mullann, 1990; Weissman, Gaskin, & Reuter, 2003).

2.2.6 Control and Uncompensated Care

Results regarding hospital control are varied. Although government control has usually been associated with a positive effect on the provision of uncompensated care (Campbell & Ahern, 1993; Feder, Hadley, & Mullner, 1984; Mann et al., 1997; McKay &

Meng, 2007; Sloan, Valvona et al., 1986; Thorpe et al., 2001), some studies have found that there is no difference between not-for-profit and for-profit hospital control (Clement, White, & Valdmanis, 2002; Norton & Staiger, 1994). Other studies have found that, *ceteris paribus*, for-profit hospitals provided less uncompensated care than not-for-profit hospitals (McKay & Meng, 2007; Thorpe et al., 2001) and non-public hospitals provide less uncompensated care (Magnus et al., 2004). Additionally, studies have found for-profit hospitals provide less uncompensated care when a government hospital is found in their market area (McKay & Meng, 2007) and not-for-profit private hospitals provide less charity care when there is a public general hospital in their market area (Thorpe & Brecher, 1987). However, uncompensated care provision is not limited to public and teaching hospitals (Zuckerman, Bazzoli, Davidoff, & LoSasso, 2001).

2.2.7 Profit and Uncompensated Care

In examining the effect of profit on uncompensated care, previous studies have come to differing conclusions. Some studies found that higher profit was associated with an increased provision of uncompensated care (Frank, Salkever, & Mitchell, 1990; McKay & Meng, 2007), while other studies found profit was not associated with uncompensated care provision (Campbell & Ahern, 1993; Gaskin, 1997; Rosko, 2001a). Similarly, a recent panel study found that operating and non-operating surpluses had an positive effect, at the $p < .10$ significance level, on provision of uncompensated care (Rosko, 2004).

2.2.8 Debt and Uncompensated Care

Corporate finance theory and the literature on hospital financing suggest that debt may constrain hospitals' capacity to deliver uncompensated care, an output fundamental to many hospitals' missions. However, studies have found that debt is positively associated with the supply of uncompensated care or a component thereof. In a panel study of 189 not-for-profit voluntary and religious California hospitals from 1988 to 1991 that evaluated the effects of lagged tax-exempt debt on the supply of charity care concluded that subsidies provided by tax-exempt debt issues were an effective way to increase the supply of charity care by hospitals (Hassan, Wedig, & Morrisey, 2000). In a cross-sectional study of 298 not-for-profit U.S. hospitals in 1997 found that a long-term debt to capitalization ratio predicted higher levels of uncompensated care provision and its bad debt component, but not for the charity care component which was insignificant (Magnus et al., 2004).

2.2.9 Managed Care and Uncompensated Care

Regarding the effect of managed care provision on uncompensated care supply, previous studies once more have disparate conclusions. In some studies, managed care, as measured by HMO penetration, had no significant effect on the provision of hospital uncompensated care (Clement et al., 2002; Frank, Salkever, & Mitchell, 1990). However, other studies found that a higher level of HMO penetration had a negative and significant effect on hospital uncompensated care provision (Mann et al., 1997; Thorpe et al., 2001). A uncompensated care study using hospital debt as an explanatory variable found that the percentage of gross patient revenues derived from managed care had a negative and significant effect on hospital uncompensated care provision (Magnus et al., 2004). For not-for-profit hospitals, one study found that as HMO penetration increased, for-profit-like performance became more important (Bertrand, Hallock, & Arnould, 2005). A study using a proportional hazards model, examined the effects of HMO penetration on the survival of safety net hospital services (i.e., those services used disproportionately by the low-income, the uninsured, and the vulnerable population) and found that the risks of shutting down hospital safety net services do not vary by different levels of overall HMO penetration (Shen, 2009).

Of particular interest for this paper, two recent studies evaluated the effect of distinct subsets of managed care on hospital uncompensated care provision. The first study using data on urban, acute-care hospitals in Florida over the period 1998 to 2002 and a hospital-level measure of managed care (i.e., percent of total patient days paid by commercial HMOs and PPOs) as contrasted to a market penetration measure, found a negative and significant managed care effect on hospital uncompensated care (i.e., uncompensated care cost as percent of operating expenses) provision in urban areas (McKay & Meng, 2007). The second study using American Hospital Association ("AHA") data aggregated to the state-level for all short-term general nonfederal hospitals over the period 1990 to 2000 and a Medicaid managed care penetration measure, found a negative and significant effect on hospital uncompensated care (i.e., uncompensated care cost per capita) provision at the state level (LoSasso & Seamster, 2007).

2.2.10 Fiscal Difficulties and Uncompensated Care

Financial difficulties may accrue to hospitals that supply uncompensated care. Hospitals require patient revenues sufficient to cover most of their financial needs, which include operating expenses and growth in working capital, long-term debt obligations, provision for technological change, and risk reserves (Cleverley & Harvey, 1990). Loss of patient revenue due to uncompensated care influences the financial health of hospitals and may jeopardize their ability to carry out their mission (Bazzoli et al., 2006; M. E. Lewin & Altman, 2000; Melnick et al., 2000; Zuckerman et al., 2001). Some work has found that provision of uncompensated care negatively affects hospitals' ability to provide the services for which they do receive compensation (Ferrier, Rosko, & Valdmanis, 2006). Related work found a negative relationship between uncompensated care and inefficiency (Rosko, 2001b) meaning costs could be reduced by the pressures of uncompensated care. There is evidence payers do not compensate adequately for severity of illness which result in financial losses for hospitals (Carpenter, Rosko, Louis, & Yuen, 1999).

2.2.11 Quality and Uncompensated Care

The Medicare Prescription Drug, Improvement, and Modernization Act of 2003 (P.L. 108-173) established financial incentives for hospitals to provide Centers for Medicare and Medicaid Services ("CMS") with data on indicators of quality care (U.S. Department of Health & Human Services, 2004). CMS selected measures of the quality of care that had been widely endorsed (Antman et al., 2004; British Thoracic Society, 2001; Mandell et al., 2003; Niederman et al., 2001) and that were considered valid and feasible for immediate public reporting (Jha, Li, Orav, & Epstein, 2005). The CMS measures reflect the quality of care for three major clinical conditions: acute myocardial infarction, congestive heart failure, and pneumonia.

Hospital quality measurement efforts have been classified into three approaches: structure, process, and outcomes (Donabedian, 1966, 2003). Recently, these three approaches were detailed and exemplified in a practical work (Romano & Mutter, 2004). Structural measures describe the conditions under which care is provided, and encompass material resources such as facilities and equipment, human resources such as the credentials and experience of health care providers, and organizational characteristics such as patient volume and team nursing. Process measures describe the content of health care, and encompass health care providers' activities in the realms of screening, diagnosis, pharmacotherapy, surgery, rehabilitation, patient education, and prevention. Outcome measures describe changes attributable to health care, and encompass mortality, morbidity, functional status and pain, as well as patients' health-related knowledge, behaviors, and satisfaction (Romano & Mutter, 2004). Outcome measures are of inherent interest to consumers (Mutter, Rosko, & Wong, 2008) because they symbolize the "bottom line" (i.e., life or death outcomes) which really matter to patients and their families and communities (Romano & Mutter, 2004).

A recent hospital management paper suggested that cost control activities could influence quality of care (Finkler & Ward, 2003). Additional work found that hospitals' with lower resources allocated to clinical services experienced poorer risk-adjusted mortality outcomes (Mukamel, Zwanziger, & Bamezai, 2002). Hospitals must compete for paying patients to offset the lost revenues and the costs associated with providing uncompensated care. This competition affects inpatient quality of care and various quality dimensions differently (Mutter, Wong, & Goldfarb, 2008). Hospitals that have strengths in certain quality dimensions tend to have weaknesses in others (Romano & Mutter, 2004). It has been shown that hospital competition improves quality in dimensions that are associated with physician skill, expertise, and decision-making, and/or are highly visible to patients and their families (Mutter, Wong et al., 2008). Following Mutter, Wong et al. (2008), this is because hospitals seeking to attract patients in a competitive environment want to show that they offer high quality care. Demonstrating high quality in dimensions that patients understand is critical to hospitals' success. Thus, hospitals pursue the best physicians in the market because they have a major role in directing patient flows.

However, it has also been shown that hospital competitiveness reduces quality in dimensions that are associated with hospital infrastructure, hospital staff, and nursing mix (Mutter, Wong et al., 2008). Again following Mutter, Wong et al. (2008), this is because hospitals facing greater competition and with the resource constraints imposed by uncompensated care provision, respond by shifting resources to supplement quality in one dimension at the expense of another dimension. For example, as resources for the dimensions of quality associated with physician expertise increase, resources for the dimensions of quality associated with infrastructure and support staff are lessened. The latter quality dimension is less visible to patients. This implies that hospitals may favor minimizing facility activities that are less related to dimensions of quality and removed from the view of paying patients. For example, hospitals may favor decreased uncompensated care provision, which is out of view and not likely to be an important consideration for paying patients when choosing a hospital.

2.3 Theoretical Models

2.3.1 Hospital Behavior

Economic models of hospitals' provision of uncompensated care build on earlier, more general microeconomic models of not-for-profit hospital behavior. Pauly (1987) notes that these models all postulate an exogenous net income constraint (e.g., a break-even point, or maximum deficit) but differ according to the nature of the hospital's objective function. He identifies a taxonomy of models: [1] those in which the hospital chooses its input and prices its output to maximize the income of a particular set of agents (e.g., medical staff physicians); [2] those in which the profits maximized in the first model are paid out as in-kind benefits to managers or trustees; and [3] those in which the output itself, or some aspect of it, such as quality, is maximized, thus implying that profit maximization does not occur (Pauly, 1987).

Newhouse (1970) developed a utility maximizing theory for the hospital industry. He advanced a model of not-for-profit behavior in which the hospital decision-maker maximizes utility as a function of quantity and quality of output provided. This utility is maximized subject to a break-even budget constraint. A trade-off between quality and quantity of output maximizes utility. The decision-maker will choose the point on the trade-off curve that yields the highest utility. Newhouse's model was used to assess the effect of the hospital's not-for-profit status on efficiency, and it predicts that not-for-profit status hinders efficiency (Newhouse, 1970).

Feldstein (1971) also proposed a model in which the objective function contains quantity and quality expressed in intertemporal terms. Quantity is expressed as the number of patient bed-days desired by the hospital and is a proportionality relationship of the hospital's desired number of beds. The number of beds, in turn, is determined by the hospital's operating deficit, the labor and non-labor input prices, the price of capital, lagged values of admissions, and mean length of stay. Quality is determined by a production function whose inputs are the prices of labor, non-labor, and capital, and is maximized, subject to a cost constraint (Feldstein, 1971).

Lee (1971) proposed a model that included types of physical capital in the objective function. The hospital engages in "conspicuous production" by seeking to minimize the difference between its desired and prevailing status. That is, hospitals maximize prestige by a vast array of technological advances (M. L. Lee, 1971).

A case of the first type of model in Pauly's (1987) taxonomy above is the "physicians' cooperative" proposed by Pauly and Redisch (1973) in which the medical staff as a group control the hospital. The objective function is net income per medical staff member, expressed as [net income = (quantity × price) – cost of labor – capital inputs]. Physician income is maximized subject to a break-even constraint; the physician group captures all profits. Uncompensated care provision in this model would be determined by the discretionary choices of the medical staff (Pauly & Redisch, 1973).

Friedman and Pauly (1981) proposed a model in which the hospital seeks to maintain the quality of its output at its long-term average level. Since demand is stochastic (random), there is a possibility that a surge in demand will cause quality to fall below its target level. The hospital incurs a penalty if this happens. The hospital seeks to minimize the expected value of its cost function, which includes the penalty discounted across all possible output levels, by choosing the appropriate level of inputs. This model formulation is consistent with the concept of a quality constraint (Friedman & Pauly, 1981).

2.3.2 Uncompensated Care Provision

2.3.2.1 Frank and Salkever Model

Frank and Salkever (1988, 1991) investigate the provision of charity care by hospitals within a theoretical framework of not-for-profit firm behavior. The authors consider several variants of not-for-profit hospitals' behavior. They first develop a theory of utility maximization in which the main arguments are net revenue and the amount of unmet need for care in the community. They then derive comparative static results of two different types of motivation for providing charity care: [1] altruism of government and private providers of charity care; and [2] rivalry in the production of charity care.

Under Frank and Salkever's (1988, 1991) altruism hypothesis, a hospital is only concerned with the total unmet need for care in the community and its alleviation by local collective resources. Therefore, the amount of charity care it provides will be reduced or "crowded-out" by other local sources of such care. Under the rivalry hypothesis, however, hospitals compete for public goodwill through the provision of charity care. The presence of another hospital will therefore cause a hospital to increase its provision of charity care to maintain goodwill. In a variant of the altruism hypothesis, Frank and Salkever (1988, 1991) examine crowding-out in the special case of heterogeneous patients (i.e., some types of patients are more attractive to a hospital than others). In their study, they use two groups – more costly and less costly. The former are primarily served by public hospitals and the later primarily by private hospitals.

In Frank & Salkever's (1988, 1991) basic (pure altruism) model, the hospital is assumed to maximize utility via an objective function $U = U(R,N)$, where, the two arguments are net revenue (R) and the amount of need of the indigent that is unmet (N), and where $U_R >$ 0 and $U_N < 0$. The hospital's cost function is $C = C(Q + D)$. Thus, net revenue (R) is defined as $R = PQ + rD + E - C(Q + D)$, where the arguments are sum of endowment income (E), revenues from services $PQ + rD$, where (P) is the fixed price, (Q) is the number of paying patients, (D) is the number of indigent patients, and (r) is the revenue per indigent patient (where $0 \leq r \leq P$).

The level of unmet need (N) is defined $N = T - D - H - G$, where the arguments are total community indigent care need (T), the number of indigents served by the hospital (D), other not-for-profit hospitals (H), and public hospitals (G). If the not-for-profit hospital chooses its own supply of indigent care (D) conditional on the amount supplied by other not-for-profit hospitals (H), then the function is $U = U[(PQ + rD + E - C(Q + D)),(T - D - H - G)]$.

Frank & Salkever (1988, 1991) use data on Maryland hospitals to test the three theoretical formulations. They find strong evidence of rivalry when using data for both inpatient and outpatient care, but not when inpatient stays only are used. Their findings suggest that crowding-out dominates rivalry in the case where a second hospital enters a single-hospital market. With respect to a price variable, they detect a strong substitution effect as opposed to an income effect.

Frank & Salkever (1988, 1991) draw two potential lessons from their results. The first is that, due to rivalry, increasing the number of hospitals in an area probably increases the provision of charity care. The second lesson is that, given, the evidence for a substitution effect, reductions in prices paid to hospitals for paying patients lead to increases in charity care provision. The implication is that indigent care funding schemes involving regional pools financed by taxes on hospital revenues are a feasible way to provide charity care without increasing the amount of resources flowing to the hospital sector (Frank & Salkever, 1988, 1991).

2.3.2.2 Extensions of Frank & Salkever Model

Frank, Salkever, and Mitchell (1989, 1990) extend and modify the Frank & Salkever (1988, 1991) model along three dimensions. First, they allow the model to take into account non-price competition by introducing an index of "quality", q, as a determinant of quantity. The quality index also is incorporated into the cost function. Second, they introduce the effect of competition among hospitals by making price a function of both Q, quantity, and X, a demand-shift parameter representing the shopping effort of bulk purchasers, such as managed care plans ($P_x < 0$). Third, they allow philanthropic donations to the hospital to be endogenous. Consistent with the model of not-for-profit firm behavior (Rose-Ackerman, 1987), they make donations a function of the amount of charity care the hospital provides and its level of need, defined by its financial position.

In their empirical work, Frank, Salkever, and Mitchell (1989, 1990) use data from Florida spanning the period 1982 to 1984 for testing the role of donations and the period 1980 to 1984 to test models of charity care provision. Unlike the earlier papers by Frank & Salkever (1988, 1991), they found strong evidence of an income effect. They infer that the downward pressure on hospital prices increasingly exerted by bulk purchasing agents will squeeze margins and consequently reduce the supply of charity care. From the modeling of donations, they conclude that the reduction in charity care will be alleviated to a small degree by increased philanthropic giving (Frank, Salkever, & Mitchell, 1989, 1990).

Gruber's (1992, 1994) simplification of Frank & Salkever's (1988, 1991) basic model assumes a monopolistic framework, where the hospitals are price setters, and the demand for hospital services is somewhat elastic with respect to the price charged. That is, hospitals are assumed to care about both their net revenues and the care that they deliver to the uninsured. Gruber's simplified model integrated the notion that the price charged private paying patients is endogenous. In his model, hospitals are assumed to maximize objectives of the form: Max $V[R,U]$, subject to $R = pq - c(q) - U$, where R is net revenues, U is uncompensated care, p

is price per unit of service, q is quantity of services, and *c(q)* is the hospital cost function; $c_q > 0$, $c_{qq} > 0$, assuming that $q = p^{-\beta}$. The goal of the modeling exercise was to assess the effect of an increase in the price elasticity of demand on uncompensated care delivery. His model predicts that hospitals will increase uncompensated care until the utility loss from reduced revenues equals the utility gain from uncompensated care provision. He studied the effect of increased price shopping on California hospital markets over the period 1984 to 1988, and found a large fall in net private revenues and net income in the least concentrated hospital markets in the state after the introduction of price shopping. Gruber argues that this could result in a dramatic fall in care to the uninsured in these markets, relative to more concentrated markets. He finds evidence that increased competition in less concentrated markets is associated with a decrease in uncompensated care provision (Gruber, 1992, 1994).

Gaskin (1997) assumes that not-for-profit hospitals maximize the utility function $U(\pi, \eta, w)$ where, $U_\pi > 0$, $U_\eta < 0$, and where, π is net income, η is the level of unmet demand for indigent care in the hospital's market, and w are exogenous hospital characteristics that determine organizational value. Unmet need equals total need for charity care services in the hospital's market, Ω, minus charity care provided at the hospital, δ, and other hospitals, Δ; that is $\eta = \Omega - \Delta - \delta$, where $\eta > 0$ (Gaskin, 1997).

Banks, Paterson, and Wendel (1997) developed separate not-for-profit and for-profit hospital models for provision of uncompensated care. Their not-for-profit model is based on standard Frank & Salkever (1988, 1991) model, as simplified by Gruber (1992, 1994). The for-profit model is based on Gray's (1991) analysis of for-profit hospital behavior. Both of the models depend on two presumptions about the underlying market for uncompensated care. First, hospitals are presumed to exercise control over the amount of uncompensated care supplied. While all hospitals must supply uncompensated care in life-threatening situations, the models focus on hospitals that supply some discretionary uncompensated care in addition to this baseline. Second, the medically indigent demand for uncompensated care is presumed to exceed hospital-desired supply, so that hospitals are always able to attract the desired number of uncompensated care patients.

Not-for-profit hospitals are presumed to maximize utility (H), which is a function of uncompensated care (U). The utility function $H(U)$ is a special case of the maximand presented by Frank & Salkever (1988, 1991) and Gruber (1992, 1994) which assumes that not-for-profit hospitals earn net revenue to subsidize charitable services. Hospital provision of U is subject to the constraint of fiscal viability; hence these hospitals maximize provision of U, subject to the constraint $\pi = P(Q;d)Q - C(Q,U) - F = 0$, where π is the not-for-profit hospital's profit function; $P(Q;d)$ is the average revenue for uncompensated care; Q is patient days of compensated care; d is the demand curve shift parameter; $C(Q,U)$ is the variable cost of producing Q and U; and F is the fixed cost. Consistent with the traditional view, this not-for-profit model indicates that such hospitals respond to a downward shift in demand by reducing U. In other words, the model not-for-profit hospitals will respond to increased competition by reducing their supply of uncompensated care.

For-profit hospitals are hypothesized to supply uncompensated care to the extent that doing so maximizes profits. Since these hospitals incur costs if the local community perceives that a hospital under produces uncompensated care (Gray, 1991), for-profit hospitals supply uncompensated care to reduce the expected penalty of under producing such care, and view uncompensated care expense as a routine cost of doing business (Banks et al., 1997).

2.3.2.3 Other Models

Thorpe and Phelps (1991) proposed a model of hospitals' provision of uncompensated care based on a more general model of charitable organizations (Rose-Ackerman, 1987). In the Rose-Ackerman (1987) model, the manager of a charity has a utility function with two arguments: its output, q, and some other characteristic of the organization, x (perhaps prestige): $U = U(q, x)$. The value of x to donors is not necessarily increasing with respect to it. Her comparative static results show how donations change with respect to total charitable output; increasing x generates an increasing cost resulting from fewer donations. Thorpe and Phelps (1991) modified her model to include the amount of paid care produced as well as the amount of charity care, q in her model. Hospital revenue is the sum of paid care sales, government grants, and private donations. The utility function is maximized, subject to a break-even constraint.

Thorpe and Phelps (1991) test their model using data from New York spanning the period 1981-1984, during which the state implemented the New York Prospective Hospital Reimbursement Methodology, an all-payer reimbursement system. State subsidies for hospitals' provision of uncompensated care changed from being straight block grants to matching grants varying from 0 to 75 percent. The empirical results provided evidence that the price-subsidy method succeeded in generating a net increase in the provision of uncompensated care. The price response varied accordingly to type of hospital: New York City teaching hospitals' was much lower than that of other hospitals. Private hospitals reduced their provision of uncompensated care in response to increased provision of it by public hospitals; thus demonstrating a crowding-out effect (Thorpe & Phelps, 1991).

Chapter 3 – Theoretical Framework and Research Hypotheses

The cost burden of uncompensated care is an increasingly difficult and long-lasting problem for hospitals. More importantly, as more people are enrolled in managed care plans the ability of hospitals to "pay" for uncompensated care becomes a heightened concern. This is because managed care plans typically negotiate substantial discounts off hospitals' established rates due to their bulk purchasing capacity and patient-channeling ability (Wu, 2009), and cost shifting is less an option than in the past due to competition (Morrisey, 1995; Zwanziger, Melnick, & Bamezai, 2000). If hospitals' profit margins decline, cost pressures could increase and potentially jeopardize hospitals' supply of uncompensated care (Bazzoli et al., 2006; M. E. Lewin & Altman, 2000; Melnick et al., 2000; Zuckerman et al., 2001).

Although a variety of alternative methods have been proposed to fund hospital services for those who cannot pay, no major policy changes appear likely. The political and economic climate in the U.S. places constraints on the manner in which the problem of hospital uncompensated care can be solved (Bookheimer, 1989).

Consequently, an enhanced understanding of the effects of managed care subsets, including government-funded managed care, on hospitals' provision of uncompensated is important to hospital administrators, trustees, industry leadership, policy makers, regulators, advocacy groups, and others at local, state, and national levels that are concerned about factors that influence hospitals' provision of uncompensated care at the state level.

3.1 Study Objective

The primary objective of this study is to examine the effects of Medicare and Medicaid managed care on Texas hospitals' uncompensated care provision.

3.2 Theoretical Framework

A particular hospital's choices about the quantity of uncompensated care it will provide depend on its objectives, characteristics, and on the nature of the market in which the hospital is located. Building generally from Frank, Salkever, and Mitchell (1989, 1990), Frank & Salkever (1988, 1991), and considering the preceding theoretical and related applied literature, this study conceptualizes provision of uncompensated care as depending upon a hospital's provision of government-funded managed care, non-government-funded managed care, profit, mission, demand for uncompensated care, and other hospitals' supply of uncompensated care, controlling for market and hospital characteristics. The term "government-funded managed care" refers to Medicare and Medicaid-funded managed care. Accordingly, the theoretical model for this study is expressed as:

Uncompensated care = *f* (government-funded managed care provision,
non-government-funded managed care provision, profit, mission,
demand for uncompensated care, other hospitals' supply of uncompensated care,
market characteristics, and hospital characteristics).

3.2.1 Managed Care Provision

As earlier stated, the objective of this study is to examine the effects of Medicare and Medicaid managed care on Texas hospitals' provision of uncompensated care.

The managed care industry had a period of rapid growth in the early 1990s, motivated by concerns of rising health care costs (Marquis et al., 2004). Since the industry's peak enrollment in 1999, managed care plans (particularly HMOs) in the private sector have experienced a slow, steady decline in enrollment. During the same period, the Medicare managed care program (i.e., Medicare+Choice) also had difficulty with retaining enrollees after a healthy expansion during most of the 1990's (Gold, 2003, April 2), although the federal government still relied on managed care as a means to control Medicare costs (Shen & Melnick, 2006). Contrary to the decline in private and Medicare enrollment, state and local governments, with hopes of easing program costs, increasingly placed their Medicaid enrollees into managed care plans (Marquis et al., 2004). States are attracted to Medicaid managed care (Hurley & Somers, 2003).

Findings from studies that used HMO penetration to measure the effects of managed care are mixed. One study (Thorpe et al., 2001) suggested that increased managed care might affect revenues (resulting from "price shopping" by managed care companies) and/or costs (due to increased incentives for efficiency). If managed care companies were able to negotiate significant price reductions (Dor, Koroukian, & Grossman, 2004), and if that effect dominated any gains from efficiency, then hospitals experiencing an increased amount of managed care would have to lessen provision of uncompensated care in order to preserve a given profit level. At the hospital level, one then would expect a higher extent of managed care to be associated with a lower uncompensated care level. Conversely, if costs fell proportionately more than prices, hospitals could provide more uncompensated care, holding profit constant, and one would expect increased managed care to be associated with a higher uncompensated care level. Studies have found that market-level HMO penetration negatively affects provision of uncompensated care (Rosko, 2001a, 2004; Thorpe et al., 2001). Similarly, a recent study found that managed care penetration, measured at the hospital-level, in terms of the percentage of private managed care (i.e., commercial HMO and PPO) patient days, negatively influenced hospitals' uncompensated care provision (McKay & Meng, 2007).

3.2.2 Profit

A hospital's profit would be expected to influence its provision of uncompensated care. Uncompensated care, which accounted for 5.6 percent of hospitals' expenses in 2004 (Evans, 2005), can have a major effect on hospital's financial performance. Even if uncompensated care is a central element of its mission, a hospital will not be able to provide such care unless it can generate sufficient funds on other care and services to cover the costs of providing care to those who cannot afford to or do not pay. Therefore, one would expect a higher level of hospital profit to result in an increased level of uncompensated care provision. However, profit might be endogenous, with an increased level of uncompensated care having an adverse effect on the level of hospitals' profit. Hospitals' profit has been associated with uncompensated care provision (Frank & Salkever, 1991; Gaskin, 1997; McKay & Meng, 2007). Operating and non-operating surpluses have also been associated with provision of uncompensated care (Rosko, 2004). Core safety net hospitals reduce uncompensated care provision in response to Medicaid financial pressure and voluntary safety net hospitals reduce uncompensated care provision when faced with the combined forces of Medicaid and private sector payment pressures (Bazzoli et al., 2006).

3.2.3 Mission

Both control and teaching commitment would be expected to influence the provision of uncompensated care. With respect to control, the primary objective of a for-profit hospital by definition is to maximize net income, which would imply minimal or no provision of uncompensated care. However, all hospitals, regardless of control type, must comply with legal requirements on providing urgently needed care without consideration of ability to pay (i.e., EMTALA), resulting in a minimum level of uncompensated care. A not-for-profit hospital typically will focus on providing services as delineated in its mission statement, subject to a net income constraint. Generally, provision of uncompensated care will be a major objective of a not-for-profit hospital, if only due to legal considerations associated with its not-for-profit, tax-exempt status. Therefore, not-for-profit hospitals would be expected to provide more uncompensated care compared to for-profit hospitals. Provision of uncompensated care is a function of a hospital's community orientation and not-for-profit hospitals' missions are generally linked to their community's needs. Community orientation, a focus on the community's needs, is high in hospitals that are not-for-profit (Proenca, Rosko, & Zinn, 2000). A local government hospital has a mandate to cover a specific population (e.g., citizens of a county) and receives appropriations from the related taxing entity. Because the funding comes from taxes, provision of uncompensated care typically will be an important objective for a local government hospital; thus, one would expect such hospitals to provide more uncompensated care than not-for-profit or for-profit hospitals.

Two panel studies found that government control positively influenced provision of uncompensated care (McKay & Meng, 2007; Thorpe et al., 2001). Two panel studies found that for-profit control negatively influenced uncompensated care provision (McKay & Meng, 2007; Thorpe et al., 2001). One cross-sectional study found that religious control had no influence on provision of uncompensated care (Rosko, 2001a).

3.2.4 Demand for Uncompensated Care

Demand for uncompensated care would be expected to influence a hospital's level of uncompensated care. For example, two otherwise equivalent hospitals might provide dissimilar levels of uncompensated care if one hospital has many more charity care or bad debt patients who cannot or do not pay, than the other. Research is varied as to whether demand influences hospitals' supply of uncompensated care. Different measures of demand for uncompensated care have been utilized in past studies. Two studies found that the rate of unemployment positively influenced uncompensated care provision (Rosko, 2001a, 2004). However, one study found that the unemployment rate had no significant influence (McKay & Meng, 2007). Per capita income was found to positively influence provision of uncompensated care (McKay & Meng, 2007). However, a different study found per capita income had no influence (Thorpe et al., 2001). The percent of uninsured was found to positively influence uncompensated care provision (Thorpe et al., 2001).

3.2.5 Other Hospitals' Supply of Uncompensated Care

The supply of uncompensated care provided by other hospitals in the area may also influence a hospital's level of uncompensated care provision (Frank & Salkever, 1988; Gaskin, 1997). For example, some previous studies found that the presence of a government hospital in the area reduced the provision of uncompensated care by other hospitals, all else equal (Banks et al., 1997; Clement et al., 2002; Thorpe & Phelps, 1991). Thus, one could expect that having a government hospital in the area, a major provider of uncompensated care, would be associated with a reduction in the provision of uncompensated care by non-government hospitals. Studies are mixed as to whether others hospitals' supply of uncompensated care influenced hospitals' provision of uncompensated care. Some studies found that other hospitals' supply positively influenced uncompensated care provision (Frank & Salkever, 1988, 1991; Gaskin, 1997; Rosko, 2004), while others found no effect (Clement et al., 2002; McKay & Meng, 2007; Rosko, 2001a). For-profit hospitals are believed to influence the supply of uncompensated care. One study found that the for-profit hospitals negatively influence uncompensated care provision (Thorpe et al., 2001). One study found that a for-profit hospital, in the presence of a government hospital in the same market, negatively influenced uncompensated care provision than when no government hospital was in the market (McKay & Meng, 2007). One study found that a not-for-profit hospital, in the presence of a government hospital in the same market, had no influence on uncompensated care provision than when no government hospital was in the market (McKay & Meng, 2007).

3.2.6 Market Characteristics

Market-specific factors may be associated with hospital's uncompensated care provision and their effects should be controlled for. Studies show that specialty hospitals and physician-owned specialty hospitals provide less uncompensated care (Cromwell et al., 2005; Greenwald et al., 2006; U.S. Department of Health & Human Services, 2005). Studies also show the market presence of specialty hospitals is associated with lower operating costs and higher operating margins in general hospitals (Schneider et al., 2007).

Physicians at physician-owned Ambulatory Surgery Centers ("ASC") are more likely than other physicians to refer well-insured patients to their facilities and route Medicaid patients to general hospital outpatient clinics (Gabel et al., 2008, March 18) thereby affecting those hospitals ability to shift the costs of caring for the low-income, uninsured, and under-insured onto paying patients.

The presence of federally subsidized outpatient clinics in a county may affect hospitals' uncompensated care provision and cost shifting in various ways. Access to health care through Federally Qualified Health Centers ("FQHC") reduces emergency room use among the uninsured (Smith-Campbell, 2000, 2005). Rural Health Centers ("RHC") may shift Medicare, Medicaid, and other paying patients away from hospitals (U.S. Department of Health & Human Services, 2006a).

Texas adjoins a porous and extended international border with Mexico. Unauthorized immigration may contribute to Texas hospitals' uncompensated care costs. Research shows that 68 percent of percent of the total number of undocumented U.S. workers are Mexican-born (Bustamante, Ojeda, & Castañeda, 2008). Immigrants to the U.S., both authorized and unauthorized, are less likely than their native-born counterparts to have health insurance (U.S. Census Bureau, 2003).

3.2.7 Hospital Characteristics

In addition to market-level factors, hospital-specific factors may affect uncompensated care provision and their effects should be controlled for. Hospitals have different services that may or may not be frequented by the uninsured. Similarly, hospitals experience dissimilar payer mixes.

Studies are different about how hospitals' bed size affects the supply of uncompensated care. One panel study found that the number of beds positively influences the amount of uncompensated care supplied (Thorpe et al., 2001) although the coefficient was quite small. One panel study found that bed size negatively influenced the amount of uncompensated care provided (McKay & Meng, 2007) but the coefficient was also small. One panel study found no significant bed size effect (Rosko, 2004). Also, one cross-sectional study found that hospitals whose size was equal to or more than 234 beds negatively influenced uncompensated care provision and that those whose size was more than 140 and less than 234 beds had no significant effect on supply (Rosko, 2001a).

Occupancy rates have been positively associated with charity care and negatively associated with bad debt in a cross-sectional study (Buczko, 1994) and had no effect on hospitals' supply of uncompensated care (Magnus et al., 2004). Bad debt and charity care are the components of uncompensated care.

Patient resource consumption may limit hospitals' ability to provide uncompensated care. A large body of research has documented the relationship between severity of illness and resource use per patient utilizing a variety of severity measures. Most of the evidence suggests that severity of illness accounts for some share of variation in resource use over and above that associated with the diagnostic group (Carpenter et al., 1999).

Hospitals' provision of uncompensated care might be impacted by the particular services it offers to the community. According to a federal descriptive report, the most common reason for uninsured hospitalizations from 1997 to 2006 was childbirth (Merrill, Stocks, & Stranges, 2009). Primary care-related emergency department visits are strongly correlated with the rate of uninsurance and poverty in Texas (Begley, Vojvodic, Seo, & Burau, 2006). Emergency department visits, as a percentage of total outpatient visits, positively influence hospitals' provision of uncompensated care (Rosko, 2001a).

Certain routes of admissions into hospitals may affect their uncompensated care provision. Admissions from the emergency room are associated with uninsured hospital stays (Merrill et al., 2009).

Debt financing may affect hospitals' uncompensated care provision. Hospital debt has been associated with uncompensated care provision (Magnus et al., 2004) and charity care provision (Hassan et al., 2000).

Government payers, other than Medicare and Medicaid (both routine and managed care), may affect hospitals' uncompensated care costs. In Texas, local county governments are responsible for providing medical aid and hospital care to the needy inhabitants of their county. Because annual funds for that purpose are limited, county governments typically negotiate discounts with local hospitals to cover as many indigents as possible.

Some types of hospitals may rely on revenues other than patient revenues to support their uncompensated care provision. If a hospital's total expenses are not covered by net patient revenue, then the hospital must rely on other forms of revenue to cover those expenses.

A cross-sectional study, using bad debt as the dependent variable (instead of uncompensated or charity care), found that multi-system membership was negatively related to bed debt provision (Buczko, 1994). In contrast, one study found no significant relationship between either alliance or system membership and the provision of uncompensated care (Rosko, 2004).

An important challenge currently facing hospitals is determining how to provide services that improve patients' health outcomes while simultaneously controlling costs. For example, the federal Medicare Prescription Drug, Improvement, and Modernization Act of

2003 (P.L. 108-173) provided a financial incentive for hospitals to report quality of care data, and more so, hospitals may soon face "pay-for-performance" payment schemes based on a set of process, structural, and outcomes measures (Medicare Payment Advisory Commission, 2005; U.S. Department of Health & Human Services, 2004). A recent hospital management paper supporting evidence-based decision-making management practices argues that quality should be considered as hospital cost control strategies are developed (Finkler & Ward, 2003). Uncompensated care is a cost hospitals seek to control or they seek to minimize other costs to make uncompensated care available. Hospitals with lower resources allocated to clinical services experienced worse risk-adjusted mortality outcomes (Mukamel et al., 2002). This suggests that as hospitals seek to improve patients' health outcomes; they may reduce uncompensated care provision.

Events outside hospitals' control may influence their level of uncompensated care provision. For instance, states may alter eligibility criteria for their Medicaid programs in response to budget pressures. These actions may force enrollees out of such programs and increase their reliance on hospital emergency rooms for care. These events may occur in or carry across various time periods.

3.3 Research Hypotheses

The objective of this study is to examine the effects of Medicare and Medicaid managed care on Texas hospitals' uncompensated care provision, controlling for other managed care provision, profit, mission, demand for uncompensated care, other hospitals' supply of uncompensated care, market characteristics, and hospital characteristics.

Considering the relevant literature, theoretical model, and the study objective above, this study has five research hypotheses.

Hypothesis 1: ***Medicare managed care net revenue, as a percentage of total net patient revenue (P_NPREV_MMCR), is negatively associated with hospitals' uncompensated care provision.***

At the hospital level, one would expect a higher level of managed care to be associated with a lower uncompensated care level. The collective findings of LoSasso & Seamster (2007) relating to Medicaid managed care and McKay & Meng (2007) relating to Commercial managed care suggest that Medicare managed care could negatively influence hospitals' uncompensated care provision.

Hypothesis 2: ***Medicaid managed care net revenue, as a percentage of total net patient revenue (P_NPREV_MMCD), is negatively associated with hospitals' uncompensated care provision.***

At the hospital level, one would expect a higher level of managed care to be associated with a lower uncompensated care level. LoSasso & Seamster (2007) studied how federal and state policies affected hospitals' uncompensated care provision and found that Medicaid managed care penetration negatively affected such provision.

Hypothesis 3: ***Commercial managed care net revenue, as a percentage of total net patient revenue (P_NPREV_MCOM), is negatively associated with hospitals' uncompensated care provision.***

At the hospital level, one would expect a higher level of managed care to be associated with a lower uncompensated care level. McKay & Meng (2007) studied Commercial managed care (i.e., private HMO and PPO patient days) and found that it negatively influenced urban Florida acute care hospitals' uncompensated care provision.

Hypothesis 4: ***Profit margin percent, net of uncompensated care expenses (P_PRFT_NETUC), is positively associated with hospitals' uncompensated care provision.***

A hospital's profit would be expected to influence its provision of uncompensated care. Even if uncompensated care is a central element of its mission, a hospital will not be able to provide such care unless it can generate sufficient funds on other care and services to cover the costs of providing care to those who cannot afford to or do not pay. Various studies including Frank & Salkever (1991), Gaskin (1997), and McKay & Meng (2007) found that hospitals' profit was positively associated with uncompensated care provision.

Hypothesis 5: ***Other hospitals' uncompensated care expense percent (P_OTHUC_C) is positively associated with hospitals' uncompensated care provision.***

The supply of uncompensated care provided by other hospitals in the area may affect uncompensated care provision. Various studies including Frank & Salkever (1988), Gaskin (1997), and Rosko (2004) found that other hospitals' supply of uncompensated care positively influences uncompensated care provision.

Chapter 4 – Methods and Materials

4.1 Study Hospitals

The study hospitals were limited to non-federal, non-state, short-term, acute care medical-surgical hospitals with at least 25 beds located in counties within the MSAs of Texas. The unit of analysis is the hospital. Federal and state hospitals are not included in this study because they do not have identifiable and distinct market areas, and their funding mechanisms and operating characteristics differ from the study hospitals. Local government hospitals are included in the study. The subject study hospitals were identified using a two-step validation method. In the first step, the study hospitals were identified as those where the last four digits of their respective Medicare Provider Numbers were "0001" through "0879", inclusive. Thus, for this study of Texas hospitals the series of subject hospitals' Medicare Provider Numbers were 450001 through 450879 and 670001 through 670879, inclusive. This provider number identification method eliminated hospitals classified by CMS as alcohol/drug, rural primary care, long-term, rehabilitation, psychiatric, and children's facility types. In the second step, the subject study hospitals identified above were crosschecked to verify that they were classified within the Texas Department of State Health Services-American Hospital Association-Texas Hospital Association Annual Survey of Hospitals ("*TDSHS-AHA-THA Annual Survey of Hospitals*") as non-federal, non-state, short-term, acute care medical-surgical hospitals. In addition to federal and state hospitals, facilities not included in the study dataset are those classified within the *TDSHS-AHA-THA Annual Survey of Hospitals* as units of hospitals, units in hospitals, pediatric, psychiatric, tuberculosis, cancer, rehabilitation, chronic disease, mental retardation, acute long-term care, alcohol, and other hospitals not easily classifiable.

The MSAs used in this study are those designated by the federal government in 2006 (Office of Management and Budget, 2006). MSAs have at least one urbanized area of 50,000 or more population, plus adjacent territory that has a high degree of social and economic integration with the core urban area as measured by commuting ties. For Texas, the geographic components of MSAs are whole counties (U.S. Department of Health & Human Services, 2008c). Hospitals located in MSAs were used in this study because facilities located elsewhere either lacked or had numerous zero values for critical explanatory variables. A majority of Texas' population and hospitals are located in its MSAs.

To show spatial distribution of the study hospitals by type of control, the hospitals' physical addresses were geocoded[6] using a research geocoding platform (Goldberg & Wilson, 2010) and mapped in STATA using a thematic mapping program (Pisati, 2007). Thematic maps illustrate the spatial distribution of one or more variables of interest within a given geographic area or unit; thematic dot maps represent spatial distribution of point data (Pisati, 2004). The hospitals' address-associated latitude and longitude point data were dot mapped to Texas county and MSA political maps. Figure 4-1 presents the county point location of the study hospitals, identified by type of control. Figure 4-2 presents the county within MSA point location of the study hospitals, also identified by type of control. Additionally, Appendix U presents detailed information about the counties and number of study hospital observations within the MSAs by county.

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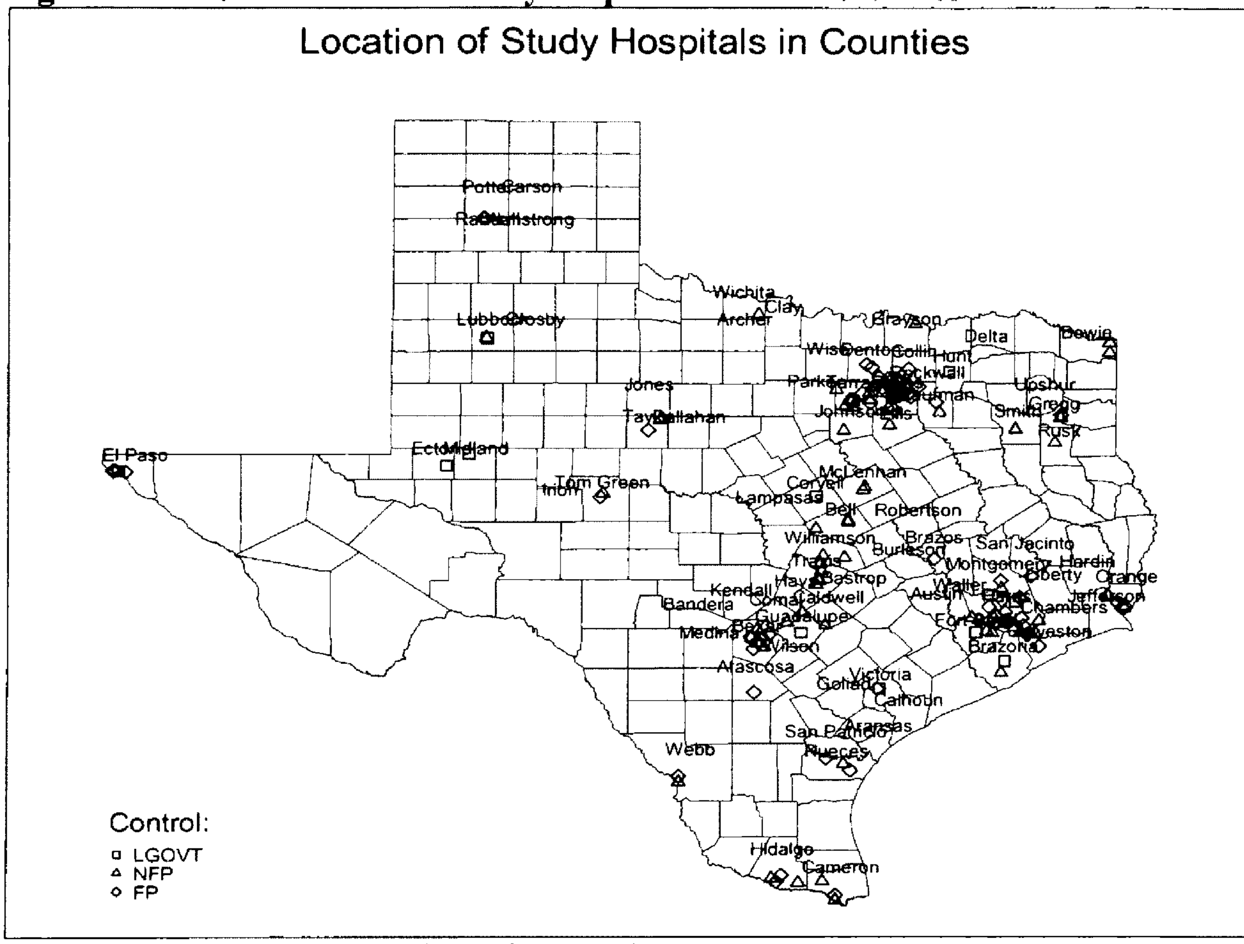
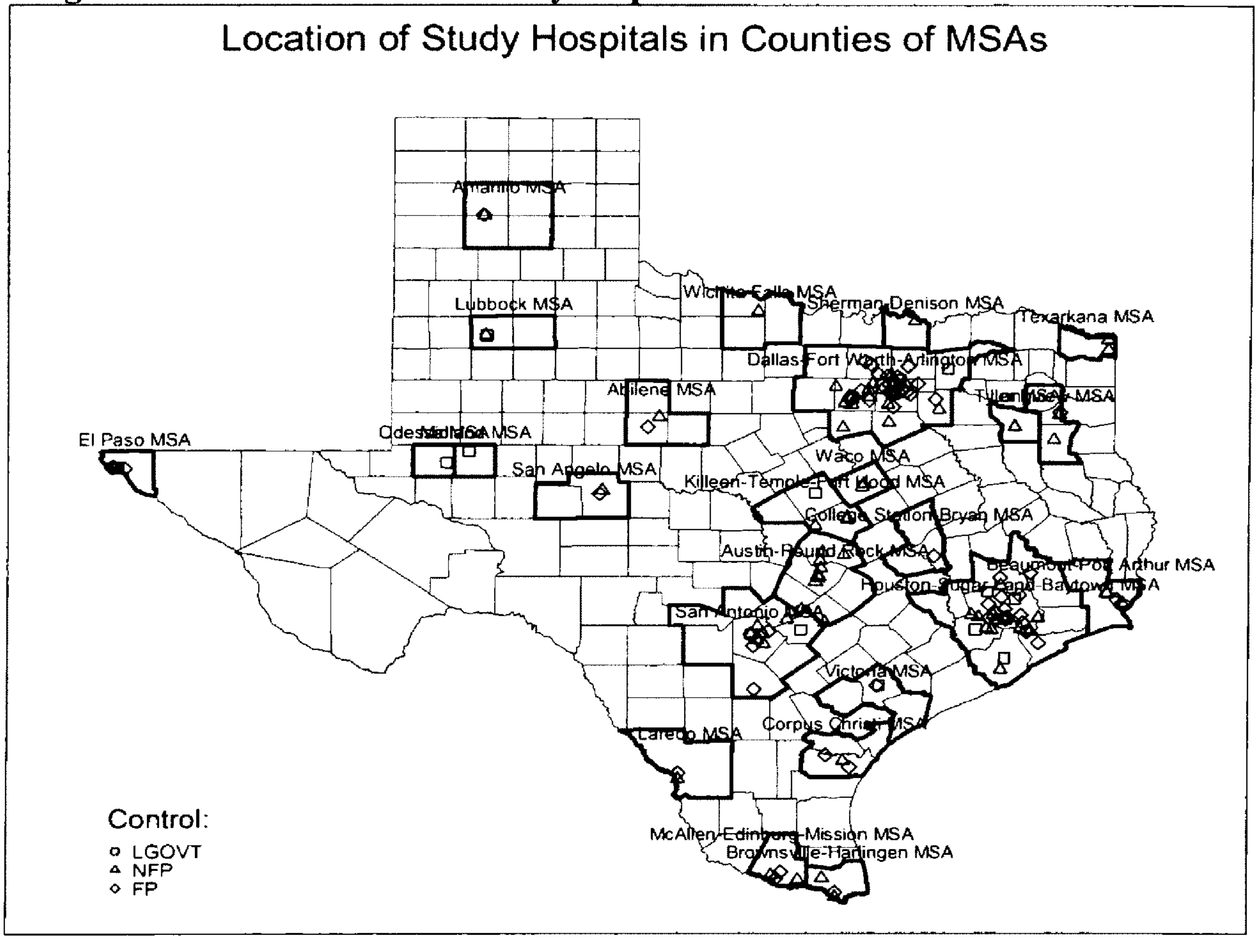
[6] Geocoding is the process of assigning geographic (i.e., latitude and longitude) coordinates to attribute data, including physical addresses.

Figure 4-1. Point location of study hospitals in Texas counties



Note: Thin lines denote counties and names shown are county names

Figure 4-2. Point location of study hospitals in counties of Texas MSAs



Note: Thin lines denote counties and thick lines denote MSAs. Names shown are MSA names.

For inclusion, the study hospitals identified in the steps above must additionally satisfy four documentation requirements. During the study period (described in the subsequent section), each study hospital must have: [1] submitted the *TDSHS-AHA-THA Annual Survey of Hospitals* for each of the years it was in operation; [2] submitted to Texas Health Care Information Council ("THCIC") administrative discharge data for each of the years it operated; [3] submitted a Medicare Cost Report for each of the years it operated; and [4] been in operation for the entire year. Additionally, there must be at least two observations for each study hospital during the study period to accommodate the one-way fixed-effect panel regression methodology (Baum, 2006, p. 222).

The subject study hospitals were selected due to Texas' unique uninsured and uncompensated care market environment, availability of sufficient and accessible historical data, and the author's professional interests.

Three approaches are frequently used to define hospital market areas: geopolitical boundaries, distances among hospitals, and patient travel from residence to the hospital (i.e., patient origin) (Garnick, Luft, Robinson, & Tetreault, 1987). Counties are a type of market area often used for studies of hospitals (Wong, Zhan, & Mutter, 2005). Using geopolitical boundaries, such as counties or Standard Metropolitan Statistical Areas ("SMSA"), have the advantages of practicality and comparability (Garnick et al., 1987). Hospital data can be compared with demographic, social, and economic data published for the same areas, and many researchers use these market areas for studies of market structure on hospital behavior. Market areas composed of several counties may be the most appropriate definition, implying that SMSAs are usually the best market area definition for urban areas (Morrisey, Sloan, & Valvona, 1988).

A single-state analysis has the advantage of controlling for the numerous regulatory and other environmental differences between states, and avoids the confounding effects of state policy on hospitals' provision of uncompensated care. It also allows for a more consistent definition of uncompensated care and other important study variables. Criteria for classifying the components of uncompensated care can vary in substance and specificity across states (Buczko, 1994). Much of what is known about the effects of managed care on hospitals' supply of uncompensated care has arisen from single-state studies (Gruber, 1994; McKay & Meng, 2007; Rosko, 2001a, 2004).

4.2 Study Period

The study period is 2000 through 2005, inclusive. During this interval, there were 155 cross-section (i) observations occurring over 6 one-year time (t) periods, resulting in $N = 750$ panel (it) observations across the entire panel. The panel is unbalanced due to the entrance (opening) and exit (closing) of hospitals during the study period, reporting gaps, and missing study variable data during certain years. The one-way fixed-effect panel data estimator used in this study does not require a balanced panel (Greene, 2007), but it does require at least two observations for each study hospital during the study period (Baum, 2006).

4.3 Data Sources

The panel dataset for this study was assembled from multiple public sources. Components of the study dataset were obtained from two state agencies, the Texas

Department of State Health Services ("TDSHS") for the *TDSHS-AHA-THA Annual Survey of Hospitals* for most hospital-specific variable measures and the THCIC for hospital-specific inpatient quality measures (i.e., risk-adjusted mortality and severity of illness measures). Other data were obtained from CMS for the Healthcare Cost Report Information System ("HCRIS") (i.e., Medicare Cost Reports) and the physician-owned specialty hospital listing. Additional data was acquired from the U.S. Department of Health and Human Services, Health Resources and Services Administration, the Bureau of Health Professions for the Area Resource File ("ARF") for population and demographic information, and the U.S. Department of Homeland Security for the unauthorized immigrant population rates. The data source for each particular variable is in Table 4-1.

The data from the preceding sources are secondary data, a type commonly used in econometric panel analysis of hospitals.

4.3.1 TDSHS-AHA-THA Annual Survey of Hospitals

The TDSHS Center for Health Statistics, in cooperation with the AHA and Texas Hospital Association ("THA"), annually collects data from all licensed hospitals in Texas using the single *TDSHS-AHA-THA Annual Survey of Hospitals* instrument (TDSHS, 2000-2005). The *Annual Survey of Hospitals* collects data elements important to the study of Texas hospitals, including organizational structure, control, service type, demographic, facilities and services, community orientation, beds, utilization, finances, staffing, Medicaid disproportionate share, charity care, community benefits, uncompensated care, and planned facility expansion. State law requires the survey. TDSHS maintains the *Annual Survey of Hospitals* database and transmits the collected data to AHA and THA. The *Annual Survey of Hospitals* is the state's only comprehensive source of hospital-specific information on issues such as uncompensated care and hospital utilization trends. The survey data are used to conduct research and support development of health policy and accompanying programs. Hospitals are required to report their annual data within 60 days following the end of the hospital's fiscal year. For each hospital, the *Annual Survey of Hospitals* provides data elements essential for constructing the dependent variable and some of the explanatory variables used in this study.

Information regarding uncompensated care provision by Texas hospitals is reported in the *TDSHS-AHA-THA Annual Survey of Hospitals*. This dataset is the current best available resource of charity care and bad debt provision information on Texas hospitals. In 2003, hospitals participating in Medicare began reporting information about their uncompensated care and charity care provision in their annual Medicare Cost Reports (U.S. Department of Health & Human Services, 2003). However, the Medicare Cost Report does not capture uncompensated care data for the entire study period and the collected data is not yet reliable (Medicare Payment Advisory Commission, 2007, pp. 50, 85-86).

4.3.2 Texas Health Care Information Council

The THCIC is a division of the TDSHS. The THCIC is responsible for collecting hospital administrative discharge data from all state-licensed hospitals, except those that are statutorily exempt from the state's healthcare information reporting requirement. Exempted hospitals include those located in a county with a population less than 35,000, or those located in a county with a population more than 35,000 and with fewer than 100 licensed beds and not located in an area that is delineated as an urbanized area by the U.S. Bureau of the Census. Exempted hospitals also include those that do not seek insurance payment or government reimbursement.

The THCIC maintains the database of administrative discharge data as the Texas Health Care Information Collection beginning with 1999 data. Additionally, the THCIC produces an annual report, beginning with 2002, on performance by Texas hospitals on certain measures of quality, including inpatient quality indicators. The annual report contains information on the performance of Texas hospitals on quality measures based on volume, mortality associated with inpatient procedures, mortality associated with inpatient conditions, and utilization. The annual report is produced from the administrative discharge data above using inpatient quality indicators developed and refined by the Agency for Healthcare Research and Quality ("AHRQ"). The AHRQ is the health services research division of the U.S. Department of Health and Human Services.

4.3.3 Centers for Medicare and Medicaid Services

4.3.3.1 Healthcare Cost Report Information System

Each year, CMS requires hospitals that bill the Medicare and Medicaid program to submit an annual cost report. Medicare-certified hospital providers are required to submit the report to a designated fiscal intermediary acting on behalf of CMS. These cost reports are a condition of participation in the Medicare program. The reports contain detailed provider information, including facility characteristics, utilization data, cost and charges by cost center (in total and for Medicare), Medicare cost settlement data, and financial statements (U.S. Department of Health & Human Services, 2000-2005). The Hospital Cost Report form is CMS-2552-96, effective for cost reporting periods ending on or after September 30, 1996. CMS maintains the cost report data in the HCRIS database. The HCRIS database comprises subsystems for the Hospital Cost Report and for other additional Medicare-certified providers that are not hospitals. The data is available in a relational database and consists of every data element included in the HCRIS extract created for CMS by the provider's fiscal intermediary. The HCRIS files are updated on a calendar quarterly basis. The quarterly updated data files contain the highest level of Medicare Cost Report status. Instructions for completing the cost report forms are found in the related Provider Reimbursement Manual (U.S. Department of Health & Human Services, 2003). Certain data from those Hospital Cost Reports whose years ended in 2000 through 2005 were used in this study.

4.3.3.2 Physician-Owned Specialty Hospital List

The federal Deficit Reduction Act of 2005, Section 5006 ("DRA"), required that the Secretary of Health and Human Services study the issue of physician investment in specialty hospitals and issue report a report to Congress. As defined by Congress, specialty hospitals are hospitals exclusively or primarily engaged in caring for one of the following categories of patients: patients with a cardiac condition or an orthopedic condition; or patients receiving a surgical procedure. The final DRA report issued by the Secretary included, in part, a national list of physician-owned specialty hospitals (U.S. Department of Health & Human Services, 2006b). The list identified Texas' physician-owned specialty hospitals for this study.

4.3.4 Area Resource File

The ARF is a national county-level health resources information database maintained by the U.S. Department of Health and Human Services, Health Resources and Services Administration (U.S. Department of Health & Human Services, 2008b). The ARF is designed for use by planners, policymakers, researchers, and others interested in the nation's health care delivery system and factors that may impact health status and health care in the U.S.. The ARF contains over 6,000 health-sector and related data elements under the broad tabbed headings of codes and classifications, health professionals, training, health facilities, utilization, expenditures, environment, and population. The ARF elements are obtained from over 50 primary data sources, including the American Medical Association, AHA, U.S. Census Bureau, CMS, Bureau of Labor Statistics, and National Center for Health Statistics. For each county, the 2007 version of the ARF database provided the data elements essential for constructing various explanatory variables used in this study.

4.3.5 U.S. Department of Homeland Security

The U.S. Department of Homeland Security, Office of Immigration Studies, Policy Directorate produces annual immigrant population estimates. The unauthorized immigrant population report published each year provides estimates of the unauthorized immigrant population residing in the U.S. as of January of the prior year for periods of entry and leading countries of birth and states of residence.

4.4 Variable Definitions

Details about the dependent variable and explanatory variables used in this study are in Tables 4-1 and 4-2. Table 4-1 exhibits the variables' name, definition (i.e., calculation or coding scheme), scale (i.e., continuous or binary), and domain (i.e., hospital or county) categorized by the theoretical constructs previously discussed. Table 4-2 exhibits the variables' name, label, type, and source.

An exposition of the dependent and explanatory variables occurs in the succeeding sections. The dependent variable is discussed in Section 4.4.1 and the explanatory variables are discussed in Section 4.4.2.

Table 4-1. Variables' theoretical construct, name, definition, scale, and level

VARIABLE NAME	DEFINITION	SCALE	DOMAIN
	DEPENDENT VARIABLE		
P_UC_TEXP	[((Bad debt + charity care) × (total expenses / total gross patient revenues)) / total expenses]	Continuous	Hospital
	EXPLANATORY VARIABLES		
	Government-Funded Managed Care Provision		
P_NPREV_MMCR	(Medicare managed care net patient revenue / total net patient revenue)	Continuous	Hospital
P_NPREV_MMCD	(Medicaid managed care net patient revenue / total net patient revenue)	Continuous	Hospital
	Other Managed Care Provision		
P_NPREV_MCOM	[Commercial managed care net patient revenue / total net patient revenue]	Continuous	Hospital
	Profit		
P_PRFT_NETUC	[(Total revenues − (total expenses − uncompensated care expenses)) / total revenues]	Continuous	Hospital
	Mission		
FP	1 if for-profit hospital; 0 otherwise	Binary	Hospital
R_INTRES_BED	[(Residents + interns) / total facility beds set-up and staffed at end of reporting period]	Continuous	Hospital
	Demand for Uncompensated Care		
P_UNEMP_C	(Number unemployed age 16+ in county / total civilian labor force age 16+ in county)	Continuous	County
	Other Hospitals' Supply of Uncompensated Care		
P_OTHUC_C	[((Bad debt + charity) × (total expenses / total gross patient revenues)) / total expenses] for other hospitals in county	Continuous	County
	Market Characteristics		
P_POSH_OPS_C	(Total physician-owned specialty hospital outpatient surgeries in county / total outpatient surgeries for hospitals in county)	Continuous	County
R_ASCHOSP_C	(Number of ambulatory surgery centers in county / total study hospitals in county)	Continuous	County
R_FQHCHOSP_C	(Number of federally-qualified health centers in county / total study hospitals in county)	Continuous	County
R_RHCHOSP_C	(Number of rural health centers in county / total study hospitals in county)	Continuous	County
DENS_UPOP_C	(Estimate of unauthorized immigrant population in county / total land area in square miles in county)	Continuous	County
	Hospital Characteristics		
LN_BEDS	Natural logarithm of total facility beds set-up and staffed at end of reporting period	Continuous	Hospital
P_OCCUP	[Total patient days / (total facility beds set-up and staffed at end of reporting period × days in year)]	Continuous	Hospital
SEV_ILL	(Sum of severity of illness scores assigned by 3M APR-DRG Grouper / total discharges)	Continuous	Hospital
R_BIRTHS_ADM	(Births / total admissions)	Continuous	Hospital

VARIABLE NAME	DEFINITION	SCALE	DOMAIN
ERMIX_NETOPS	[Emergency room visits / (total outpatient visits − outpatient surgeries)]	Continuous	Hospital
R_ADM_ERVIS	(Total admissions / emergency room visits)	Continuous	Hospital
PLANT_AGE_R	[1 / (accumulated depreciation / current depreciation expense)]	Continuous	Hospital
P_NPREV_OGOV	(Other government net patient revenue / total net patient revenue)	Continuous	Hospital
R_TEXP_NPREV	(Total expenses / total net patient revenue)	Continuous	Hospital
D_NETWORK	1 if hospital is member of a network; 0 otherwise	Binary	Hospital
IQI_17_R	(1 / risk-adjusted mortality rate for acute stroke)	Continuous	Hospital
IQI_32_R	(1 / risk-adjusted mortality rate for acute myocardial infarction, without transfer cases)	Continuous	Hospital
D_YR_2000	1 if observation from 2000; 0 otherwise	Binary	Hospital
D_YR_2001	1 if observation from 2001; 0 otherwise	Binary	Hospital
D_YR_2002	1 if observation from 2002; 0 otherwise	Binary	Hospital
D_YR_2003	1 if observation from 2003; 0 otherwise	Binary	Hospital
D_YR_2005	1 if observation from 2005; 0 otherwise	Binary	Hospital

Table 4-2. Variables' name, label, and data source

VARIABLE NAME	VARIABLE LABEL	DATA SOURCE
	DEPENDENT VARIABLE	
P_UC_TEXP	Uncompensated care expense percent	TDSHS
	EXPLANATORY VARIABLES	
	Government-Funded Managed Care Provision	
P_NPREV_MMCR	Medicare managed care net patient revenue percent	TDSHS
P_NPREV_MMCD	Medicaid managed care net patient revenue percent	TDSHS
	Other Managed Care Provision	
P_NPREV_MCOM	Commercial managed care net patient revenue percent	TDSHS
	Profit	
P_PRFT_NETUC	Profit margin percent, net of uncompensated care expense	TDSHS
	Mission	
FP	For-profit hospital	TDSHS
R_INTRES_BED	Intern and resident to staffed bed ratio	HCRIS, TDSHS
	Demand for Uncompensated Care	
P_UNEMP_C	County unemployment percent	ARF
	Other Hospitals' Supply of Uncompensated Care	
P_OTHUC_C	Other county hospitals' uncompensated care expense percent	TDSHS
	Market Characteristics	
P_POSH_OPS_C	County physician-owned specialty hospital outpatient surgery percent	DHHS, TDSHS
R_ASCHOSP_C	County ambulatory surgery center to hospital ratio	ARF, TDSHS
R_FQHCHOSP_C	County federally-qualified health center to hospital ratio	ARF, TDSHS
R_RHCHOSP_C	County rural health center to hospital ratio	ARF, TDSHS
DENS_UPOP_C	County unauthorized immigrant population density	ARF, DHS
	Hospital Characteristics	
LN_BEDS^{NL}	Number of staffed beds	TDSHS
P_OCCUP	Occupancy percent	TDSHS
SEV_ILL	Severity of illness	THCIC
R_BIRTHS_ADM	Births per admission	TDSHS
ERMIX_NETOPS	Emergency room mix of outpatient visits, net of outpatient surgeries	TDSHS
R_ADM_ERVIS	Admissions per emergency room visit	TDSHS
PLANT_AGE_R	Reciprocal physical plant age	TDSHS
P_NPREV_OGOV	Other government net patient revenue percent	TDSHS
R_TEXP_NPREV	Total expenses percent of total net patient revenue	TDSHS
D_NETWORK	Network member	TDSHS
IQI_17_R	Risk-adjusted mortality reciprocal rate for acute stroke	THCIC
IQI_32_R	Risk-adjusted mortality reciprocal rate for acute myocardial infarction, without transfer cases	THCIC
D_YR_2000	Year 2000	TDSHS
D_YR_2001	Year 2001	TDSHS
D_YR_2002	Year 2002	TDSHS

VARIABLE NAME	VARIABLE LABEL	DATA SOURCE
D_YR_2003	Year 2003	TDSHS
D_YR_2005	Year 2005	TDSHS

Note: [NL] Natural logarithm transformed

Data Source Legend

ARF: U.S. Department for Health & Human Services, Health Resources & Services Administration
DHS: U.S. Department of Homeland Security, Office of Immigration Studies, Policy Directorate
DHHS: U.S. Department for Health & Human Services, Centers for Medicare & Medicaid Services
HCRIS: U.S. Department for Health & Human Services, Healthcare Cost Report Information System
TDSHS: Texas Department of State Health Services, Annual Survey of Hospitals
THCIC: Texas Health Care Information Council

4.4.1 Dependent Variable

The dependent variable **P_UC_TEXP** is the hospital's uncompensated care costs as percent of total expenses. This variable is the dependent variable used in the McKay & Meng (2007) panel study. The calculation is in Table 4-1. To remove the effects of size, uncompensated care in this study was calculated as percentage of total expenses. Because the amount of uncompensated care that hospitals' provide is typically accounted for and reported in terms of forgone charges, the ratio of total expenses to total gross patient revenue is applied to uncompensated care charges to deflate the charges to hospitals' costs. To facilitate comparisons across providers, total expenses scaled the uncompensated care costs. Such ratios avoid problems associated with the effects of cost inflation (Mann et al., 1997, p. 225). An uncompensated care cost ratio that uses a numerator and denominator based on the same measure of resource use provides better estimates of such costs (Weissman, 1996; Weissman et al., 2003). The inputs for this variable were derived from the *TDSHS-AHA-THA Annual Survey of Hospitals*. Ideally, operating cost would be used as the denominator for calculating this variable; however, such data was not available from the *Annual Survey of Hospitals*. Therefore, because total expense data was available in the *Annual Survey of Hospitals*, a total expense-to-gross patient charge ratio was used to determine uncompensated care cost in this study, in lieu of the more commonly used operating cost-to-gross patient charge ratio. The Rosko (2001a) and McKay & Meng (2007) studies used operating expenses as the numerator. The simplest cost-to-charge ratio equals the hospital's total expenses divided by its gross patient revenues and is a recommended approach for policy studies (Hoerger & Waters, 1993, pp. 47, 115). It is important to mention that use of this ratio to convert uncompensated care charges to costs implicitly assumes that the ratio between charges and costs for the services received by uncompensated care patients is the same as the average ratio for all the hospital's patients. However, this is not likely to be the case in practice. For example, if the mark-up on services received by uncompensated care patients is higher than the hospital's average mark-up, the ratio will overstate the hospital's uncompensated care costs. Higher charges for services could cause the low-income, uninsured, and under-insured to delay or forgo hospital care because of the cost. Conversely, if the mark-up is lower (i.e., cost shifting), the ratio will understate the hospital's costs of uncompensated care. Lower charges for services could encourage the low-income, uninsured, and under-insured to not delay or forgo hospital care.

Previous studies have used various methods to measure uncompensated care provision. Charge-oriented methods have used uncompensated care charges – either the total amount (Campbell & Ahern, 1993; Magnus et al., 2004), or as percentage of total charges (Desai, Lukas, & Young, 2000; Needleman, Lamphere, & Chollet, 1999; Weissman et al., 2003). Expense-oriented methods have used uncompensated care expenses, measured either by the total amount (Davidoff et al., 2000; Thorpe et al., 2001), or as a percentage of total expenses (Clement et al., 2002; McKay & Meng, 2007; Rosko, 2001a; Sutton & Stensland, 2004; Thorpe et al., 2001). A recent study used adjusted uncompensated care admissions to measure uncompensated care provision (Rosko, 2004).

The most commonly cited cause for uncompensated care is the utilization of healthcare services by the uninsured, low-income underinsured, Medicaid beneficiaries, and those with special health care needs, inclusive of minorities and immigrants (M. E. Lewin & Altman, 2000).

4.4.2 Explanatory Variables

Consistent with the literature and this study's theoretical model, the explanatory variables are classified into eight theoretical constructs as shown in Tables 4-1 and 4-2. The theoretical constructs are government-funded managed care provision, other managed care provision, profit, mission, demand for uncompensated care, other hospitals' supply of uncompensated care, controlling for individual market characteristics and hospital characteristics.

4.4.2.1 Government-Funded Managed Care Provision

Two key study variables specify the two types of government-funded managed care captured by the *TDSHS-AHA-THA Annual Survey of Hospitals*. The variable **P_NPREV_MMCR** measures the effect of Medicare managed care net revenue on uncompensated care provision. It is percentage of Medicare managed care net patient revenue to total patient net revenue, a continuous measure. The passage of the federal Balanced Budget Act of 1997 (P.L. 105-33) gave Medicare beneficiaries the option to receive their Medicare benefits through private health insurance plans, instead of through the original Medicare plan (i.e., Parts A and B). These programs were known as "Medicare+Choice" or "Part C" plans and were established to give beneficiaries the option of enrolling in a variety of private plans, including HMOs (since the 1970s), preferred provider organizations, provider-sponsored organizations, and private fee-for-service plans (Kaiser Family Foundation, 2003). In 2003 for Texas, Medicare+Choice enrollees as a percent of total Medicare beneficiaries, ranged between 1 and 10 percent (Kaiser Family Foundation, 2003). The federal Medicare Prescription Drug, Improvement, and Modernization Act of 2003 (P.L. 108-173) made "Medicare+Choice" plans more attractive to Medicare beneficiaries by the addition of prescription drug coverage, became known as "Medicare Advantage" plans, and created another options such as regional preferred provider organizations (Kaiser Family Foundation, 2004). Traditional or "fee-for-service" Medicare has a standard benefit package that covers medically necessary care members can receive from nearly any hospital or doctor in the country. For people who choose to enroll in a Medicare Advantage plan, Medicare pays the private health plan a capitated rate, or a set amount, every month for each member. Medicare Advantage plans are required to offer coverage that meets or exceeds the standards set by the original Medicare program, but they do not have to offer every benefit in the same way. A plan may pay less than Medicare for some benefits, including hospital care. A vast majority of Medicare Advantage Plans are HMOs (Kaiser Family Foundation, 2004). Another distinction between Medicare Advantage and traditional Medicare are that Medicare Advantage health plans encourage preventive care and wellness and closely coordinate patient care (America's Health Insurance Plans, 2008), which may influence hospital's Medicare admissions and payments.

Medicare Advantage Plan penetration in Texas was 16.7 percent in 2000, 10.8 percent in 2001, 7.9 percent in 2002, 6.4 percent in 2003, 6.2 percent in 2004, and 7.5 percent in 2005 (Kaiser Family Foundation, 2009). A recent study, based on AHRQ data, found that seniors in Medicare Advantage spent fewer days in a hospital, were subject to fewer hospital re-admissions, and were less likely to have "potentially avoidable" admissions for common conditions ranging from uncontrolled diabetes to dehydration, on a risk-adjusted basis (America's Health Insurance Plans, 2009).

The variable **P_NPREV_MMCD** measures the effect of Medicaid managed care net revenue on uncompensated care provision. It is the percentage of Medicaid managed care net patient revenue to total patient net revenue, a continuous measure. In response to rising health-care costs and national interest in cost-effective ways to provide quality health care, Texas initially established Medicaid managed care programs in its major urban and surrounding counties in the mid-1990s (Texas Health & Human Services Commission, 2009, pp. 5.3-5.5). Medicaid managed care programs were implemented in a stepwise manner across the state's major metropolitan areas between 1993 and 1999. Medicaid managed care was not implemented in the remaining (i.e., lesser populated) metropolitan and rural areas until 2006. In 1994 for Texas, 2.9 percent of the Medicaid population was enrolled in managed care, 29 percent were enrolled in 2000, and 42.86 percent of the Medicaid population were enrolled in managed care in 2005 (Texas Health & Human Services Commission, 2009, p. 5.13).

In 2003, the Texas Legislature modified many aspects of the state's Medicaid program in order to cut costs due to a large shortfall then projected for the state's annual budget beginning in 2004. Besides directing the consolidation of the state's health and human services agencies, the legislation also contained a number of measures designed to save money in the Medicaid program, primarily by targeting eligibility and benefit reductions (Warner, Jahnke, & Kimbell, 2005). Among the changes, the legislation resulted in slower Medicaid enrollment and re-enrollment, established cost-sharing requirements, discontinued some levels of coverage, required prior authorization for high-cost medical services, discontinued reimbursement for graduate medical education[7], and decreased reimbursement rates by 5 percent for Medicaid acute care providers, including physicians[8] and hospitals (Texas Health & Human Services Commission, 2003). The slowdown in Medicaid eligibility

[7] GME Medicaid funds were later restored only for teaching hospitals.
[8] Physician reimbursement decreases were eventually limited to 2.5 percent. However, hospital reimbursement reductions remained at 5 percent.

and enrollment could increase the number of uninsured patients treated by hospitals in the state because persons without coverage would likely rely on the emergency room for routine medical care. Similarly, the 5 percent reimbursement reduction to hospitals could negatively influence their ability to provide uncompensated care at prior period levels.

Access to care for low-income uninsured persons is lower in states with high Medicaid managed care penetration, compared to uninsured persons in states with low Medicaid managed care penetration. Efforts to achieve cost savings under managed care may result in financial pressures that limit cross-subsidization of care to the medically indigent, particularly for those providers who are heavily dependent on Medicaid revenue (Cunningham, 1999). A recent review of 14 studies, including some regarding Texas, found compelling evidence that Medicaid managed care programs yield savings, up to 19 percent compared to fee-for-service Medicaid (America's Health Insurance Plans, 2004). A recent study found that Medicaid managed care had no consistent effect on access to care for the uninsured (Haberer, Garrett, & Baker, 2005). The use of managed care in Medicaid was one of the major state-level policy initiatives of the 1990s (LoSasso & Seamster, 2007). In principal, the impact of expanded Medicaid managed care on uncompensated care provision should be negative based on the combination of two forces: First, Medicaid managed care could be associated with lower reimbursement rates for Medicaid-insured patients, preventing the cross-subsidization of revenue and reducing the ability to provide uncompensated care. If non-safety net hospitals that might newly contract with the state under Medicaid managed care are able to skim low-cost Medicaid patients, leaving high-cost patients to the safety net hospitals, the same pressure will result. Second, expanded Medicaid managed care could also be associated with greater enrollment in Medicaid among persons eligible, which could in turn reduce uncompensated care (Currie & Fahr, 2005).

Similar to the McKay & Meng (2007) study, this work also uses hospital-level (not market-level) measures of managed care penetration, but the measures here include both types of government-funded managed care (i.e., Medicare and Medicaid managed care) and also commercial managed care (i.e., HMO and PPO managed care), as contrasted to solely commercial managed care as in the McKay & Meng (2007) study. Compared to the McKay & Meng (2007) study, this study jointly measures the effects of three major types (i.e., Medicare, Medicaid, and Commercial) of managed care penetration in terms of percentages of net patient revenue, as contrasted to a single (i.e., Commercial) measure of managed care penetration using a percentage of total patient days. For this study, it was preferable to have a total net patient revenue denominator to facilitate comparisons across hospitals. Rosko (2001a) used a single measure of managed care penetration measure based on Medicare HMO enrollment. A hospital-level measure of managed care penetration is preferable to a market-level measure (Rosko, 2004).

From Davidoff, LoSasso, Bazzoli, and Zuckerman (2000), Medicaid managed care penetration can affect not-for-profit and for-profit hospitals in two ways. The first is the impact on patient revenues as Medicaid moves from fee-for-service payments to some other payment mechanism. Although there are no readily available data on the level of Medicaid managed care payment rates to hospitals, there is evidence that states set Medicaid HMO capitation rates so as to achieve savings relative to fee-for-service costs (Holahan et al., 1998). If Medicaid HMO payment rates to hospitals were reduced relative to fee-for-service, one would expect offsetting substitution and income effects to arise. The growth in Medicaid managed care might reduce uncompensated care provision at not-for-profit hospitals if the income effect dominates, but could increase provision at for-profit hospitals. This seems to be counterintuitive, but as the fees paid for Medicaid patients fall, a substitution effect results in which uncompensated care patients are less unattractive to for-profit hospitals relative to Medicaid patients. Second, to their potential direct effect on payment rates, Medicaid managed care also may affect hospitals by reducing inpatient use rates or changing the distribution of patients across facilities. This could affect the total amount of revenues that hospitals receive from Medicaid, and, on the margin, could cause some hospitals to gain or lose eligibility for DSH payments; DSH payments often follow the patient. The effect on DSH payments either would amplify or ameliorate the effect of changing payment rates. Revenue reductions would tend to reduce uncompensated care among not-for-profit hospitals, particularly if DSH payments were reduced or eliminated. The opposite could hold if Medicaid managed care led to revenue increases. Among for-profit hospitals, the underlying model would suggest effects are the reverse of those in not-for-profit hospitals.

4.4.2.2 Other Managed Care Provision

The variable **P_NPREV_MCOM** measures the effect of Commercial managed care (i.e., HMO and PPO) net revenue on uncompensated care provision. It is the percentage of Commercial managed care net patient revenue to total net patient revenue, a continuous measure. An early study found that the level of uncompensated care was lower in markets with greater HMO penetration (Mann et al., 1997). A more recent panel study using a hospital-level measure of private managed care penetration (i.e., commercial HMO and PPO patient days as a percent of total patient days) found that managed care provision was negatively associated with hospitals' supply of uncompensated care (McKay & Meng, 2007).

Two other earlier panel studies using market-level measures of managed care penetration found that HMO penetration was negatively associated with hospitals' uncompensated care provision (Rosko, 2004; Thorpe et al., 2001).

4.4.2.3 Profit

The variable **P_PRFT_NETUC** is the hospitals' total net profit margin percent, net of uncompensated care expenses. It measures the effect of profit on the hospital's uncompensated care provision, a continuous measure. The calculation is in Table 4-1. According to two earlier studies (Frank & Salkever, 1991; Gaskin, 1997) an important determinant of uncompensated care provision is the hospital's financial surplus (i.e., profit effect). A prior study found that as uncompensated care provision increased, several indicators of hospitals' fiscal status declined and closure became more likely (Sloan, Blumstein et al., 1986). Another early study found that financial surpluses in prior years may affect decisions to provide services in the current year (Rosko, 1990). This implies that hospitals under financial pressure may try improving their situation by reducing expenses, including reduction of uncompensated care provision. A recent panel study found that a lagged surplus measure positively, but moderately $(p < .10)$ influenced hospitals' uncompensated care provision (Rosko, 2004). The McKay & Meng (2007) study used a current year net profit margin measure (i.e., net of uncompensated care expenses) that positively and significantly $(p \leq .01)$ influenced uncompensated care provision. However, other panel studies (Frank & Salkever, 1991; Gaskin, 1997; McKay & Meng, 2007) and a cross-sectional study (Rosko, 2001a) reported insignificant forms of profit effects. A similarly-aimed cross-sectional study evaluating the association of debt financing with not-for-profit hospitals' provision of uncompensated care found that lagged operating margin, or the ratio of net operating income to operating revenues, had no significant effect on hospitals' supply of uncompensated care (Magnus et al., 2004).

Notwithstanding the above, past literature suggests that when hospitals get additional discretionary income, very little of it is spent to supply incremental charity care (Thorpe & Brecher, 1987; Thorpe & Phelps, 1991). In contrast, a more recent study found that income associated with savings from tax-exempt debt was associated with an increase in incremental charity care (Hassan et al., 2000).

Although a lagged profit measure was used in some of the earlier research studies above, a current year net profit margin measure is used in this study. The amount of a hospital's profit is typically an important annual budget target and is a key annual management performance objective. Profit planning is essential to for-profit hospitals, but it is also crucial to not-for-profit hospitals. A hospital's profit target is measured and managed in real-time during the course of a hospital's fiscal year. Accounting theory suggests that business transactions (i.e., revenues and expenses) be recognized during the period to which they relate (Cleverley, 1997). Thus, profit is a product of the current year's budget and management efforts. Any association of profit with a year, other than that in which it was earned, could introduce unwanted bias into study results.

4.4.2.4 Mission

The variables **FP** and **R_INTRES_BED** specify the two types of hospitals' missions used in this study. Following Davidoff, LoSasso, Bazzoli, and Zuckerman (2000), public (i.e., government) hospitals, as providers of last resort to indigent patients, should be expected to have a complementary role to not-for-profit and for-profit hospitals in their markets. Selected hospital and market characteristics that are correlated with reductions in uncompensated care provision for not-for-profit or for-profit hospitals should have the opposite effect on public hospitals, as long as the public hospital has excess capacity. Alternatively, factors that are correlated with increases in uncompensated care provision by not-for-profit or for-profit hospitals should decrease public hospital uncompensated care unless there is excess demand in the community.

The variable **FP** indicates for-profit control and is dummy coded 1 if true and 0 otherwise. Local government and not-for-profit controlled hospitals are the omitted comparison groups. This variable was not time invariant due to several ownership conversions during the study period. It was preferable to include a second control category so that there could be one comparison group. However, government control was time invariant and not-for-profit control was significantly correlated with for-profit control. Accordingly, the decision for this study was to proceed with for-profit control due its numerous dissimilarities with local government and not-for-profit controlled hospitals. This variable captures the effect of for-profit hospitals compared to local government and not-for-profit hospitals. An early descriptive study found that government hospitals provide large amounts of uncompensated care (Mann et al., 1997). A current panel study found that government hospitals are positively associated with the supply of uncompensated care (McKay & Meng, 2007). An earlier cross-sectional study found that government hospitals were positively associated with bad debt provision, a component of uncompensated care (Buczko, 1994). A current panel study found that for-profit hospitals, relative to not-for-profit hospitals, negatively influenced the supply of uncompensated care (McKay & Meng, 2007). The McKay & Meng (2007) study also reported that for-profit hospitals in markets where there, in addition, was a government hospital also negatively influenced the supply of uncompensated care than if no government hospital was in the market. A similarly-focused cross-sectional study evaluating the association of debt financing with not-for-profit hospitals' provision of uncompensated care found that non-public hospitals were negatively associated with supply of uncompensated care (Magnus et al., 2004). McKay & Meng (2007) used not-for-profit hospitals as the omitted comparison.

Several earlier studies reported that teaching status was associated with increased uncompensated care provision (Banks et al., 1997; Frank, Salkever, & Mitchell, 1990; Thorpe et al., 2001). The variable **R_INTRES_BED** indicates the intensity in which the hospital is involved in the teaching of interns and residents. This variable captures the effect of teaching intensity. It is the ratio of interns plus residents to set-up and staffed beds at the end of the reporting period, which is a continuous measure. A recent study reported that membership on the Association of American Medical Colleges' Council of Teaching Hospitals ("COTH") (Association of American Medical Colleges, 2005) was positively associated with the supply of uncompensated care (McKay & Meng, 2007). However, a COTH membership variable is not utilized in this study because those hospitals' COTH membership status was time invariant during the study period. An earlier study reported that minor teaching hospitals[9] had no significant impact on the supply of uncompensated care (Rosko, 2001a). An earlier study reported that hospitals that had one or more residency programs negatively, but moderately $(p < .10)$ influenced equivalent uncompensated care admissions (Frank & Salkever, 1991). Another study found that the ratio of interns to beds

[9] Minor teaching hospitals generally are those institutions with an intern and resident-to-bed ratio of less than 0.25. Major teaching hospitals are defined as those institutions with an intern and resident-to-bed ratio of 0.25 or greater (Cromwell, Adamache, & Drozd, 2006; Medicare Payment Advisory Commission, 2002; U.S. Government Accountability Office, 2005). However, other "major" and "minor" teaching hospital intern and resident-to-bed ratios have been utilized in various studies (Kupersmith, 2005).

positively influenced inpatient uncompensated care (Gaskin, 1997). In contrast, a more recent study, using the ratio of interns and residents to beds, as in this work, reported no significant influence on uncompensated care provision (Rosko, 2004). Although this study variable is used in this study under a mission theoretical construct, it is also a structural measure of quality (Donabedian, 1966, 2003; Romano & Mutter, 2004) and could be used as a quality of care measure under a hospital characteristic construct or quality of care construct. A recent hospital inefficiency study used this variable in that manner (Mutter, Rosko et al., 2008).

4.4.2.5 Demand

A single fundamental measure of demand for uncompensated care is used in this study. The variable **P_UNEMP_C** represents the annual unemployment rate in the county, a continuous variable. This variable captures the effect of unemployment. Employment is an important determinant of the percentage of the population younger than 65 who have health insurance (Enthoven & Fuchs, 2006; Pauly, 2001; U.S. Census Bureau, 2002). Thus, the annual unemployment rate in the county is used in this study as a proxy for those without health insurance. Uninsured hospitalizations increased more than overall hospital stays between 1997 and 2006 (Merrill et al., 2009). Low health insurance coverage may be associated with poor health outcomes and slower improvements in socioeconomic status (Smith, 2004) which may increase demand for hospital care and uncompensated care.

A recent panel study of urban Florida hospitals using data for the period 1998 to 2002 used this variable as proxy for the need for uncompensated care and reported this measure was negatively, but insignificantly associated with uncompensated care provision (McKay & Meng, 2007). An recent study of private, not-for-profit Pennsylvania hospitals using data for the period 1995 to 1998 used this variable as proxy for the need for uncompensated care and reported it was positively associated with adjusted uncompensated care admissions, but was only moderately significant $(p < .10)$ (Rosko, 2004). An earlier cross-sectional study of private, not-for-profit Pennsylvania hospitals using data for 1995 reported this measure was positively and significantly associated with an unadjusted uncompensated care percentage measure (Rosko, 2001a).

4.4.2.6 Other Hospitals' Uncompensated Care Supply

The variable **P_OTHUC_C** represents other county hospitals' uncompensated care expense percent, a continuous measure. This variable captures the effect of other hospitals' uncompensated care provision. The calculation is in Table 4-1. Two earlier studies (Frank & Salkever, 1991; Gaskin, 1997) found an important determinant of hospitals' uncompensated care provision is the amount of uncompensated care provided by other hospitals in the market (i.e., the crowding-out effect). A similar measure was used in several earlier studies and the results as to its influence were mixed. Some studies found this measure positively influenced equivalent uncompensated care admissions (Frank & Salkever, 1991), positively influenced inpatient and outpatient uncompensated care (Gaskin, 1997), and positively influenced adjusted uncompensated care admissions, although moderately $(p < .10)$ so (Rosko, 2004). However, three recent studies, two panel studies (Hassan et al., 2000; McKay & Meng, 2007) and a cross-sectional study (Rosko, 2001a) found that this measure was not significantly associated with uncompensated care provision.

4.4.2.7 Market Characteristics

The variables **P_POSH_OPS_C**, **R_ASCHOSP_C**, **R_FQHCHOSP_C**, **R_RHCHOSP_C**, and **DENS_UPOP_C** represent the market-level characteristics controlled for in this study.

The variable **P_POSH_OPS_C** indicates the annual percentage of physician-owned specialty hospital outpatient surgeries in the county, a continuous measure. This variable is the proportion of physician-owned specialty hospital outpatient surgeries to total outpatient surgeries in the county. This variable captures the effect of physician-owned specialty hospitals. The calculation is in Table 4-1. The recent, rapid proliferation of specialty hospitals, or "niche hospitals", has the attention of the federal government and a variety of states – especially Texas. In 2003, more than 100 niche hospitals were operating nationwide, and at least another 26 were under construction (U.S. General Accounting Office, 2003). Most niche hospitals are for-profit entities owned in whole or in part by physicians (GAO, 2003). Two-thirds of them are located in just seven states – Arizona, California, Kansas, Louisiana, Oklahoma, South Dakota, and Texas. Texas leads the nation with the highest number of niche hospitals – almost twice as many as in California, which ranks second (Fahlman & Chollet, 2006). By February 2005, Texas had 47 physician-owned niche hospitals and 29 more under development (Texas Hospital Association, 2005). The presence of physician-owned specialty hospitals in a county could affect the amount of hospitals' uncompensated care provision because better insured or higher-reimbursed surgery patients may be steered to these facilities, thus, limiting general hospitals' ability to cost shift. A recent study mandated by the Texas Legislature and commissioned by the TDSHS reported that from 2000 to 2004, the average number of inpatient surgeries performed in niche hospitals grew three times as fast (11.6 percent) as that in general hospitals (less than 4 percent); and among general hospitals in health services areas with at least one niche hospital, the average number of inpatient surgeries dropped 7.7 percent (Chollet et al., 2006, p. 5). This suggests that outpatient surgeries may also influence general hospitals. Specialty hospitals influence general hospitals' financial performance (Schneider et al., 2007). A recent study of Texas niche and general hospitals reported that niche hospitals provided less uncompensated care than general hospitals based on uncompensated care as a percent of revenues (Chollet et al., 2006). Niche hospitals perform more outpatient surgeries than general hospitals (Chollet et al., 2006, p. 19). Recent studies report that specialty hospitals provide less uncompensated care (Cromwell et al., 2005; Greenwald et al., 2006). A recent CMS study reported that physician-owned specialty cardiac and orthopedic/surgery hospitals provided less uncompensated care than not-for-profit hospitals (U.S. Department of Health & Human Services, 2005). A more current study found that specialty cardiac hospitals admitted smaller and significant proportions of self-pay patients than did general hospitals (Cram, Pham, Bayman, & Vaughan-Sarrazin, 2008). In this study, Texas physician-owned specialty hospitals were identified from a national physician-owned specialty hospital list compiled by CMS as part of a recent physician-owned specialty hospitals study (U.S. Department of Health & Human Services, 2005, 2006b).

The variable **R_ASCHOSP_C** indicates the ratio of ASCs to study hospitals in the county, a continuous measure. This variable captures the effect of ambulatory surgery centers. The presence of ASCs in a county could affect the amount of hospitals' uncompensated care provision because better insured surgery patients may be steered to these facilities, thus, limiting hospitals' ability to cost shift. Competitive forces make cost shifting difficult. Specialty facilities provide less charity care (Schneider, Ohsfeldt, Morrisey, Zelner, & Miller, 2005). Physicians at physician-owned ASCs are more likely than other physicians to refer well-insured patients to their facilities and route Medicaid patients to hospital outpatient clinics (Gabel et al., 2008, March 18).

The variable **R_FQHCHOSP_C** indicates the ratio of FQHCs to study hospitals in the county, a continuous measure. This variable captures the effect of federally qualified health centers. The availability of FQHCs in a county could affect the amount of hospital's uncompensated care provision due to reduced emergency room use and the shift of care away from hospitals. FQHCs include community health centers, migrant health centers, programs that provide health care for the homeless, public housing primary care programs and urban Indian and tribal health centers (National Conference of State Legislatures, 2008). While anyone may seek services at an FQHC, nearly 71 percent of health center patients have family incomes at or below the poverty level. In addition, about 39 percent of health center's patients are uninsured and 35 percent depend on Medicaid (National Association of Community Health Centers, 2008). In 2007, Texas FQHC patients were covered by Medicaid/Children's Health Insurance Program (27 percent), Medicare (6 percent), private insurance (8 percent), and other public programs (3 percent). The remaining 56 percent were uninsured (Texas Association of Community Health Centers, 2008). Access to affordable health care through an FQHC reduces reliance on emergency departments among the uninsured (Smith-Campbell, 2000, 2005). A recent study found that access to safety-net providers, including FQHCs, increases care for uninsured persons (Hadley & Cunningham, 2004) and populations in medically underserved areas served by FQHCs have significantly lower preventable hospitalizations (A. J. Epstein, 2001). Much earlier studies found evidence of reduced emergency room use and a sizable shift of care out of hospitals after publicly-supported community health centers had opened (Freeman, Kiecolt, & Allen, 1982; Okada & Wan, 1980). Lack of access to primary care is related to higher rates of hospitalization for preventable conditions in Texas (Begley, Slater, Engel, & Reynolds, 1994). The absence of an FQHC is associated with a substantial excess in uninsured emergency department visits in rural counties (Rust et al., 2009) which may spill over to emergency department visits in adjoining urban counties. FQHCs involved in managed care serve significantly smaller proportions of uninsured patients but a higher proportion of Medicaid users than those not involved in managed care (Shi, Politzer, Regan, Lewis-Idema, & Falik, 2001).

The variable **R_RHCHOSP_C** indicates the ratio of Rural Health Centers ("RHC") to study hospitals in the county, a continuous measure. This variable captures the effect of rural health centers. Although the hospitals in this study are located in metropolitan statistical areas, many metropolitan counties subparts that are rural or considered rural for purposes of certain government health care programs. Among other reasons, RHCs were established to encourage utilization of mid-level providers (i.e., nurse practitioners and physicians assistants) for treatment of Medicare and Medicaid patients living in rural areas (U.S. Department of Health & Human Services, 2006a). This suggests that RHCs may favor Medicare, Medicaid, and other paying patients over uninsured patients. RHCs can qualify for enhanced Medicare/Medicaid reimbursement, but they do not receive funding explicitly for care of the uninsured (Rust et al., 2009). In the alternative, like FQHCs, the availability of RHCs in a county could affect the amount of hospital's uncompensated care provision due to reduced emergency room use and shift of care away from hospitals. RHCs provide access to essential preventive care for vulnerable rural residents (Regan, Schempf, Yoon, & Politzer, 2003). Rurality may be positively associated with hospitalization for ambulatory sensitive conditions (Laditka, Laditka, & Probst, 2009).

The variable **DENS_UPOP_C** indicates the population density of unauthorized immigrants in a county, a continuous measure. This variable captures the effect of unauthorized (illegal) immigration. The calculation is in Table 4-1. For the years 2001 through 2004 in this study, the estimated number of persons residing in a county that are unauthorized immigrants is interpolated from federal immigration estimates of the percentage of unauthorized immigrants residing in Texas in 2000 and 2005.

Federal estimates of the number of unauthorized immigrant population residing in Texas show that 5.23 percent of Texas' population were unauthorized immigrants in 2000 and 5.95 percent in 2005 (Hoefer, Rytina, & Campbell, 2006). Texas metropolitan areas are destinations of immigrants (J. Lee, 2009). Texas' local governments bear the burden of uncompensated health care costs for undocumented immigrants (Texas Comptroller of Public Accounts, 2006). However, a recent state-level study reported that there was no significant relationship between hospitals' uncompensated care expenditures and states' percentage of non-citizen immigrants (Castel et al., 2003). A more current work reported that illegal aliens contribute to hospitals' uncompensated care costs (Green & Martin, 2004). A recent study reported that undocumented immigrants are less likely to gain health insurance and more likely to lose coverage compared to native-born citizens (Prentice, Pebley, & Sastry, 2005). More than one-half, 52.6 percent, of Mexican immigrants do not have health insurance compared to 13.5 percent of natives (Camarota, 2001). Another study reported that immigrants have little impact on the number of uninsured (Holahan, Ku, & Pohl, 2001).

4.4.2.8 Hospital Characteristics

The variables **LN_BEDS**, **P_OCCUP**, **SEV_ILL**, **R_BIRTHS_ADM**, **ERMIX_NETOPS**, **R_ADM_ERVIS**, **PLANT_AGE_R**, **P_NPREV_OGOV**, **P_TEXP_NPREV**, **D_NETWORK**, **IQI_17_R**, **IQI_32_R**, **D_YR_2000**, **D_YR_2001**, **D_YR_2002**, **D_YR_2003**, and **D_YR_2005** represent the hospital-level characteristics that are controlled for in this study.

The variable **LN_BEDS** indicates the natural logarithm of the number of hospital beds set-up and staffed at the end of the reporting period, a continuous variable. The underlying bed data was transformed to achieve a proximate normal distribution. This variable captures the size effect. The calculation is in Table 4-1. Several studies found that bed size is associated with uncompensated care provision. Some studies suggest bed size is positively associated with uncompensated care provision (Frank & Salkever, 1991; Gaskin, 1997; Rosko, 2004; Thorpe et al., 2001). Other studies suggest bed size is negatively associated with uncompensated care provision (Magnus et al., 2004; McKay & Meng, 2007). A cross-sectional study found that for bed size more than or equal to 234, size was negatively associated with uncompensated care percentage and negatively associated with unadjusted uncompensated care percentage, although each coefficient was moderately $(p < .10)$ significant (Rosko, 2001a).

The variable **P_OCCUP** indicates the hospital's occupancy percentage, a continuous variable. The calculation is in Table 4-1. This variable captures the crowd-out effect. Beds occupied by paying patients could reduce or "crowd-out" the number of beds available for non-paying uncompensated care patients. An early cross-sectional study found that occupancy positively influenced the supply of charity care, a component of uncompensated care provision, but negatively influenced the supply of bad debt, the other component of uncompensated care (Buczko, 1994). However, a later panel debt-uncompensated care study reported inconsistent occupancy effects (Hassan et al., 2000). Alternatively, a higher occupancy rate may be indicative of better financial performance, depending on payer mix, and more discretionary income that could be used for uncompensated care provision. However, higher occupancy may have increased marginal costs, which would decrease funds available for uncompensated care provision.

The variable **SEV_ILL** indicates the average of the hospital's patient severity of illness scores for all payers, a continuous variable. It is the effect of severity or complexity of illnesses treated at the hospital for all patients. The individual-level severity of illness scores[10] are produced by THCIC using the 3M™ All Patient Refined Diagnosis Related Groups ("APR-DRG") software[11,12] (Texas Health Care Information Council, 2000-2005). Severity of illness is related to resource use (Carpenter et al., 1999) which is related to expense per admission (Rosko & Carpenter, 1994). A higher average severity of illness score may indicate elevated resource consumption and possibly less funds available for uncompensated care provision. Conversely, a lower average severity of illness score may indicate lesser resource consumption and more funds available for uncompensated care provision. Hospitalized patients of lower socioeconomic status have longer stays and require more resources (A. M. Epstein, Stern, & Weissman, 1990).

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[10] The severity of illness levels indicates the level of physiologic decomposition. The related 3M APR-DRG Grouper score coding scheme is 1=minor, 2=moderate, 3=major, and 4=extreme.
[11] For APR-DRG methodology, see (Averill, Goldfield, Hughes, Bonazelli et al., 2003).
[12] For software details, see (3M™ Health Information Systems, 2009)

Most licensed hospitals in Texas are required to submit discharge data to the THCIC[13] using the uniform bill (i.e., UB-92) format, also called the "HCFA-1450". The discharge data contain information on patient demographics, date of admission, source of admission, length of stay, discharge status (alive or dead), diagnosis (including primary and secondary ICD-9-CM and diagnostic related group [DRG] codes), charges, source of payment, and procedure codes. The discharge data also contain a severity of illness measure based on the APR-DRG scale with four levels: minor, moderate, major, or extreme (Averill, Goldfield, Hughes, Muldoon et al., 2003; Averill et al., 1997). The APR-DRG severity of illness scale categorizes severity based on the hospital ICD-9-CM discharge diagnosis and procedure codes. The scale is developed for a patient according to the secondary diagnosis and procedures associated with physiologic decompensation or organ system loss of function (Averill, Goldfield, Muldoon, Steinbeck, & Grant, 2002). A patient's severity of illness with a specific condition is "major" if there is significant organ system loss of function. APR-DRGs are an expansion of the CMS-DRGs and the All Patient DRGs ("AP-DRGs")[14] to be more representative of non-Medicare populations and incorporates severity of illness and risk of mortality subclasses into the DRGs (Averill et al., 1997). The APR-DRGs increase the specificity of the basic DRGs used by CMS for payment to hospitals for Medicare beneficiaries. The CMS-DRGs alone are weak measures of severity of illness, risk of mortality, prognosis, treatment difficulty, and need for intervention for the hospitalized patient population (Casto & Layman, 2006, p. 91). Taken together, the APR-DRG and the severity of illness further refine CMS-DRGs and AP-DRGs to provide a more precise

[13] See Section 4.3.2 for types of exempted hospitals.
[14] Developed by the New York State Department of Health and 3M™ Health Information Systems.

classification of patients. Patients with multiple disease or injury conditions along with significant organ system loss of function are considered to have "extreme" severity of illness.

A large body of research has documented the relationship between severity of illness and resource use per patient utilizing a variety of severity measures (Averill et al., 1992; Carpenter et al., 1999; Iezzoni, Ash, Cobb, & Moskowitz, 1988; Iezzoni, Ash, Coffman, & Moskowitz, 1991; Rosko & Carpenter, 1993, 1994; Thomas & Ashcraft, 1991). Most of the evidence suggests that severity of illness accounts for some share of variation in resource use over and above that associated with the related diagnostic group (Carpenter et al., 1999). A cross-sectional intra-DRG severity of illness classifications and hospital profitability study using not-for-profit Pennsylvania hospitals from 1989 found expense per admission was positively related to severity of illness (Rosko & Carpenter, 1994). A cross-sectional cost function study using not-for-profit Pennsylvania hospitals from 1989 found a scalar hospital-specific severity of illness measure was a strong predictor of costs (Rosko & Carpenter, 1993). A similarly performing all payer case-mix measure was used in a study of the effects of managed care on uncompensated care provision in California hospitals during 1980 through 1989 (Mann, Melnick, Bamezai, & Zwanziger, 1995). Payer-specific measures of severity of illness (i.e., case-mix indices for Medicare, Medicaid, private payers, and other payers) measures were used in a panel study of payment sources and costs in a sample of 500 U.S. hospitals during 1980 through 1987 which found that differences in hospital treatment costs, including uncompensated care, were related to expected source of payment (Dor & Farley, 1996).

The variable **R_BIRTHS_ADM** represents the number of births per admission at the hospital, a continuous measure. This variable captures the effect of births mix of admissions.

A cross-sectional study found a similar bassinet days percent measure to be positively associated with uncompensated care provision (Rosko, 2001a). According to a federal descriptive report, the most common reason for uninsured hospitalizations from 1997 to 2006 was childbirth (Merrill et al., 2009). Recall that Texas is adjacent to an international border with Mexico and illegal immigration is commonplace. For undocumented Latinos, their particular rates of hospitalization are comparable to all persons nationally, except for childbirth. Almost half of married undocumented Latinos give birth to a child in the U.S. (Berk, Schur, Chavez, & Frankel, 2000). In 2006, illegal immigrants accounted for a majority of maternity patients in a local Texas government hospital (Preston, 2006) and other Texas hospitals might be similarly impacted.

The variable **ERMIX_NETOPS** indicates the proportion of total outpatient visits, net of outpatient surgeries that were emergency room visits, a continuous measure. This variable captures the emergency room effect. Primary care-related emergency department visits are strongly correlated with the rate of uninsurance and poverty in Texas (Begley et al., 2006). One cross-sectional study (Rosko, 2001a) and a panel study (Rosko, 2004) found a form of this variable to be positively associated with uncompensated care provision. An earlier cross-sectional study found the percent of emergency outpatient visits positively influenced bad debt charges, a component of uncompensated care provision (Buczko, 1994). An earlier descriptive study found that the relative proportion of bad debt write-offs was substantially higher for emergency patients (Weissman et al., 1992).

The variable **R_ADM_ERVIS** represents the ratio of admissions to emergency room visits, a continuous measure. This variable captures the effect of emergency room admissions. According to a recent descriptive report, about 60 percent of uninsured stays begin in the emergency department compared to 44 percent of overall hospital stays (Merrill et al., 2009). An earlier descriptive report found that about 82 percent of acute conditions are admitted from the emergency department (Elixhauser & Owens, 2006). An much earlier study found that patients with lower socioeconomic status were more likely to enter the hospital via the emergency department than other patients and that patients admitted via the emergency department use far more resources than patients in the same diagnosis related group admitted by other means (Stern, Weissman, & Epstein, 1991).

The variable **PLANT_AGE_R** represents the reciprocal of the age of the hospital's property, plant, and equipment, a continuous measure. It is used in this study as a crude proxy for the debt effect. The calculation is in Table 4-1. The original age value calculated for this measure was not suitable for gauging the effect of this proxy for debt. To simplify analysis and improve interpretation, a reciprocal transformation was used to rescale the variable. The reciprocal value is the quotient obtained from division of 1 by the age of the hospital's property, plant, and equipment. Thus, larger reciprocal values mean lower physical plant ages. If a hospital has old and outdated facilities, it could affect the quality of care rendered to its patients. It could also lead physicians to practice at facilities where they believe their patients could be better served. If the hospital's physical plant is older, capital investment in the facility may be diminishing, suggesting that the facility has less debt. If so, more hospital funds could be available for uncompensated care provision. It could also suggest that the hospital is experiencing fiscal difficulties and as a result, fewer funds are available for uncompensated care provision. In contrast, if the hospital's physical plant is newer, this may suggest that capital investment in the facility is ongoing or that it is a newer facility, suggesting that the facility's debt load may be higher which could discourage uncompensated care provision.

Differing from the logic above, a study found that subsidies provided by tax-exempt debt increased the supply of charity care (Hassan et al., 2000). That study argued that one might view not-for-profit hospitals' provision of charity care as a payment for access to low-cost tax-exempt debt. Also, a recent study found that debt financing was positively and significantly associated with uncompensated care provision (Magnus et al., 2004). In that study, the authors reasoned that debt financing eased the use of internally generated cash flows – by freeing up cash – that could be used for uncompensated care provision. The authors offered two supporting theories. First, that the need to pay back debt and meet bond covenants may not be as demanding on cash flows as believed. Second, that debt financing may support the development of programs that generate new cash flows that are used to fund uncompensated care.

The *TDSHS-AHA-THA Annual Survey of Hospitals* does not capture the exact financial data that formed the significant explanatory debt variable used by Magnus, Smith, & Wheeler (2004). Although this study's particular proxy for the Magnus et al. (2004) debt variable has not yet been identified in the literature in the context of this study, its use arises from the aforementioned data limitation and is a practical alternative for approximating the effect of physical plant age (ostensively debt) on hospitals' provision of uncompensated care.

The variable **P_NPREV_OGOV** is the proportion of government net patient revenue, other than Medicare and Medicaid (both routine and managed care net patient revenue), to total net patient revenue. The calculation is in Table 4-1. This variable captures the effect of government payers, other than Medicare and Medicaid (both routine and managed care), on uncompensated care expense percent. Government payers, other than Medicare and Medicaid, may affect hospitals' uncompensated care costs. In Texas, local county governments are responsible for providing medical aid and hospital care to the needy inhabitants of their county. Because annual funds for that purpose are limited, county governments typically negotiate discounts with local hospitals to cover as many indigents as possible. Empirical support for this variable comes from McKay and Meng (2007) who used a similarly performing measure to gauge the effect of a particular government payer (i.e., Medicaid) on uncompensated care provision in urban Florida hospitals during 1998 to 2002.

The variable **P_TEXP_NPREV** is the proportion of total expenses to total net patient revenue, a continuous measure. The calculation is in Table 4-1. This variable captures the effect of non-patient revenue. It is used in this study to gauge the degree to which total expenses are covered, in whole or in part, by the hospital's total net patient revenue. If total expenses are not covered by total net patient revenue, then the hospital is relying on other forms of revenue to cover those expenses. Thus, this variable measures the degree to which the hospital relies on other forms of revenue (i.e., tax appropriations, other operating revenues, and/or non-operating revenue). Values larger than one indicate hospitals' reliance on other forms of revenue, in addition to total net patient revenue, to cover total expenses. Operating expenses might be a more appropriate numerator for this variable; however, that particular data item is not captured in the *TDSHS-AHA-THA Annual Survey of Hospitals*. A path analysis study using 1994-1996 data on urban U.S. hospitals used a reimbursement measure (i.e., ratio of cost to Medicare payment) which performed like this variable (Trinh & O'Connor, 2002). Their measure is modified and expanded somewhat for this study to identify the degree of hospitals' reliance on other forms of revenue, in addition to total net patient revenue, to cover total expenses.

The variable **D_NETWORK** indicates hospital membership in a network, a binary measure coded 1 if true and 0 otherwise. This variable captures the network membership effect. A recent cross-sectional study found that affiliation with a health system or health network was positively related to hospitals' responsiveness to community needs (S.-Y. D. Lee et al., 2003), which could include uncompensated care provision. A cross-sectional study using U.S. data from 1995 found that among both network and system hospitals, those that provide more services at the network or system level tend to have better financial performance than those that do not (Bazzoli, Chan, Shortell, & D'Aunno, 2000). Thus, network or system membership and better hospital financial performance may indicate that either more funds or fewer funds are available for uncompensated care provision. A later panel study using not-for-profit Pennsylvania hospitals found that membership in a health system did not influence provision of uncompensated care (Rosko, 2004). Unfortunately, the *TDSHS-AHA-THA Annual Survey of Hospitals* does not contain alliance or system-membership information for the entire study period, but it does include network membership data for the entire period.

The Medicare Prescription Drug, Improvement, and Modernization Act of 2003 (P.L. 108-173) established financial incentives for hospitals to provide CMS with data on indicators of quality care (U.S. Department of Health & Human Services, 2004). CMS selected, among others, measures of the quality of care that reflect major medical conditions that are considered valid and feasible for public reporting, including acute stroke and acute myocardial infarction (Jha et al., 2005). The variables **IQI_17_R** and **IQI_32_R** are fundamental quality measures of patient outcomes and in this study they represent the reciprocal measure of hospitals' case risk-adjusted mortality rates for acute stroke and acute myocardial infarction (excluding transfer cases), respectively. The calculation is in Table 4-1. Risk-adjusted mortality rates are considered outcome measures of quality (Donabedian, 1966, 2003; Romano & Mutter, 2004). These two measures are based on administrative discharge data that consists of diagnoses and procedures along with information about the patient's age, gender, accompanying medical conditions and discharge status that is submitted to the THCIC. The THCIC is a state agency that gathers information from hospitals and HMOs and publishes public reports to help consumers compare and choose their hospitals and health plans. The THCIC measures are derived using software developed by the AHRQ that analyzes the administrative discharge data and assesses performance on certain indicators that studies have shown are related to quality. The THCIC/AHRQ derived risk-adjusted mortality rates are transformed for this study into a reciprocal value (see discussion in later paragraph). The measures utilize condition-specific, risk-adjusted mortality rates estimated by the Inpatient Quality Indicator ("IQI") module of the publicly available *AHRQ Quality Indicators for Windows* software (U.S. Department of Health & Human Services, 2008a). Hospital-level variations among IQI rates may be associated with differences in quality of care (Andrews, Russo, & Pancholi, 2007). Although a single concise measure of a hospital's quality of care performance might be ideal, the condition-specific measures used in this study may be more accurate indicators of performance than a single all-causes mortality rate. An earlier study found that correlations between standardized (i.e., single all-cases) hospital mortality ratios for diagnoses and procedures frequently used to assess hospital quality are quite low (Rosenthal, 1997).

The *AHRQ Quality Indicators for Windows* software estimates six inpatient quality indicator risk-adjusted mortality rates. The two rates used in this study (i.e., acute stroke and acute myocardial infarction, without transfers) have been associated with uninsured hospital admissions (Elixhauser & Russo, 2006). The other remaining inpatient quality indicator risk-adjusted mortality rates available from the *Quality Indicators for Windows* software, but not used in this study, relate to congestive heart failure, pneumonia, gastrointestinal hemorrhage, and hip fracture. Elixhauser and Russo (2006) did not associate the gastrointestinal hemorrhage and hip fracture with uninsured hospital admissions. The rates for congestive heart failure and pneumonia were not used in this study due to problems they later created within the difference matrix of the Hausman specification test. This Hausman specification test is for choosing between fixed- or random-effects.

A recent hospital management journal article advocating the use of evidence-based decision-making management practices argues that quality should be considered when hospital cost control strategies are developed (Finkler & Ward, 2003, p. 354). Their message is that cost control decisions affect patient outcomes, saying, "…it would be foolish for managers to make cost containment decisions without carefully developing an understanding of the likely quality consequences of those decisions". A study found that hospitals with lesser fiscal resources allocated to clinical services experienced poorer risk-adjusted mortality outcomes (Mukamel et al., 2002). Hospitals have increased investment in quality improvement projects and in personnel and systems to improve documentation of care (Laschober, Maxfield, Felt-Lisk, & Miranda, 2007). During the study period, quality of care received heightened attention from hospitals due largely CMS's evolving incentive payment methodology previously described. Hospitals' investment in quality improvement projects (primarily to reduce risk-adjusted mortality rates) may reduce or restrict funds otherwise available for provision of uncompensated care. Although not yet introduced to the study of uncompensated care provision, patient outcome measures have been used in recent hospital cost-related studies. A hospital performance study (McKay & Deily, 2005) and three hospital cost-inefficiency studies (Deily & McKay, 2006; McKay & Deily, 2008; Mutter, Rosko et al., 2008) exemplify this point. The Mutter, Rosko, & Wong (2008) cost-inefficiency study utilized, among others, one of the IQI patient outcome measures used in this study.

In this study, the risk-adjusted mortality rates above were derived using the *AHRQ Quality Indicators for Windows* software downloaded from the AHRQ website, inclusive of THCIC's adjustments to facilitate fitting the data to the software. The particular inpatient quality indicators used in this study were selected based on the two most common observations submitted to THCIC during the study period. The *Quality Indicators for Windows* software used for this study is identical to that utilized by THCIC for public reporting. Where comparable years were available, the study's calculated inpatient quality indicator rates were contrasted to those published by THCIC and were found to be identical.

From the *AHRQ Quality Indicators for Windows* software, higher risk-adjusted mortality rates signify more deaths. In contrast, lower risk-adjusted mortality rates indicate fewer deaths. In this study, to facilitate analysis of risk-adjusted mortality rates and simplify interpretation, the calculated mortality rates from the *Quality Indicators for Windows* software were transformed into reciprocal rates. The reciprocal rate is the quotient obtained from division of 1 by the *Quality Indicators for Windows*-generated risk-adjusted mortality rate. Thus, higher reciprocal rates mean lower risk-adjusted mortality rates, signifying fewer deaths.

The variable **IQI_17_R** is the reciprocal of the hospital's *AHRQ Quality Indicators for Windows* software-generated risk-adjusted mortality rate for acute stroke. This variable captures the effect of quality of care for acute stroke. The calculation is in Table 4-1. Elixhauser and Russo (2006) found that this principal diagnosis was associated with 3.8 percent of uninsured hospital admissions and ranked 20th among the twenty most frequent conditions causing hospitalization among the uninsured in 2003.

The variable **IQI_32_R** is the reciprocal of the hospital's *AHRQ Quality Indicators for Windows* software-generated risk-adjusted mortality rate for acute myocardial infarction, excluding transfer cases. This variable captures the effect of quality of care for acute myocardial infarction. The calculation is in Table 4-1. Elixhauser and Russo (2006) found that this principal diagnosis was associated with 4.4 percent of uninsured hospital admissions and ranked 10th among the twenty most frequent conditions causing hospitalization among the uninsured in 2003.

The variables **D_YR_2000**, **D_YR_2001**, **D_YR_2002**, **D_YR_2003**, and **D_YR_2005** indicate the years of the observation. Each is a binary measure dummy coded 1 if true and 0 otherwise. These variables control for the effect of time. The omitted comparison year is 2004, which is the year Texas' Medicaid eligibility, hospital rate, and the benefit reductions were effective, as previously discussed. McKay & Meng (2007) used individual year dummies in their study of urban Florida hospitals during 1998 to 2002.

4.5 Methods

4.5.1 Panel Data

Panel data are repeated observations on the same cross-sectional unit observed for several periods. In econometric applications, firms (i.e., hospitals) are commonly observed. Panel data have both a spatial and temporal dimension. The spatial dimension refers to the cross-section of units (e.g., hospitals), and the temporal dimension refers to the time of observations (e.g., years). Thus, in panel data the explanatory variables vary over two dimensions rather than one.

The notation in a panel data regression differs from a normal cross-section or time-series regression in that the panel data regression has a double subscript on its variables, such as

$$y_{it} = \alpha + X'_{it}\beta + u_{it} \quad i = 1,...,N; \quad t = 1,...,T,$$

with i denoting firms and t denoting time. The i subscript indicates the cross-section dimension and the t indicates the time-series dimension. α is a scalar, β is $K \times 1$ and X_{it} is the it-th observation on K explanatory variables.

Well-known panel data sets in the U.S. are the Medical Expenditure Panel Survey, the National Longitudinal Surveys of Labor Market Experience, and the Michigan Panel Study of Income Dynamics. These data are typical of panel data in that they are short and wide, consisting of a very large number of cross-sectional (i) units observed over a small number of periods (t).

4.5.1.1 Advantages of Panel Data

In general, panel data sets, like that used in this study, provide a number of advantages for econometric research over purely cross-sectional or time series data sets alone (Baltagi, 2008; Greene, 2008; Gujarati, 2003; Hsiao, 2003; Kennedy, 2008; Maddala, 2001; Wooldridge, 2002).

Greene (2008) noted that the fundamental benefit of a panel data set over a cross section alone is that it allows a researcher great flexibility in modeling differences in behavior across individuals or firms. Panel data is expensive to obtain because it involves tracking individuals or firms over multiple periods. However, panel data have several attractive features that justify the additional cost of acquisition. First, panel data can be used to deal with heterogeneity in the micro units. In cross-sections, there are a myriad of unmeasured explanatory variables that affect the behavior of the individuals or firms being analyzed. (Heterogeneity means that these micro units are all different from one another in fundamental unmeasured ways.) Omitting these variables causes bias in estimation. The same is true for omitted time series variables that influence the behavior of the micro units uniformly, but differently in each period. Panel data facilitate correction of this problem. The ability to deal with this omitted variable problem is the main attribute of panel data. Second, panel data create more variability, by combining variation across micro units with variation over time, thus alleviating multicollinearity problems. With this more informative data, estimation that is more efficient is possible. Third, panel data can be used to examine issues that cannot be studied using cross-sectional or time series data alone. Finally, panel data allow better analysis of dynamic adjustment. Cross-sectional data alone offers no information about dynamics. Time series data are necessarily lengthy to provide good estimates of dynamic behavior, and then typically relate to aggregate dynamic behavior. Knowledge of individual dynamic reactions can be crucial to understanding economic phenomena. Panel data avoid the need for lengthy time series by exploiting information on the dynamic reactions of each of several individuals or firms (Hsiao, 2003).

4.5.2 Violations of Spherical Assumptions

The theoretical justification for use of the classical ordinary least squares regression model ("OLS") is the Gauss-Markov Theorem (Plackett, 1950). Two leading violators of the Gauss-Markov spherical assumptions are heteroskedasticity and autocorrelation (Greene, 2008).

Cross-sectional data alone are often plagued by the problem of heteroskedasticity (Gujarati, 2003). Time-series data alone often display autocorrelation or serial correlation across panels, but are generally homoskedastic. Thus, panel data may exhibit both heteroskedasticity and autocorrelation ailments since the data is comprised of both cross-section and time-series elements. However, in a panel data set, the substantive problem is cross-observation correlation, or autocorrelation. Correlation has a more substantial influence on the estimated covariance matrix of the OLS estimator than does heteroskedasticity (Greene, 2008).

In the presence of both heteroskedasticity and autocorrelation, the usual OLS estimators may not be the best linear unbiased estimators. Although the OLS estimators are linear, unbiased, and asymptotically normally distributed, the estimators are no longer minimum variance among all linear unbiased estimators. More concisely, the OLS estimators are not efficient relative to other linear and unbiased estimators and, thus, they may not be the best linear unbiased estimators. As a result, the usual t, F, and χ^2 statistics may not be legitimate.

4.5.3 Unobserved Effects

In panel data sets, bias and inefficiency in estimation may result from the assumption that the dependent variable is generated by a conditional probability function in which the parameter vector is the same for all observations. Such is equivalent to assuming that all the observations are part of one large homogeneous group when, in fact, each observation belongs to both a specific cross-sectional group and a specific time-period group. Each group may have associated with it unobserved effects that are not captured by the included exogenous variables. The variation attributable to them would therefore be reflected in the disturbance term. If the unobservable effects are correlated with the included exogenous variables, the estimators will be biased and inefficient. If they are not correlated, the estimators will be unbiased, but still inefficient.

The unobserved effects can be viewed as being determined by two types of variables: those that vary across cross-sectional units, but are invariant across time (i.e., fixed-effects), and those that vary across time, but are invariant across cross-sectional units (i.e., random-effects). In the hospital data to be used in this study, examples of fixed-effects could be unobserved hospital-specific characteristics such preferences of hospital administrators or boards of trustees for provision of uncompensated care. Random-effects could include introduction of managed care, changes in employment rates, changes in uninsured rates, economic downturns, reductions in government reimbursement, and population shifts, which affect all hospitals.

4.5.4 One-Way Panel Data Models

The two forms of one-way panel data models are fixed-effects and random-effects. The panel estimating method used in this study is a one-way fixed-effects model. However, the final estimating method could have differed. Subject to the outcomes of various statistical tests, the actual estimating model could have been OLS or a one-way random-effects model. Portions of the following sections make use of (Verbeek, 2004).

4.5.4.1 One-Way Fixed-Effects Model

One possible way to handle the unobserved effects in the empirical estimation process is to treat them as fixed within a given group or unit. The one-way fixed-effects model ("FEM") examines group differences in intercepts, assuming the same slopes and constant variance across groups. The fixed-effect estimator estimates short-run effects because it is based on the time series component of panel data. This model estimates $E\{y_{it} \mid x_{it}, \alpha_i\} = x'_{it}\beta + \alpha_i$. FEMs use least squares dummy variable ("LSDV"), within effect, and between effect estimation methods. OLS regressions using dummies are FEMs. The FEM is a linear regression model in which the intercept term varies over the individual units i, such as

$$y_{it} = \alpha_i + x'_{it}\beta + u_{it}, \quad u_{it} \sim IID\left(0, \sigma_u^2\right),$$

where it is usually assumed that all x_{it} are independent of all u_{it}. In the usual regression framework, by including a dummy variable for each unit i, the model can be re-written as,

$$y_{it} = \sum_{j=1}^{N} \alpha_j d_{ij} + x'_{it}\beta + u_{it},$$

where $d_{ij} = 1$ if $i = j$ and 0 elsewhere. There are a set of N dummy variables in the model. The parameters $\alpha_1, \ldots, \alpha_N$ and β can be estimated by OLS. The implied estimator for β is the LSDV estimator. It is numerically unattractive to have a regression model with so many regressors. The estimator for β can also be obtained if the regression is performed in deviations from individual means. This implies that the individual effects α_i are eliminated by transformation. The transformation is $\bar{y}_{it} = \alpha_i + \bar{x}_i'\beta + u_i$, where $\bar{y}_i = T^{-1}\sum_t y_{it}$ or $\bar{y}_i = \frac{1}{T}\sum_t y_{it}$, and similarly for the other variables. Thus, $y_{it} - \bar{y}_i = (x_{it} - \bar{x}_i)'\beta + (u_{it} - \bar{u}_i)$. This is a regression model in deviations from individual means and does not include the individual effects α_i. The transformation is a within transformation. The OLS estimator for β obtained from the transformed model is the *within estimator* or *fixed-effects estimator*, and it is identical to the LSDV estimator, without the dummies. The within (fixed-effects) estimator is given by

$$\hat{\beta}_{FE} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T} (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)' \right)^{-1} \sum_{i=1}^{N}\sum_{t=1}^{T} (x_{it} - \bar{x}_i)(y_{it} - \bar{y}_i).$$

All x_{it} are assumed independent of all u_{it} and the fixed-effects estimator is unbiased for β. The within estimator$\left(\hat{\beta}_{FE}\right)$ has a normal distribution if u_{it} is normally distributed, requiring $E\{(x_{it} - \bar{x}_i)u_{it}\} = 0$. The x_{it} are uncorrelated with u_{it} and $\bar{x}_i$ have no correlation with the error term implied by $E\{x_{it}u_{is}\} = 0$ for all s, t.

The covariance matrix for the fixed-effects estimator$\left(\hat{\beta}_{FE}\right)$, assuming that u_{it} is independently and identically distributed across i and t with variance σ_u^2, is given by

$$V\{\hat{\beta}_{FE}\} = \sigma_u^2 \left(\sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)' \right)^{-1}.$$

A consistent estimator for σ_u^2 is obtained as the within residual sum of squares divided by $N(T-1)$. That is,

$$\begin{aligned} \hat{\sigma}_u^2 &= \frac{1}{N(T-1)} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(y_{it} - \hat{\alpha}_i - x_{it}' \hat{\beta}_{FE} \right)^2 \\ &= \frac{1}{N(T-1)} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(y_{it} - \bar{y}_i - (x_{it} - \bar{x}_i)' \hat{\beta}_{FE} \right)^2. \end{aligned}$$

Essentially, the FEM concentrates on differences 'within' individuals. It explains to what extent y_{it} differs from $\bar{y}_i$ and does not explain why $\bar{y}_i$ is different from $\bar{y}_j$. Parametric assumptions about β impose that a change in x has the same effect, *ceteris paribus*, whether it is a change from one t to the other, or a change from one i to the other.

There are several strategies for estimating FEMs. The LSDV model uses dummy variables, whereas the *within effect model* does not. These strategies produce identical parameter estimates of non-dummy explanatory variable. The *between effect model* fits the model using group means of dependent and explanatory variables without dummies.

The LSDV model is widely used because it is relatively easy to estimate and interpret substantively. The LSDV model is $y_{it} = (\alpha + \mu_i) + X_{it}'\beta + v_{it}$. The LSDV model, however, becomes problematic when there are many groups or subjects in panel data. If T is fixed and $N \to \infty$, only the coefficients of the regressors are consistent. The coefficients of dummy variables, $\alpha + \mu_i$, are not consistent since the number of these parameters increases as N increases (Baltagi, 2008). This is the incidental parameter problem. Under this circumstance, LSDV is useless, calling for a different strategy (i.e., the within effect model).

The within effect model does not need dummy variables, but it uses deviations from group means. Thus, this model is the OLS of $(y_{it} - \bar{y}_{i\bullet}) = \beta'(x_{it} - \bar{x}_{i\bullet}) + (u_{it} - \bar{u}_{i\bullet})$ without an intercept, where $\bar{y}_{i\bullet}$ denotes dependent variable mean of group i, $\bar{x}_{i\bullet}$ denotes explanatory variable mean of group i, and $\bar{u}_{i\bullet}$ denotes error mean of group i. The incidental parameter problem is no longer an issue. The parameter estimates of the within effect model are identical to those of LSDV. The within effect model in turn has several advantages. This model does not report dummy coefficients, but they can be computed using $d_g^* = \bar{y}_{g\bullet} - \beta'\bar{x}_{g\bullet}$, where $\bar{y}_{g\bullet}$ denotes dependent variable mean of dummy variable group g and $\bar{x}_{g\bullet}$ denotes explanatory variable mean of dummy variable group g. Since no dummy is used, the within effect model has larger degrees of freedom for error, resulting in small mean square error (MSE) and incorrect (larger) standard errors of parameter estimates. The standard error can be adjusted using,

$$se_k^* = se_k \sqrt{\frac{df_{error}^{Within}}{df_{error}^{LSDV}}} = se_k \sqrt{\frac{nT - k}{nT - n - k}}.$$

Finally, the R^2 of the within effect model is not correct because the intercept is suppressed.

The between group effect model, also called the group mean regression, uses group means of the dependent and explanatory variable. This data aggregation reduces the number of observation down to n. OLS regression is performed on $\bar{y}_{i\bullet} = \alpha + \bar{x}_{i\bullet} + u_i$, where $\bar{y}_{i\bullet}$ denotes dependent variable mean of group i and $\bar{x}_{i\bullet}$ denotes explanatory variable mean of group i. Portions of the next section make use of (Verbeek, 2004).

Two recent studies, Rosko (2004) and McKay & Meng (2007), assessed various influences on the supply of uncompensated care using the one-way fixed-effect model.

4.5.4.2 One-Way Random-Effects Model

As an alternative to the fixed technique, the unobserved effects could be regarded as random in origin, and thus a part of the error term. The random-effects model ("REM"), in contrast to the FEM, estimates variance components for groups and error, assuming the same intercept and slopes. The REM estimates $E\{y_{it} \mid x_{it}\} = x_{it}'\beta$. The difference among groups (or periods) lies in the variance of the error term. This model is estimated by generalized least squares ("GLS") when the Ω matrix (i.e., the variance structure among groups), is known. The GLS method is used to estimate the variance structure when Ω is not known. A typical example is the groupwise heteroskedastic regression model (Greene, 2008). There are various estimation methods for GLS, including maximum likelihood methods and simulations (Baltagi & Chang, 1994). It is commonly assumed in regression analysis that all factors that affect the dependent variable, but that have not been included as regressors, are summarized by a random error term. The assumption there is that the α_i are random factors, independently and identically distributed over individuals. Thus, the REM is

$$y_{it} = \alpha + x_{it}'\beta + \mu_i + v_{it}, \quad \mu_i \sim IID\left(0, \sigma_\mu^2\right); \; v_{it} \sim IID\left(0, \sigma_v^2\right),$$

where $u_{it} = \mu_i + v_{it}$ and $(\mu_i + v_{it})$ is treated as an error term consisting of two components: an individual specific component, which does not vary over time μ_i, and a remainder component v_{it}, which is assumed to be uncorrelated over time. All correlation of the error terms over time is attributed to the individual effects of μ_i. The μ_i and v_i are mutually independent and independent of x_{js} (for all j and s). The OLS estimator for α and β is unbiased and consistent. The composite error term $(\mu_i + v_{it})$ exhibits a particular form of autocorrelation (unless $\sigma_\mu^2 = 0$). Thus, the routinely computed standard errors for the OLS estimator are incorrect and a more efficient (GLS) estimator can be obtained by exploiting the structure of the error covariance matrix.

The GLS estimator for β is written as

$$\hat{\beta}_{GLS} = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)' + \psi T \sum_{i=1}^{N} (x_i - \bar{x})(x_i - \bar{x})' \right)^{-1} \times \left(\sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)(y_{it} - \bar{y}_i) + \psi T \sum_{i=1}^{N} (\bar{x}_i - \bar{x})(\bar{y}_i - \bar{y}) \right),$$

where $\psi = \sigma_v^2 / \sigma_v^2 + T\sigma_\mu^2$ and $\bar{x} = (1/(NT)) \Sigma_{i,t}\, x_{it}$ denotes the overall average of x_{it}.

Deriving $\hat{\beta}_{GLS} = \Delta \hat{\beta}_B + (I_k - \Delta)\hat{\beta}_{FE}$, where

$$\hat{\beta}_B = \left(\sum_{i=1}^{N} (\bar{x}_i - \bar{x})(\bar{x}_i - \bar{x})' \right)^{-1} \sum_{i=1}^{N} (\bar{x}_i - \bar{x})(\bar{y}_i - \bar{y})$$

is the *between estimator* for β, which is the OLS estimator in the model for individual means $y_{it} = \alpha + \bar{x}_i \beta + \mu_i + \bar{v}_i$, $i = 1, \ldots, N$. The matrix Δ is a weighting matrix and is proportional to the inverse of the covariance matrix of the between estimator $(\hat{\beta}_B)$. Thus, the GLS estimator is a matrix-weighted average of the between estimator and the within estimator, where the weight depends upon the relative variances of the two estimators (the more accurate one gets the higher weight).

The between estimator effectively discards the time series information in the data set. The GLS estimator is the optimal combination of the within estimator and the between estimator, and is more efficient than either of the two estimators. The OLS estimator (with $\psi = 1$) is also a linear combination of the two estimators, but not efficient. GLS will be more efficient that OLS. If the explanatory variables are independent of all v_{it} and all μ_i, the GLS estimator is unbiased. GLS is a consistent estimator for N or T or both $\to\infty$, if $E\{\bar{x}_i v_{it}\}=0$ and $E\{\bar{x}_i \mu_i\}=0$.

Since the variance components σ_μ^2 and σ_v^2 are unknown in practice, the FGLS estimator can be used. The σ_v^2 is obtained from the within residuals. The error variance for the between regression is $\sigma_\mu^2+(1/T)\sigma_v^2$ which is estimated by

$$\hat{\sigma}_B^2=\frac{1}{N}\sum_{i=1}^{N}\left(\bar{y}_i-\hat{\mu}_B-\bar{x}_i'\hat{\beta}_B\right)^2,$$

where $\hat{\alpha}_B$ is the between estimator for μ. Thus, the consistent estimator for σ_μ^2 is

$$\hat{\sigma}_\mu^2=\hat{\sigma}_B^2-\frac{1}{T}\hat{\sigma}_v^2.$$

This estimator is adjusted by subtracting the number of regressors $K+1$ in the denominator of $\hat{\sigma}_B^2$. The resulting FGLS estimator is the random-effects estimator for β (and α) denoted in the covariance matrix below as $\hat{\beta}_{RE}$.

The covariance matrix for the random-effects estimator is

$$V\{\hat{\beta}_{RE}\}=\sigma_v^2\left(\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it}-\bar{x}_i)(x_{it}-\bar{x}_i)'+\psi T\sum_{i=1}^{N}(\bar{x}_i-\bar{x})(\bar{x}_i-\bar{x})'\right)^{-1},$$

which indicates that the random-effects estimator is more efficient than the fixed-effects estimator provided $\psi>0$. The gain in efficiency is due to use of the between variation in the data $(\bar{x}_i-\bar{x})$. The $V\{\hat{\beta}_{RE}\}$ covariance matrix above is estimated by the OLS expressions in the transformed model.

The REM has the very practical advantage of conserving degrees of freedom in estimation in comparison to the FEM. Offsetting this advantage, however, is the possibility that the estimators will be biased due to correlation between the error associated with each cross-sectional unit and the other explanatory variables, a problem that is not present in the FEM. The random-effects estimator should only be used whenever the composite error is uncorrelated with the explanatory variables (Kennedy, 2008).

4.5.4.3 Summary of One-Way Panel Models

Table 4-3 provides a summary matrix of the two types of one-way panel models' intercepts, error variances, slopes, and estimations.

Table 4-3. One-way panel model matrix

	Fixed-Effects Model	Random-Effects Model
Intercepts	Varying across groups/times	Constant
Error Variances	Constant	Varying across groups/times
Slopes	Constant	Constant
Estimation	LSDV, within, between	GLS, FGLS

4.6 Model Estimation

4.6.1 Estimating Method

The panel estimating method for this study was a one-way fixed-effects model. The commercial econometric software used for this study and discussed below provided the statistical tests necessary for determining the one-way fixed-effect model was the appropriate estimation method.

4.6.2 Estimating Equation

The preceding literature review, theoretical framework, and research hypotheses provide the foundation for determining the explanatory variables used in this study. The generic one-way fixed-effect panel estimating equation is,

$$y_{it} = u_i + \beta_1 x_{it} + \beta_2 s_i + \beta_3 z_t + \varepsilon_{it},$$

where, u_i is the hospital-level effect, x_{it} are variables that vary across hospitals and time (e.g., occupancy percent), s_i are time-invariant variables that only vary across hospitals (e.g., county), z_t are hospital-invariant variables that vary solely over time (e.g., county-level unemployment percent), and ε_{it} is the disturbance term. However, there are no time-invariant variables s_i in this study's estimating equation. Expanding the generic panel equation above, the one-way fixed-effect panel data estimating equation used in this study was,

$$\begin{aligned}
Y_{it} = {} & u_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + \beta_6 X_{6it} + \beta_7 Z_{1t} \\
& + \beta_8 X_{7it} + \beta_9 Z_{2t} + \beta_{10} Z_{3t} + \beta_{11} Z_{4t} + \beta_{12} Z_{5t} + \beta_{13} Z_{6t} + \beta_{14} X_{8it} + \beta_{15} X_{9it} \\
& + \beta_{16} X_{10it} + \beta_{17} X_{11it} + \beta_{18} X_{12it} + \beta_{19} X_{13it} + \beta_{20} X_{14it} + \beta_{21} X_{15it} + \beta_{22} X_{16it}, \\
& + \beta_{23} X_{17it} + \beta_{24} X_{18it} + \beta_{25} X_{19it} + \beta_{26} Z_{7t} + \beta_{27} Z_{8t} + \beta_{28} Z_{9t} + \beta_{29} Z_{10t} \\
& + \beta_{30} Z_{11t} + \varepsilon_{it}
\end{aligned}$$

where,

Y_{it} = Uncompensated care expense percent: P_UC_TEXP

<u>Government-Funded Managed Care Provision</u>

X_{1it} = Medicare managed care net patient revenue percent: P_NPREV_MMCR

X_{2it} = Medicaid managed care net patient revenue percent: P_NPREV_MMCD

Other Managed Care Provision

X_{3it} = Commercial managed care net patient revenue percent: P_NPREV_MCOM

Profit

X_{4it} = Profit margin percent, net of uncompensated care expense: P_PRFT_NETUC

Mission

X_{5it} = For-profit hospital: FP

X_{6it} = Intern and resident to staffed bed ratio: R_INTRES_BED

Demand for Uncompensated Care

Z_{1t} = County unemployment percent: P_UNEMP_C

Other Hospitals' Supply of Uncompensated Care

X_{7it} = Other county hospitals' uncompensated care expense percent: P_OTHUC_C

Market Characteristics

Z_{2t} = County physician-owned specialty hospital outpatient surgery percent: P_POSH_OPS_C

Z_{3t} = County ambulatory surgery center to hospital ratio: R_ASCHOSP_C C

Z_{4t} = County federally qualified health center to hospital ratio: R_FQHCHOSP_C

Z_{5t} = County rural health center to hospital ratio: R_RHCHOSP_C

Z_{6t} = County unauthorized immigrant population density: DENS_UPOP_C

Hospital Characteristics

X_{8it} = Number of staffed beds: LN_BEDS

X_{9it} = Occupancy percent: P_OCCUP

X_{10it} = Severity of illness: SEV_ILL

X_{11it} = Births per admission: R_BIRTHS_ADMT

X_{12it} = Emergency room mix of OP visits, net of OP surgeries: ERMIX_NETOPS

X_{13it} = Admissions per emergency room visit: R_ADM_ERVIST

X_{14it} = Physical plant age: PLANT_AGE_R

X_{15it} = Other government net patient revenue percent: P_NPREV_OGOV

X_{16it} = Total expenses to total net patient revenue ratio: P_TEXP_NPREV

X_{17it} = Network member: D_NETWORK

X_{18it} = Risk-adjusted mortality reciprocal rate for acute stroke: IQI_17_R

X_{19it} = Risk-adjusted mortality reciprocal rate for acute myocardial infarction: IQI_32_R

Z_{7t} = Year 2000: D_YR_2000

Z_{8t} = Year 2001: D_YR_2001

Z_{9t} = Year 2002: D_YR_2002

Z_{10t} = Year 2003: D_YR_2003

Z_{11t} = Year 2005: D_YR_2005

Other details about the dependent variable and explanatory variables are provided in Tables 4-1 and 4-2. Table 4-1 provides the variables' name, definition, scale, and domain, classified by their theoretical construct. Table 4-2 identifies the variables' name, label, and source.

4.6.3 Software

Statistical tests and the estimation were carried out using the commercial STATA statistics and data analysis software package[15] (StataCorp., 2007a). This package has sufficient panel data regression features for this study and related statistical tests for determining the appropriate model estimation method and diagnosing multicollinearity, correlation, and heteroskedasticity.

4.6.4 Software Statistical Procedures and Commands

Appendixes A through D provide information on STATA's panel procedures and commands. Appendix A shows a summary of the panel estimating commands. Appendix B shows a summary of the panel poolability, spherical, and model selection commands. Appendix C shows a summary of panel post-estimation commands. Appendix D shows a summary of the multicollinearity test commands.

[15] Version 10.1, updated through January 20, 2010.

Chapter 5 – Estimation and Results

5.1 Observations

The study period is 2000 through 2005, inclusive. There were 155 cross-section groups (i), over six one-year time periods (t), resulting in a study file containing $N = 750$ observations (it) during the study period. A minimum of two observations per cross-sectional group (i) was the threshold amount for inclusion in this study. Because there were gaps in the data, the panel was unbalanced. Of the 155 cross-section groups, 45.8 percent had observations occurring in all six years of the study period. The remaining 54.2 percent of the cross-section groups had other patterns of observations. Additional information about the cross-section groups, including frequencies and patterns of the study dataset's observations, are in Appendix E.

Table 5-1 below presents a summary of the annual observations and shows that the number of observations tend to increase and then decrease across the study period. The number of observations in year 2000 is the smallest, compared to succeeding years. This was due to the phase-in of THCIC's quality data reporting requirements.

Table 5-1. Summary annual of observations

	2000	2001	2002	2003	2004	2005	Total
Number of observations	105	124	131	136	126	128	750
Percent	14.00	16.53	17.47	18.13	16.80	17.07	

Table 5-2 below, which presents a summary of hospital control, shows that not-for-profit hospitals were prevalent. The table also shows for-profit hospitals were the second largest category of study hospitals followed by local government hospitals.

Table 5-2. Summary of annual observations by hospital control

Control	2000	2001	2002	2003	2004	2005	Total	Percent
Not-for-profit	51	60	65	68	62	65	371	49.5
For-profit	45	51	51	52	50	47	296	39.5
Local government	9	13	15	16	14	16	83	11.0
Total	105	124	131	136	126	128	750	

5.2 Outliers

Outliers are observations in a data set that are substantially different from the bulk of the data (Wooldridge, 2003), or observations that have extreme values (Vogt, 1999). Potential outliers were identified for each study variable across the study period using a numerical method that recognized outliers as those data points that were more than two absolute *z*-score deviations from the focal hospital's variable mean. Above, potential outliers were identified using within (i.e., intra)-hospital values versus between (i.e., inter)-hospital values. The outliers identified above were assessed individually considering the particular environment and circumstances of the focal hospital. Most identified outliers were not automatically rejected and were retained in the study. However, two observations containing outlier **PLANT_AGE** data points were dropped from the study dataset. For the two discarded observations, the recorded outlier values were extreme and nothing like adjacent year's values for those particular hospitals. They appeared to be data entry errors. Retention of the other outlier values was justified because they were integral to the study. Automatic rejection of outliers is not always a wise procedure (N. D. Draper & Smith, 1998, p. 76).

5.3 Estimation

All estimations were carried out using the commercial STATA statistics and data analysis software package (StataCorp., 2007a) and the panel data procedures outlined in the related longitudinal/panel data technical manual (StataCorp., 2007b). STATA's panel commands require that the data be organized in long form, with each observation a distinct individual – time pair; in this study a hospital – year pair. A sample of the data organized in the long form is in Appendix F; the first observation is for ID 9 (i.e., hospital 9) in year 1; the second observation is for ID 9 in year 2, and so on. The panel identifier variable ID takes values 1 through 155 and the time variable YEAR takes values 1 through 6. In STATA, the panel-data commands require that the panel and time identifiers be set in that order to make the data suitable for panel analysis as shown in Appendix G; the STATA program output indicates the data are available in all periods, but the panel variable ID is unbalanced due to gaps in the YEAR variable. Finally, the delta shows the time variable increments uniformly by one.

5.3.1 Multicollinearity

Multicollinearity exists when two or more explanatory variables are highly correlated; making it difficult to determine their separate effects on the dependent variable (Vogt, 1999). Two common methods of detecting multicollinearity are use of variance inflation factors ("*VIF*") and the correlation matrix. As a rule of thumb, a $VIF_i > 10$ indicates harmful collinearity (Gujarati, 2003; Kennedy, 2008). According to Kennedy (2008), a high value (about 0.8 or 0.9 in absolute value) of one of the correlation coefficients $\left(\rho_{x,y}\right)$ in the correlation matrix indicates high correlation between the two reference explanatory variables.

Two quantitative tests for the presence of multicollinearity were performed. First, the explanatory variable *VIF*s were calculated following the required OLS regression of the dependent variable on the explanatory variables. For each explanatory variable, the resulting *VIF* values were less than 10, suggesting no multicollinearity within the explanatory variables. The STATA program output showing the individual *VIF* values is in Appendix H. Second, a matrix of the correlation coefficients between all pairs of the explanatory variables was generated. For each (x, y) pair of the explanatory variables, the related $\rho_{x,y}$ was less than the absolute value of 0.8, suggesting no high correlation between the combinations of explanatory variables. The STATA program commands for multicollinearity testing is in Appendix D. The STATA program output showing the pairwise correlation coefficients is in Appendix I.

Although the examinations above found no evidence of multicollinearity, Hsiao (2003), states that panel data reduces problems of data multicollinearity. In addition, Kennedy (2008) points out that panel data tends to minimize multicollinearity problems and makes estimation more efficient because the data creates more variability by combining variation across micro units with variation over time.

5.3.2 Non-Spherical Disturbances

5.3.2.1 Autocorrelation

Autocorrelation is correlation across observations in the groups in a panel (Greene, 2008). Serial correlation in linear panel-data models biases the standard errors and causes the results to be less efficient. Although heteroskedasticity in u_{it} is always a potential problem, serial correlation is more important (Wooldridge, 2002). In a panel data set, correlation across observations within a group is likely to be a more substantial influence on the estimated covariance matrix of the least square estimator than is heteroskedasticity (Greene, 2008).

Two quantitative tests for the presence of forms of correlation were conducted. The first test carried out was for autocorrelation in the idiosyncratic errors of a linear panel-data model discussed by (Wooldridge, 2002, pp. 282-283). Wooldridge's (2002) method above uses the residuals from a regression in first-differences on their lags and tests that the coefficient on the lagged residuals is equal to $-.5$. The test is robust to conditional heteroskedasticity and in relatively large samples this test has good power properties (Drukker, 2003). Using an alpha level of .05, the Wooldridge (2002) test for autocorrelation was significant, $F(1,131) = 12.434$, $p < .001$ indicating the null-hypothesis of no first order autocorrelation should be rejected and the presence of autocorrelation. The STATA program output for the Wooldridge (2002) test for autocorrelation is in Appendix J.

The second test carried out was for serial correlation using the Durbin-Watson statistic for panel data generalization of (Bhargava, Franzini, & Narendranathan, 1982) as discussed in (Baltagi, 2008; Verbeek, 2004) and implemented in STATA by (Merryman, 2007). This generalized-Durbin-Watson statistic for panel data (dw_p) tests the null hypothesis $\rho = 0$ versus the one-sided alternatives of $0 < \rho < 1(-1 < \rho < 0)$ using the within residuals rather than the OLS residuals. According to Bhargava, et al. (1982), p. 536, for a large number of cross-sections, it is sufficient to simply test for $dw_p < 2$ when testing against positive serial correlation. In the study dataset there are a large number of cross-sections, $i = 155$. Using the simple $dw_p < 2$ test threshold described above, the Bhargava, et al.

(1982) test statistic $dw_p = 1.26116$ is less than 2 indicating the null hypothesis of no positive serial correlation should be rejected and the presence of positive serial correlation. The STATA program output for the dw_p test statistic is at the bottom line of Appendix K.

The overall conclusion from the two quantitative correlation tests above is that the study dataset exhibits serial/autocorrelation.

5.3.2.2 Heteroskedasticity

Regression disturbances whose variances are not constant across observations are heteroskedastic (Greene, 2008, p. 158). Heteroskedasticity in linear panel-data models biases the standard errors and causes the results to be less efficient. Assessment for the presence of heteroskedasticity in this study was carried out using both qualitative and quantitative methods.

Two qualitative or visual inspections for the presence of heteroskedasticity were undertaken. Ideally, the scatter of a residual versus fitted plot should be fairly even and patternless, with no hints of curvature or disturbance by outliers. First, visual inspection of the residual versus fitted plot of values from the within regression shows asymmetrical scatter, curvature, cornucopia basket shape, and dissociation of a group of plot points. The residual versus fitted scatter plot from STATA is in Figure 5-1. Second, visual inspection of a box plot of the studentized (jackknifed) residuals plotted by percentiles of the linear prediction also shows uneven variance. The studentized (jackknifed) residuals box plot from STATA is in Figure 5-2.

The two qualitative inspections suggest the presence of heteroskedasticity.

Figure 5-1. Heteroskedasticity scatter plot of residual versus fitted values

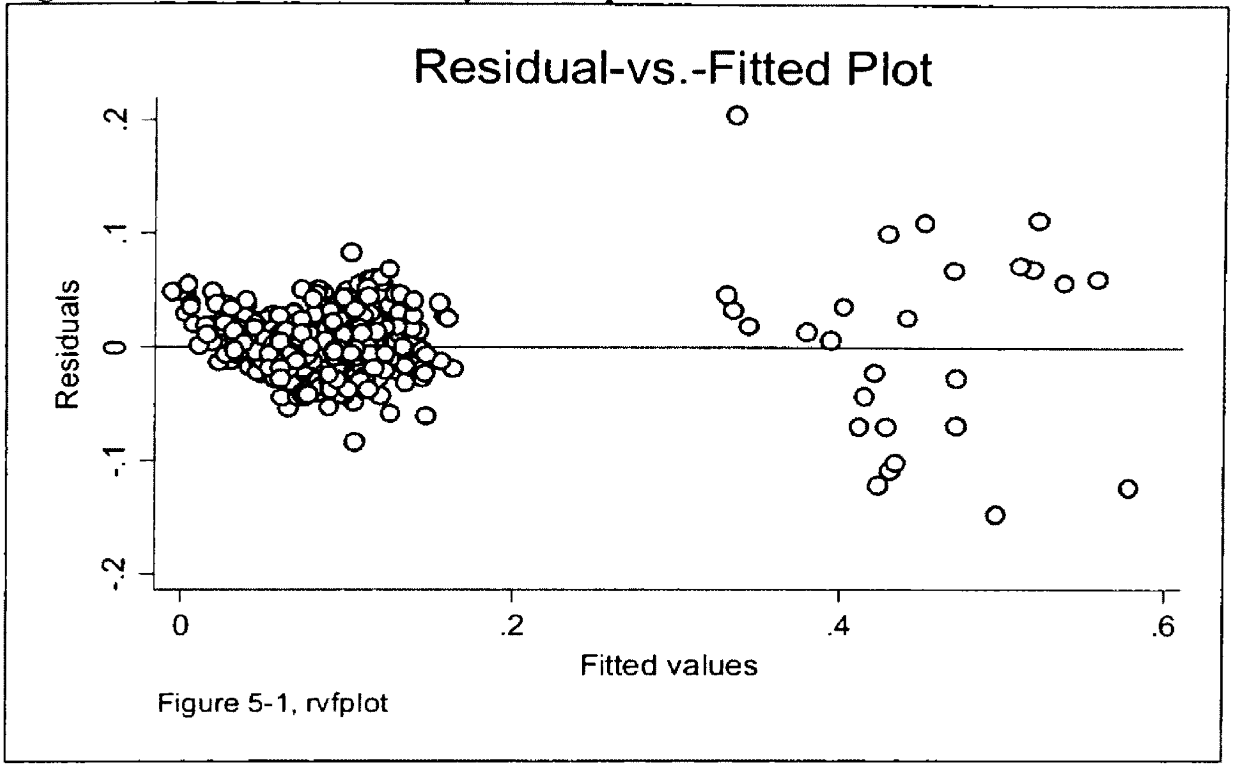
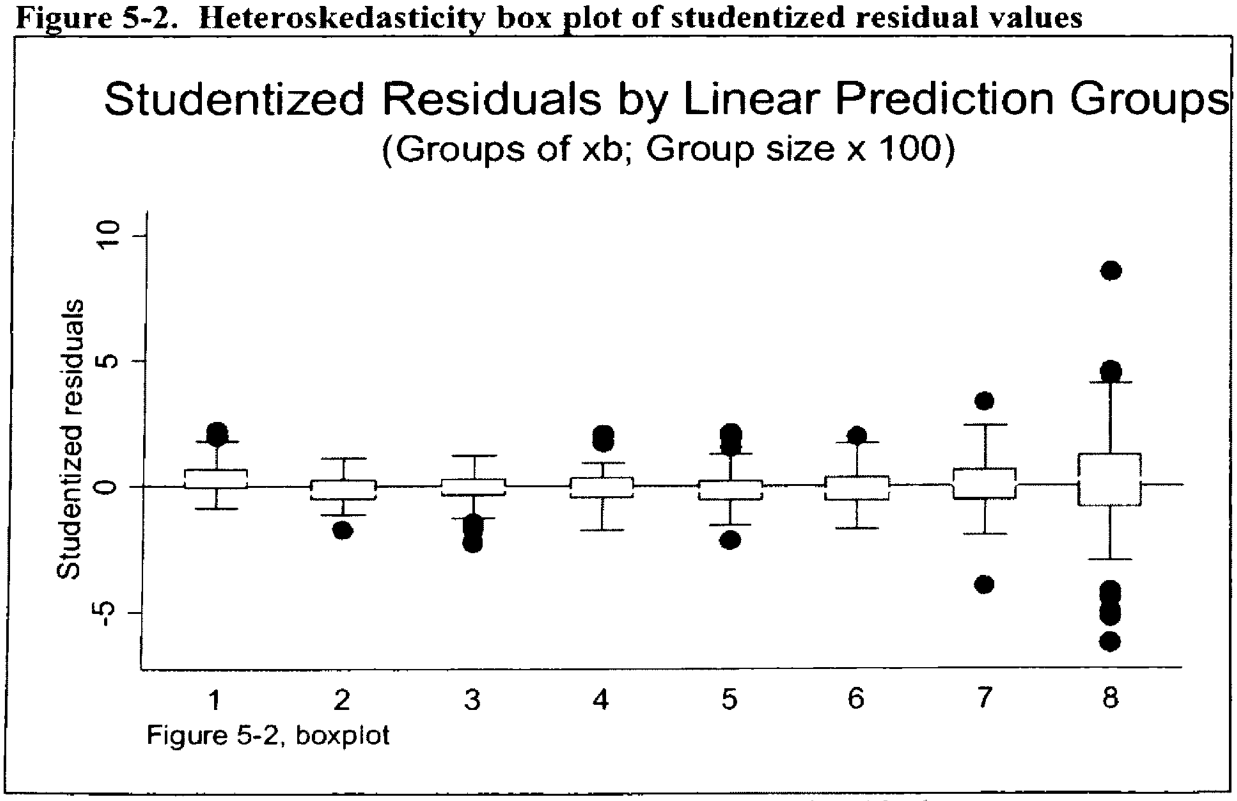


Figure 5-2. Heteroskedasticity box plot of studentized residual values



Note: Studentized residual values are jackknifed studentized residuals

Two quantitative tests for the presence of heteroskedasticity were conducted. The first test calculates a modified Wald statistic for groupwise heteroskedasticity in the residuals of a fixed effect regression model, following the method in Greene (2008), p. 166, but modified to allow for unbalanced panels. This test assesses the hypothesis $\sigma_i^2 = \sigma_{i=1}$, Ng, where Ng is the number of cross-sectional units. The most likely deviation from homoskedastic errors in the context of panel data is likely to be error variances specific to the cross-sectional unit. Using an alpha level of .05, the Greene (2008) test for heteroskedasticity, adjusted for unbalanced panels, was significant, $\chi^2(155) = 4.0e+31$, $p < .001$ indicating the null-hypothesis of no heteroskedasticity should be rejected and the presence of groupwise heteroskedasticity. The STATA program output for the Greene (2008) test for heteroskedasticity is in Appendix L.

The second test for heteroskedasticity was conducted using the (Bickel, 1978) version of the Breusch-Pagan LM test (Breusch & Pagan, 1979). The Bickel test is asymptotically powerful (Hammerstrom, 1981) and is suitable for use as a diagnostic tool (Cook & Weisberg, 1983). The convenience of this test is that it evaluates for both within and between heteroskedasticity. First, the within regression was estimated and the residuals and predictions were obtained. Then the squared residuals were regressed on powers of the predictions up to the seventh power from the same model[16]. Using an alpha level of .05, the Bickel (1978) version of the Breusch-Pagan (1979) LM test was significant using a Wald F test, $F(7,742) = 44.400$, $p < .001$ indicating that the null-hypothesis of no within or between heteroskedasticity should be rejected and the presence of within and between

[16] Prediction power value based on $T + 1$.

heteroskedasticity. The STATA program output for the Bickel (1978) version of the Breusch-Pagan (1979) LM test is in Appendix M.

The collective conclusion from all of the qualitative and quantitative heteroskedasticity tests above is that the study dataset is heteroskedastic.

5.3.3 Pooling versus Individual Effects

After evaluating for the presence of serial/autocorrelation and heteroskedasticity, the next step in the model specification search was to determine whether the model should be estimated using pooled OLS. One of the main motivations behind pooling a time series of cross sections is to widen the data set in order to get better and more reliable estimates of the model parameters. Baltagi (2008) recommends using the Chow (1960) test to test for poolability of the data for use in OLS. The STATA software executes the fixed effect panel regression and automatically produces the Chow (1960) test using the restricted residual sums of squares from OLS on the pooled model and the unrestricted residual sums of squares from the within regression. The null hypothesis $u_1 = u_2 = \ldots = u_{N-1} = 0$ was evaluated using an F-test. Using an alpha level of .05, the Chow (1960) test was significant, $F(154,566) = 17.094$, $p < .001$ indicating the presence of individual effects and the model should not estimated using pooled OLS. The STATA program output for the Chow (1960) test is in Appendix N.

5.3.4 Standard Errors versus Robust Standard Errors

From the above diagnostics, the conclusion is that there are both serial/autocorrelation and heteroskedasticity in the study data set. Both the random-effects and fixed-effects models assume that the presence of α_i captures all correlation between the unobservables in different periods. That is, ε_{it} is assumed uncorrelated over individuals and time. If the X_{it} variables are strictly exogenous, the presence of autocorrelation in ε_{it} does not result in inconsistency of the standard estimators. It does, however, invalidate the standard errors and resulting tests (Verbeek, 2004, p. 355). In the words of Cameron and Trivedi (2005, p. 702), "*NT* correlated observations have less information than *NT* independent observations."

Attention has been previously drawn to robust standard error estimation in the context of a fixed-effects model variant, the differences-in-differences model (Bertrand, Duflo, & Mullainathan, 2004). Valid statistical inference requires controlling for both serial correlation and heteroskedasticity (Cameron & Trivedi, 2005, p. 705). A finding of serial correlation warrants obtaining a fully robust asymptotic variance matrix estimator, provided that T is small relative to N (Wooldridge, 2002, pp. 275-276). For the within estimator, (Arellano, 1987) suggested a simple method for obtaining robust estimates of the standard errors that allows for a general variance-covariance matrix as in (White, 1980) for fixed-effects models and the robust standard errors are robust to heteroskedasticity and serial correlation of arbitrary form (Baltagi, 2008, p. 90; Wooldridge, 2002, p. 275). The robust (i.e., clustered) estimator applied to mean-differenced data is consistent in general and behaves well in finite samples (Kézdi, 2004). Panel-robust standard errors can be obtained without assuming specific functional forms for either within-individual error correlation or heteroskedasticity (Cameron & Trivedi, 2005, p. 705). The robust standard errors improve on the usual standard errors because the resulting inferences are asymptotically valid when the regression residuals are heteroskedastic (Angrist & Pischke, 2009). Kézdi (2004) recommends that researchers should routinely estimate the robust estimator in moderate-sized and large samples. This study's dataset is of moderate size, $N = 750$. Alternatively, one could use the usual standard errors that do not adjust for correlation between observations. However, the usual standard errors are derived assuming homoskedasticity (Angrist & Pischke, 2009) and their use can lead to standard errors that are too small (Petersen, 2009) and create large *t*-statistics which lead to statistical significance even when it does not exist (Thompson, 2009). Estimates that are robust to the form of dependence in the data produce unbiased standard errors and correct confidence intervals; estimates that are not robust to the form of dependence in the data produce biased standard errors and confidence intervals that are often too small (Petersen, 2009).

Normal standard errors produced in the presence of the non-spherical correlation and/or heteroskedasticity disturbances produce biased results. Because this study dataset exhibits both serial/autocorrelation and heteroskedasticity and efficient estimates are desired, the decision here is to proceed with an estimation using robust standard errors clustered on hospitals (i.e., ID), in lieu of estimation that produces the usual standard errors. Alternatively, one could proceed with an estimation using robust standard errors double clustered on hospitals (i.e., ID) and periods (i.e., YEAR). However, such dual clustering will not dramatically improve standard error estimates if there are far more firms than time periods (Thompson, 2009, pp. 2-3). In this study dataset there are many more firms (i.e., hospitals) than time periods; $i = 155 > t = 6$.

5.3.5 Robust Hausman Specification Test

The essential distinction in microeconometrics analysis of panel data is that between fixed and random models. Having previously determined that individual effects are present in the study dataset and that the model should not be estimated with pooled OLS, the next step in the model specification search was to determine whether to treat the individual effects as fixed or random. Hausman (1978) suggested a standard test for the null hypothesis of no correlation between the individual effects and X_{it} (i.e., the effects are random) to assist in the fixed versus random model determination. However, a serious shortcoming of the standard Hausman test above is that it requires the random-effects estimator to be efficient. This in turn requires that the α_i and ε_{it} are independent and identically distributed ("i.i.d."), an invalid assumption if cluster-robust standard errors for the random-effects estimator differ substantially from default standard errors (Cameron & Trivedi, 2009, p. 261). Thus, the standard Hausman (1978) specification test for fixed- or random-effects is not appropriate in the case of this study because, as concluded earlier, the study dataset suffers from both serial/autocorrelation and heteroskedasticity and that estimation using robust standard errors is indicated to obtain efficient estimates. For the more likely case that the random-effects estimator is not fully efficient, Wooldridge (2002, p. 291) suggests estimating the Hausman (1978) auxiliary OLS regression

$$y_{it} - \hat{\lambda}\bar{y}_i = \left(1-\hat{\lambda}\right)\mu + \left(x_{1it} - \hat{\lambda}\bar{x}_{1i}\right)' \beta_1 + \left(x_{1it} - \bar{x}_{1i}\right)' \gamma + v_{it}$$

where x_1 denotes only time-varying regressors, and testing $\gamma = 0$ using panel-robust standard errors. If the effects are random, though not necessarily such that α_i and ε_{it} are i.i.d., then $v_{it} = \left(1-\hat{\lambda}\right)\alpha_i + \left(\varepsilon_{it} - \hat{\lambda}\bar{\varepsilon}_i\right)$ is still uncorrelated with the regressors though v_{it} is no longer asymptotically i.i.d., so cluster-robust standard errors need to be used. If the effects are fixed then the error v_{it} is correlated with the regressors, leading to significance of additional functions of the regressors such as $\left(x_{it} - \bar{x}_i\right)$. This robust version of the auxiliary regression for the Hausman (1978) test is preferred to one that assumes v_{it} is asymptotically i.i.d., on the usual grounds of minimizing distributional assumptions (Cameron & Trivedi, 2005, pp. 718-719).

As suggested by Wooldridge (2002), p. 291, to account for serial correlation across time as well as heteroskedasticity, the Hausman (1978) auxiliary specification test above for $\gamma = 0$ was carried out in STATA using cluster-robust standard errors as advised by (Cameron & Trivedi, 2005, pp. 718-719) via procedures made available by (Cameron & Trivedi, 2009, p. 262 Errata; Hoechle, 2007, p. 307). Using an alpha level of .05, the Wald F-test for $\gamma = 0$ was significant, $F(30,154) = 4.008$, $p < .001$. Thus, the Hausman (1978) auxiliary specification test strongly rejects the null hypothesis of no correlation between the individual effects and X_{it} (i.e., effects are random) indicating that the individual effects are fixed. The STATA program output for the Hausman (1978) auxiliary specification test is in Appendix O.

Although not used for this study because of the presence of serial/autocorrelation and heteroskedasticity in the data, the standard Hausman (1978) specification test for fixed- or random-effects is presented for comparison and shows that the individual effects were fixed. The STATA program output is in Appendix P. For the standard Hausman (1978) specification test using the consistent (fixed-effects) estimator, $\chi^2(30) = 300.49$, $p < .001$ and using the efficient (random-effects) estimator, $\chi^2(30) = 218.17$, $p < .001$.

5.3.6 Overidentifying Restrictions

A test of fixed- vs. random-effects can also be thought of as a test of overidentifying restrictions (Schaffer & Stillman, 2010). The fixed-effects estimator uses the orthogonality conditions that the regressors are uncorrelated with the idiosyncratic error ε_{it} (i.e., $E(X_{it} \times \varepsilon_{it}) = 0$). The random-effects estimator uses the additional orthogonality conditions that the regressors are uncorrelated with the group-specific error u_i (i.e., $E(X_{it} \times u_i) = 0$). These additional orthogonality conditions are essentially overidentifying restrictions. Using an alpha level of .05, the overidentifying restrictions Sargan-Hansen statistic clustered on hospitals (i.e., ID) was significant using robust standard errors, $\chi^2(30) = 116.201$, $p < .001$. Thus, the overidentifying restrictions test also strongly rejects the null hypothesis of no correlation between the individual effects and X_{it} (i.e., effects are random) indicating the individual effects are fixed. The STATA program output for the Schaffer & Stillman (2010) overidentifying restrictions test is in Appendix Q.

The Hausman (1978) auxiliary and Schaffer & Stillman (2010) overidentifying restrictions tests above both indicate the individual effects are fixed. Thus, the specification search concludes here with the decision to proceed using a one-way fixed-effects model. Therefore, subsequent testing for random-effects is not pursued and the random-effects model is not estimated or presented.

5.3.7 Fixed-Effects Estimation Using Robust Standard Errors

Recall that the study dataset suffers from serial/autocorrelation and heteroskedasticity. A path frequently followed in this situation is to estimate a panel model using FGLS. Even so, considering the study dataset has 155 panels and 6 time periods, the FGLS method is not an option because its estimation of standard errors is problematic unless T is greater than or equal to N (Beck & Katz, 1995, p. 637; Wiggins, 2009). The FGLS method requires estimating the covariance matrix of the heteroskedastic and correlated errors and then transforming the data to remove the covariance. However, the estimated covariance matrix is singular if the number of time points (T) is less than the number of cross-sectional units (N) in the panel. The singularity of the covariance matrix makes application of FGLS impossible (Beck, Katz, Alvarez, Garrett, & Lange, 1993, pp. 945-946). In STATA, the particular FGLS estimation method for dealing with a heteroskedastic error structure and cross-sectional correlation returns results based on a generalized inverse of a singular matrix unless the number of periods is greater than or equal to the number of panels (StataCorp., 2007b, p. 145).

Recall also the Hausman (1978) auxiliary specification test and Schaffer & Stillman (2010) overidentifying restriction test previously discussed both indicated the individual effects are fixed. A straightforward way to deal with both the serial/autocorrelation and heteroskedasticity afflictions, avoid misleading inferences, and gain efficient estimates is to estimate the regressions with fixed-effects and cluster-robust standard errors (Cameron & Trivedi, 2005, p. 705, 2009; Verbeek, 2004, p. 355; Wooldridge, 2002, pp. 275, 291). The STATA software produces an estimator of the variance-covariance estimator that is robust to cross-sectional heteroskedasticity and within-panel (serial) correlation that is asymptotically equivalent to that proposed by Arellano (1987), while the coefficients remain the same as before the correction for autocorrelation and heteroskedasticity (Nichols & Schaffer, 2007; StataCorp., 2007b, p. 402). Baltagi (2008) suggests for the within estimator, the Arellano (1987) method is a easy approach to obtaining robust estimates of the standard errors that allow for a general variance-covariance matrix on the υ_{it} as in White (1980). The heteroskedasticity-robust variance matrix estimator for cross-sectional regression (with or without a degrees-of-freedom adjustment), applied to the fixed-effects estimator for panel data with serially uncorrelated errors, is inconsistent if the number of time periods is fixed (and greater than 2) as the number of entities increases (Stock & Watson, 2008).

5.4 Results

5.4.1 Descriptive Statistics

For each year, the dataset included only non-federal, non-state, short-term, acute care medical-surgical hospitals with at least 25 beds located in counties within the MSAs of Texas, subject to the selection criteria previously discussed in Section 4.1. The study period was 2000 through 2005. The descriptive statistics for the regression variables are in Table 5-3 below. Means only descriptive statistics for the individual years are in Table 5-4 below. The detailed STATA program summary output, including number of observations, mean, standard deviations, and minimum and maximum values is in Appendix R.

The descriptive results of dependent variable and those explanatory variables related to the research hypotheses are briefly discussed in the succeeding sections. The dependent variable is discussed in Section 5.4.1.1.1 and the key explanatory variables are discussed in Section 5.4.1.1.2.

Table 5-3. Panel descriptive statistics

VARIABLE LABEL	MEAN	S.D.	MIN.	MAX.
DEPENDENT VARIABLE				
Uncompensated care expense percent	0.093	0.079	0.008	0.635
EXPLANATORY VARIABLES				
Government-Funded Managed Care Provision				
Medicare managed care net patient revenue percent	0.023	0.040	0.000	0.437
Medicaid managed care net patient revenue percent	0.031	0.035	0.000	0.243
Other Managed Care Provision				
Commercial managed care net patient revenue percent	0.361	0.174	0.000	0.814
Profit				
Profit margin percent, net of uncompensated care expense	0.151	0.113	-0.669	0.643
Mission				
For-profit hospital	0.395	0.489	0	1
Intern and resident to staffed bed ratio	0.052	0.135	0.000	0.935
Demand for Uncompensated Care				
County unemployment percent	0.058	0.020	0.015	0.136
Other Hospitals' Supply of Uncompensated Care				
Other county hospitals' uncompensated care expense percent	0.109	0.051	0.000	0.255
Market Characteristics				
County physician-owned specialty hospital outpatient surgery percent	0.034	0.061	0.000	0.366
County ambulatory surgery center to hospital ratio	1.368	0.835	0.000	4.500
County federally-qualified health center to hospital ratio	0.467	0.742	0.000	4.667
County rural health center to hospital ratio	0.206	0.581	0.000	6.000
County unauthorized immigrant population density	57.990	48.990	1.798	148.525
Hospital Characteristics				
Number of staffed beds^{NL}	5.400	0.669	3.219	7.240
Occupancy percent	0.630	0.129	0.215	0.983
Severity of illness	1.803	0.138	1.038	2.259
Births per admission	0.160	0.081	0.000	0.404
Emergency room mix of outpatient visits, net of outpatient surgeries	0.403	0.164	0.019	1.000
Admissions per emergency room visit	0.338	0.187	0.081	2.270
Reciprocal physical plant age	0.160	0.133	0.046	0.994
Other government net patient revenue percent	0.025	0.036	0.000	0.260
Total expenses percent of total net patient revenue	0.994	0.190	0.506	2.214
Network member	0.471	0.499	0	1
Risk-adjusted mortality reciprocal rate for acute stroke	11.140	5.369	2.469	61.801
Risk-adjusted mortality reciprocal rate for acute myocardial infarction	11.653	4.454	1.378	43.852
Year 2000	0.140	0.347	0	1
Year 2001	0.165	0.372	0	1
Year 2002	0.175	0.380	0	1

VARIABLE LABEL	MEAN	S.D.	MIN.	MAX.
Year 2003	0.181	0.386	0	1
Year 2005	0.171	0.376	0	1
N = 750				

Note: [NL] Natural log transformed; S.D. denotes standard deviation; MIN denotes minimum value; MAX denotes maximum value.

Table 5-4. Annual descriptive statistics (mean values only)

VARIABLE LABEL	2000 MEANS	2001 MEANS	2002 MEANS	2003 MEANS	2004 MEANS	2005 MEANS
DEPENDENT VARIABLE						
Uncompensated care expense percent	0.086	0.087	0.090	0.093	0.100	0.099
EXPLANATORY VARIABLES						
Government-Funded Managed Care Provision						
Medicare managed care net patient revenue percent	0.036	0.040	0.021	0.011	0.016	0.017
Medicaid managed care net patient revenue percent	0.019	0.029	0.029	0.032	0.038	0.035
Other Managed Care Provision						
Commercial managed care net patient revenue percent	0.329	0.347	0.357	0.373	0.382	0.373
Profit						
Profit margin percent, net of uncompensated care expense	0.146	0.159	0.165	0.137	0.150	0.148
Mission						
For-profit hospital	0.429	0.411	0.389	0.382	0.397	0.367
Intern and resident to staffed bed ratio	0.049	0.048	0.054	0.055	0.054	0.053
Demand for Uncompensated Care						
County unemployment percent	0.045	0.050	0.065	0.070	0.061	0.053
Other Hospitals' Supply of Uncompensated Care						
Other county hospitals' uncompensated care expense percent	0.108	0.106	0.105	0.106	0.116	0.111
Market Characteristics						
County physician-owned specialty hospital outpatient surgery percent	0.028	0.022	0.025	0.041	0.046	0.039
County ambulatory surgery center to hospital ratio	1.170	1.190	1.256	1.382	1.527	1.646
County federally-qualified health center to hospital ratio	0.371	0.360	0.409	0.416	0.579	0.652
County rural health center to hospital ratio	0.218	0.250	0.194	0.203	0.161	0.214
County unauthorized immigrant population density	57.353	58.058	54.301	58.737	61.130	58.335
Hospital Characteristics						
Number of staffed beds^{NL}	5.426	5.378	5.384	5.373	5.409	5.435
Occupancy percent	0.615	0.613	0.643	0.648	0.628	0.626
Severity of illness	1.784	1.803	1.819	1.850	1.757	1.801
Births per admission	0.164	0.157	0.160	0.158	0.162	0.161
Emergency room mix of outpatient visits, net of outpatient surgeries	0.384	0.391	0.397	0.414	0.416	0.410
Admissions per emergency room visit	0.364	0.365	0.335	0.318	0.331	0.320
Physical plant age	0.177	0.162	0.160	0.153	0.156	0.154
Other government net patient revenue percent	0.021	0.024	0.024	0.027	0.028	0.028
Total expenses percent of total net patient revenue	0.979	0.992	0.978	1.009	1.001	1.001
Network member	0.343	0.355	0.374	0.949	0.381	0.367
Risk-adjusted mortality reciprocal rate for acute stroke	9.844	10.917	9.859	12.181	11.721	12.051
Risk-adjusted mortality reciprocal rate for acute myocardial infarction	10.864	11.336	11.527	12.327	11.206	12.462

Year 2000	1.000	0.000	0.000	0.000	0.000	0.000
Year 2001	0.000	1.000	0.000	0.000	0.000	0.000
Year 2002	0.000	0.000	1.000	0.000	0.000	0.000
Year 2003	0.000	0.000	0.000	1.000	0.000	0.000
Year 2005	0.000	0.000	0.000	0.000	0.000	1.000
	n =105	*n* =124	*n* =131	*n* =136	*n* =126	*n* =128

Note: [NL] Natural logarithm transformed

5.4.1.1 Discussion of Descriptive Statistics

5.4.1.1.1 Dependent Variable

The dependent variable in this study is the uncompensated care expense as percent of *total* expenses **(P_UC_TEXP)**. Table 5-3 above, which presents panel descriptive statistics for the regression variables, shows that uncompensated care expense percent was 9.264 percent, on average, over the period 2000 through 2005. As a point of comparison, McKay & Meng (2007) found that uncompensated care expense as a percentage of *operating expenses* was approximately 6 percent for urban Florida hospitals over the period 1998 through 2002. Table 5-4 above, which presents annual mean descriptive statistics for the regression variables, shows an increasing trend of uncompensated care expense percent over the initial five years of the study period and a slight decline in the final year. Table 5-5 below, which presents mean uncompensated care expense percent by control and year, shows considerable differences between control groups; local government hospitals have the highest at 21.8 percent, and for-profit hospitals have the lowest at 6.51 percent. Table 5-5 also shows there is an increasing trend of uncompensated care expense percent across the study period.

Table 5-5. Uncompensated care expense percentages

P_UC_TEXP	2000	2001	2002	2003	2004	2005	Average
LGOVT	.2139	.2086	.2209	.2054	.2354	.2215	.2178
NFP	.0841	.0838	.0837	.0852	.0901	.0923	.0866
FP	.0621	.0589	.0592	.0680	.0745	.0679	.0651
Average	.0858	.0866	0.899	.0928	.1001	.0995	.0926

Note: LGOVT = Local government; NFP = Not-for-profit; FP = For-profit

5.4.1.1.2 Key Explanatory Variables

The key explanatory variables discussed in this section are those associated with the five research hypotheses in Section 3.3. The related theoretical constructs are government-funded managed care provision (i.e., Medicare and Medicaid), other managed care provision (i.e., Commercial HMO and PPO), profit, and other hospitals' supply of uncompensated care.

5.4.1.1.2.1 Government-Funded Managed Care

5.4.1.1.2.1.1 Medicare Managed Care Net Patient Revenue Percent

The first research hypothesis postulates that Medicare managed care net patient revenue, as a percent of total net patient revenue **(P_NPREV_MMCR)**, is negatively associated with hospitals' uncompensated care provision. Table 5-3 above, which presents panel descriptive statistics for the regression variables, shows that Medicare managed care net patient revenue was 2.293 percent, on average, over the period 2000 through 2005. Table 5-4 above, which presents annual mean descriptive statistics for the regression variables, shows small and fluctuating Medicare managed care net patient revenue percentages. It shows an increasing trend during the initial two years of the study period, a decreasing trend in the third to fourth years, and a small upward trend in the last two years. Table 5-6 below, which presents mean Medicare managed care net patient revenue percent by control and year, shows small percentages and differences between control groups; local government hospitals have percentages of Medicare managed care net patient revenue of less than one percent and for-profit hospitals have the highest percentage. Table 5-6 also shows a decreasing and then increasing time trend with 2003 being the lowest year.

Table 5-6. Medicare managed care net patient revenue percentages

P_NPREV_MMCR	2000	2001	2002	2003	2004	2005	Average
LGOVT	.0075	.0091	.0042	.0011	.0013	.0023	.0039
NFP	.0364	.0404	.0210	.0105	.0118	.0140	.0216
FP	.0422	.0474	.0251	.0149	.0257	.026	.0300
Average	.0364	.0400	.0207	.0110	.0161	.0169	.0229

Note: LGOVT = Local government; NFP = Not-for-profit; FP = For-profit

5.4.1.1.2.1.2 Medicaid Managed Care Net Patient Revenue Percent

The second research hypothesis asserts that Medicaid managed care net patient revenue, as a percent of total net patient revenue **(P_NPREV_MMCD)**, is negatively associated with hospitals' uncompensated care provision. Table 5-3 above, which presents panel descriptive statistics for the regression variables, shows that Medicaid managed care net patient revenue was 3.081 percent, on average, over the period 2000 through 2005. Table 5-4 above, which presents annual mean descriptive statistics for the regression variables, shows small Medicaid managed care net patient revenue percentages and an increasing percentage trend during the initial five years of the study period and a slight decline in the final year. Table 5-7 below, which presents mean Medicaid managed care net patient revenue percent by control and year, shows not-for-profit hospitals have smaller percentages of Medicaid managed care net patient revenue, compared to local government and for-profit hospitals. Local government and for-profit hospitals have approximately the same percentages. Table 5-7 also shows an increasing trend of Medicaid managed care net patient revenue percent between 2000 and 2004 and slight decrease in 2005.

Table 5-7. Medicaid managed care net patient revenue percentages

P_NPREV_MMCD	2000	2001	2002	2003	2004	2005	Average
LGOVT	.0112	.0402	.0435	.0391	.0465	.0337	.0372
NFP	.0153	.0253	.0259	.0257	.0274	.0260	.0246
FP	.0254	.0300	.0297	.0391	.0489	.0475	.0368
Average	.0193	.0288	.0294	.0324	.0381	.0348	.0308

Note: LGOVT = Local government; NFP = Not-for-profit; FP = For-profit

5.4.1.1.3 Other Managed Care Provision

The third research hypothesis contends that Commercial managed care (i.e., HMO and PPO) net patient revenue, as a percent of total net patient revenue percent **(P_NPREV_MCOM)**, is negatively associated with hospitals' uncompensated care provision. Table 5-3 above, which presents panel descriptive statistics for the regression variables, shows that Commercial managed care *net patient revenue* was 36.139 percent, on average, over the period 2000 through 2005. As a point of general comparison, McKay & Meng (2007) found that Commercial managed care *patient days* were approximately 20 percent for urban Florida hospitals over the period 1998 through 2002. Table 5-4 above, which presents annual mean descriptive statistics for the regression variables, shows more than one-third of total net patient revenue is attributable to Commercial managed care. Table 5-4 also shows an increasing percentage trend of Commercial managed care net patient revenue during the initial five years and a slight decline in the final year of the study period. Table 5-8 below, which presents mean Commercial managed care net patient revenue percent by control and year, shows not-for-profit hospitals have the highest and local government hospitals have the smallest percentages of Commercial managed care net patient revenue, compared to not-for-profit and for-profit hospitals. Table 5-8 also shows an increasing trend of Commercial managed care net patient revenue percent between 2000 and 2004 and slight decrease in 2005.

Table 5-8. Commercial managed care net patient revenue percentages

P_NPREV_MCOM	2000	2001	2002	2003	2004	2005	Average
LGOVT	.1962	.2462	.2259	.2135	.2497	.2143	.2253
NFP	.3515	.3588	.3878	.4143	.4334	.4186	.3960
FP	.3292	.3597	.3567	.3680	.3561	.3648	.3562
Average	.3286	.3474	.3571	.3730	.3823	.3733	.3614

Note: LGOVT = Local government; NFP = Not-for-profit; FP = For-profit

5.4.1.1.4 Profit

The fourth research hypothesis postulates that profit margin percent, net of uncompensated care expenses **(P_PRFT_NETUC)**, is positively associated with hospitals' uncompensated care provision. Table 5-3 above, which presents panel descriptive statistics for the regression variables, shows that profit margin percent, net of uncompensated care expenses, was 15.08 percent, on average, over the period 2000 through 2005. As a point of comparison, McKay & Meng (2007) found that profit margin percent, net of uncompensated care expenses, was approximately 10 percent for urban Florida hospitals over the period 1998 through 2002. Table 5-4 above, which presents annual mean descriptive statistics for the regression variables, shows profit margin percent, net of uncompensated care expenses, fluctuated somewhat during the study period. Profit margin percent increased during the initial three years of the study period and oscillated during the final three years. Table 5-9 below, which presents mean profit margin percent, net of uncompensated care expense, shows differences between control groups; local government hospitals have larger percentages of profit margin percent, compared to not-for-profit and for-profit hospitals. Local government hospitals' profit margin percent is more than double than that for not-for-profit hospitals. Table 5-9 also shows de minimis profit margin percent variation in across the study period.

Table 5-9. Profit margin percentages

P_PRFT_NETUC	2000	2001	2002	2003	2004	2005	Average
LGOVT	.2178	.2300	.2361	.2188	.2627	.2531	.2376
NFP	.1064	.1198	.1285	.0914	.1222	.1215	.1150
FP	.1755	.1865	.1919	.1711	.1536	.1480	.1714
Average	.1455	.1588	.1655	.1369	.1503	.1476	.1508

Note: LGOVT = Local government; NFP = Not-for-profit; FP = For-profit

5.4.1.1.5 Other Hospitals' Supply of Uncompensated Care

The final research hypothesis asserts that other hospitals' uncompensated care expense percent (**P_OTHUC_C**), is positively associated with hospitals' uncompensated care provision. Table 5-3 above, which presents panel descriptive statistics for the regression variables, shows that other hospitals' uncompensated care expense percent was 10.862 percent, on average, over the period 2000 through 2005. As a point of comparison, McKay & Meng (2007) found that other hospitals' uncompensated care expense was approximately 7 percent, on average, for urban Florida hospitals over the period 1998 through 2002. Table 5-4 above, which presents annual mean descriptive statistics for the regression variables, shows other county hospitals' uncompensated care expense percent was consistent during the initial four years, increased, and was consistent during the final two years of the study period. Table 5-10 below, which presents mean other county hospitals' uncompensated care expense percent, shows differences between control groups; local government hospitals have smaller percentages of other hospitals' uncompensated care expense, compared to not-for-profit and for-profit hospitals. Table 5-10 also shows a consistent trend of other county hospitals' uncompensated care expense percent across the study period.

Table 5-10. Other hospitals' uncompensated care expense percentages

P_OTHUC_C	2000	2001	2002	2003	2004	2005	Average
LGOVT	.0809	.0854	.0771	.0675	.0817	.0652	.0755
NFP	.1044	.1035	.1084	.1098	.1176	.1157	.1101
FP	.1175	.1149	.1089	.1118	.1236	.1204	.1161
Average	.1080	.1063	.1050	.1056	.1160	.1111	.1086

Note: LGOVT = Local government; NFP = Not-for-profit; FP = For-profit

5.4.2 One-Way Fixed-Effects Regression Results

Table 5-11 below presents the one-way fixed-effects (within) panel data regression estimates, clustered on ID (i.e., hospitals) for robust standard errors. The robust standard errors adjust the usual standard errors for the presence of heteroskedasticity and serial/autocorrelation in the study dataset, as previously discussed. The estimating equation is in Section 4.6.2.

The 10 percent alpha level $(p \leq .10)$ was the criterion for significance of the individual variable *t*-tests from the panel regression. Additionally, the detailed STATA program output for the one-way fixed-effects (within) panel data regression estimates, clustered on ID (i.e., hospitals) for robust standard errors, is in Appendix S. Exposition of the one-way fixed-effects regression results begins in Section 5.4.2.1.

Although not used for this study because of the presence of serial/autocorrelation and heteroskedasticity in the data, the detailed STATA program output for the one-way fixed-effects (within) panel data regression estimates, with the *usual standard errors*, is presented for comparison in Appendix T.

Table 5-11. One-way fixed-effects (within) estimates

VARIABLE	COEFF.	*t*-STAT	SIG.	S.E.
Government-Funded Managed Care Provision				
Medicare managed care net patient revenue percent	-0.02558	-1.716	°	(0.01491)
Medicaid managed care net patient revenue percent	-0.07635	-1.368		(0.05582)
Other Managed Care Provision				
Commercial managed care net patient revenue percent	-0.03320	-3.243	**	(0.01024)
Profit				
Profit margin percent, net of uncompensated care expense	0.11878	3.615	***	(0.03286)
Mission				
For-profit hospital	-0.00987	-1.656	°	(0.00596)
Intern and resident to staffed bed ratio	-0.03499	-1.893	°	(0.01849)
Demand for Uncompensated Care				
County unemployment percent	0.12243	1.563		(0.07831)
Other Hospitals' Supply of Uncompensated Care				
Other county hospitals' uncompensated care expense percent	-0.00482	-0.139		(0.03459)
Market Characteristics				
County physician-owned specialty hospital outpatient surgery percent	0.04131	2.963	**	(0.01394)
County ambulatory surgery center to hospital ratio	0.00009	0.046		(0.00188)
County federally-qualified health center to hospital ratio	0.00249	1.145		(0.00217)
County rural health center to hospital ratio	-0.00733	-1.998	*	(0.00367)
County unauthorized immigrant population density	0.00023	0.592		(0.00038)
Hospital Characteristics				
Number of staffed beds[NL]	-0.02992	-2.545	*	(0.01176)
Occupancy percent	-0.02187	-1.359		(0.01610)
Severity of illness	-0.02146	-2.271	*	(0.00945)
Births per admission	-0.07864	-2.167	*	(0.03629)
Emergency room mix of outpatient visits, net of outpatient surgeries	0.01232	1.743	°	(0.00707)
Admissions per emergency room visit	-0.01573	-0.837		(0.01880)
Physical plant age	-0.00326	-0.487		(0.00670)
Other government net patient revenue percent	-0.04005	-0.598		(0.06697)
Total expenses percent of total net patient revenue	0.10375	2.945	**	(0.03522)
Network member	0.00228	1.316		(0.00173)
Risk-adjusted mortality reciprocal rate for acute stroke	0.00014	1.818	°	(0.00008)
Risk-adjusted mortality reciprocal rate for acute myocardial infarction	0.00006	0.383		(0.00015)
Year 2000	-0.00532	-2.003	*	(0.00266)
Year 2001	-0.00798	-3.417	***	(0.00233)
Year 2002	-0.00846	-4.740	***	(0.00178)
Year 2003	-0.00698	-3.849	***	(0.00181)
Year 2005	-0.00119	-0.674		(0.00176)
Constant	0.20161	2.534	*	(0.07957)

Note: Dependent variable: P_UC_TEXP. R^2 (Within) = 0.331 and R^2 (Overall) = 0.383. N = 750; i =

155; and $t = 6$. Standard errors in parentheses are robust standard errors clustered on ID. COEFF = coefficient; t-STAT = t-statistic; S.E. = standard error. *** $p<.001$; ** $.001<p<.01$; * $.01<p<.05$; ° $.05<p<.10$ (two-tailed tests). [NL] Natural logarithm transformed.

5.4.2.1 Government-Funded Managed Care Provision

In this study, the two key study variables **P_NPREV_MMCR** and **P_NPREV_MMCD** relate to the government-funded managed care construct. Rosko (2004) and McKay & Meng (2007) provide an empirical basis for using Medicare and Medicaid managed care variables in a study of uncompensated care provision.

The effect of Medicare managed care net patient revenue percent **(P_NPREV_MMCR)** was significant, $t = -1.716$, $.05 < p < .10$. The percentage form of the variable permits easy interpretation of the coefficient, so the estimate implies a one percent increase in hospitals' Medicare managed care net patient revenue as a percentage of net patient revenue, on average and holding other variables constant, was associated with a .02558 percent *decrease* in hospitals' uncompensated care cost as a percentage of total expenses. Medicare managed care could affect hospitals' provision of uncompensated care because a vast majority of Medicare Advantage Plans are through HMOs, which usually require steep discounts. The importance of this result is the conclusion that increasing levels of Medicare managed care net patient revenue percent are associated with decreases in Texas MSA hospitals' uncompensated care expense percent. ***Based on this result, Hypothesis 1 is accepted.***

The effect of Medicaid managed care net patient revenue percent **(P_NPREV_MMCD)** was not significant, $t = -1.368$, $p = .173$. Medicaid managed care is thought to affect hospitals' provision of uncompensated care because in most, but not all, Texas MSA counties Medicaid is implemented through HMOs, which usually require steep discounts. The insignificance of this variable leaves open the possibility that hospitals' payments from Medicaid managed care plans were not discounted enough to reduce their uncompensated care provision significantly. In addition, recalling that not all Texas counties had been converted to Medicaid managed care during the study period; this result could suggest that their effects influenced this result. Finally, this result could also suggest that Medicaid managed care net patient revenue percent is simply an insignificant portion of overall net patient revenue. The insignificance of this variable appears to imply that the effect of Medicaid managed care net patient revenue percent represents a localized component of uncompensated care provision. However, the sign of the coefficient is negative. ***Based on this result, Hypothesis 2 is rejected.***

5.4.2.2 Other Managed Care Provision

The effect of commercial managed care net patient revenue percent **(P_NPREV_MCOM)** was significant, $t = -3.243$, $.001 < p < .01$. The percentage form of this variable permits simple explanation of the coefficient, so the estimate implies a one percent increase in hospitals' commercial managed care net patient revenue percent, on average and holding other variables constant, was associated with a .03320 percent *decrease* in hospitals' uncompensated care cost as a percentage of total expenses. This finding is consistent with the findings of McKay & Meng (2007) for urban Florida acute care hospitals over the period 1998 through 2002. The importance of this result is the conclusion that, increasing levels of commercial managed care net patient revenue are associated with decreases in Texas MSA hospitals' uncompensated care expense percent.

If managed care companies were able to negotiate significant price discounts, and that effect dominated any cost efficiency gains, then hospitals experiencing an increased amount of managed care would have to reduce the provision of uncompensated care in order to maintain a given profit level. Following McKay & Meng (2007), at the hospital level, one would expect a higher extent of managed care to be associated with a lower level of uncompensated care. Conversely, if costs fall proportionately more than prices, hospitals could provide more uncompensated care, holding profit constant, and increased managed care would be expected to be associated with a higher level of uncompensated care. ***Based on this result, Hypothesis 3 is accepted.***

5.4.2.3 Profit

The effect of profit margin percent, net of uncompensated care expense **(P_PRFT_NETUC)**, was significant, $t = 3.618$, $p < .001$. The percentage form of this variable permits simple explanation of the coefficient, so the estimate implies a one percent increase in hospitals' profit margin percent, net of uncompensated care expense, on average and holding other variables constant, was associated with a .11878 percent *increase* in hospitals' uncompensated care expense as a percentage of total expenses. A hospital's profit would be expected to positively influence its provision of uncompensated care (i.e., the income effect). Even if uncompensated care is a fundamental element of a hospital's mission, a hospital could not provide uncompensated care unless it can earn enough on all services to cover the costs of providing such care. This finding is consistent with the findings of Frank, Salkever, & Mitchell (1990) and McKay & Meng (2007). This finding is also consistent with the findings of Rosko (2004) whose lagged profit measure was significant at alpha level .10. The importance of this result is the conclusion that increasing levels of profit margin percent, net of uncompensated care expense, are associated with increases in Texas MSA hospitals' uncompensated care expense percent. ***Based on this result, Hypothesis 4 is accepted.***

5.4.2.4 Mission

In this study, there are two variables relating to the mission theoretical construct. The first variable for-profit hospital **(FP)** is dummy-coded 1 if true and 0 otherwise. The comparison group is local government and not-for-profit hospitals. The effect of for-profit hospital **(FP)** was significant, $t = -1.656$, $.05 < p < .10$. For-profit hospitals located in Texas MSAs, on average and holding other variables constant, have *less* uncompensated care expense percent compared to local government and not-for-profit hospitals. This finding is consistent with that of McKay & Meng (2007) for urban Florida acute care hospitals during 1998 to 2002. The primary objective of for-profit hospitals is to maximize net income, which would imply little provision of uncompensated care. Gray (1991) hypothesized that for-profit hospitals supply uncompensated care to the extent that doing so maximizes profits. Norton & Staiger (1994) suggested that for-profit hospitals select locations with favorable community characteristics, which could include low community expectation regarding charitable care. However, all hospitals must satisfy legal requirements regarding urgently needed care without consideration of ability to pay which usually results in at least some minimum level of uncompensated care in for-profit hospitals. Not-for-profit hospitals usually focus on providing services associated with its mission statement, subject to a net income constraint. Generally, provision of uncompensated care would be a major objective of not-for-profit hospitals if only due to legal considerations associated with their nonprofit status. Frank & Salkever (1991) and Gruber (1994) hypothesized that not-for-profit hospitals earn net revenue to subsidize charitable services. Accordingly, not-for-profit hospitals would be expected to provide more uncompensated care than for-profit hospitals. Local government hospitals in Texas have a statutory duty to provide medical aid and hospital care for indigent county residents and receive related public funding for such. Because they receive significant funding from supplemental federal programs (i.e., Medicaid DSH), provision of uncompensated care is an significant objective for a local government hospital due to their safety net status, thus, local government hospitals would be expected to provide more uncompensated care than either not-for-profit or for-profit hospitals. The importance of this result is the conclusion that for-profit hospitals located in Texas MSAs are associated with less in uncompensated care expense percent, compared to local government and not-for-profit hospitals.

The second mission construct variable relates to teaching intensity, the effect of intern and resident to staffed bed ratio **(R_INTRES_BED)** was significant, $t = -1.893$, $.05 < p < .10$. The estimate implies that as the intern and resident to staffed bed ratio increases one unit, uncompensated care cost as a percentage of total expenses *decreases* .03435 percent. An important mission of teaching hospitals is medical education; fulfilling this element of mission usually means that patients' ability to pay is relatively less important than it is for non-teaching hospitals. Thus, teaching hospitals would be expected to provide more uncompensated care compared to non-teaching hospitals. Although this variable addresses the same theoretical construct, but measured differently, the finding in this study is contrary to that of McKay & Meng (2007) who found Council of Teaching Hospitals membership to be positive and significant for uncompensated care provision for urban Florida acute care hospitals. The result is inconsistent with Rosko (2004) whose sign for the intern and resident to bed ratio in his adjusted uncompensated care admissions model was positive, but not significant, for not-for-profit hospitals in Pennsylvania. The finding in this study was unexpected and is counterintuitive. In the study dataset of $N = 750$: $n = 270$ (36 percent) of the hospitals have interns and residents. Of those hospitals with interns and residents, $n = 167$ (61.85 percent) are not-for-profit; $n = 55$ (20.37 percent) are for-profit; and $n = 48$ (17.78 percent) are local government. Thus, the majority of the study hospitals that have interns and residents are not-for-profit. The mean uncompensated care expense percent for not-for-profit hospitals is .0866; for for-profit hospitals .0651; and for local government hospitals .2179. A two-sample group mean comparison *t*-test for combined not-for-profit and for-profit hospitals' uncompensated care expense percent, compared to local government hospitals', was negative and significant, $t = -7.402$, $p < .001$. Thus, not-for-profit and for-profit hospitals together provide significantly less uncompensated care expense percent than local government hospitals. Therefore, a possible interpretation is that not-for-profit and for-profit hospitals dominate this measure because, together, they have more interns and residents than do local government hospitals and their joint uncompensated care expense percent is significantly less than that of local government hospitals, which creates systematic effects on the group of study hospitals. The importance of this result is the conclusion that increasing teaching intensity (i.e., intern and resident to staffed bed ratio) is associated with less uncompensated care expense percent in Texas MSA hospitals.

5.4.2.5 Demand for Uncompensated Care

The effect of county unemployment percent **(P_UNEMP_C)** was not significant, $t = 1.563$, $p = .120$. This result is inconsistent with Rosko (2004) in his adjusted uncompensated care admissions model who also found this measure to be positive and moderately significant for private, not-for-profit Pennsylvania hospitals during 1995 to 1998. However, this result is consistent with McKay & Meng (2007) who found an MSA-level version of this variable to be insignificant for urban Florida acute care hospitals during 1998 to 2002. Employment is thought to be important determinant of the percentage of the population younger than 65 who have health insurance. Lack of health insurance is believed to contribute to hospitals' uncompensated care provision. The insignificance of this variable appears to imply that the effect of county unemployment percent represents a localized component of uncompensated care provision. However, the sign of the coefficient is positive.

5.4.2.6 Other Hospitals' Supply of Uncompensated Care

The effect of other hospitals' uncompensated care expense percent **(P_OTHUC_C)** was not significant, $t = -0.139$, $p = .889$. This finding is consistent with that of McKay & Meng (2007) who also found this measure to be insignificant for urban Florida acute care hospitals during 1998 to 2002. However, this finding is inconsistent with Gaskin (1997) in his inpatient and outpatient uncompensated care random effects models who found this measure to be positive and significant for New Jersey hospitals during 1986 to 1990. This finding is also inconsistent with Rosko (2004) in his adjusted uncompensated care admissions model who found this measure to be positive and moderately significant for private, not-for-profit Pennsylvania hospitals during 1995 to 1998. Earlier empirical work found an important determinant of hospitals' uncompensated care provision is the amount of uncompensated care provided by other hospitals in the market (i.e., the theoretical crowding-out effect). A local government hospital in the county may reduce the provision of uncompensated care by other hospitals because there is little unmet need in the market due to its presence, all else equal. Thus, having a local government hospital in the county, a major supplier of uncompensated care, would be associated with a reduction in the provision of uncompensated care by other not-for-profit and for-profit hospitals (see Table 5-5). The insignificance of this variable appears to imply that the effect of other hospitals' uncompensated care expense percent represents a localized component of uncompensated care provision. ***Based on this result, Hypothesis 5 is rejected.***

5.4.2.7 Market Characteristics

The federal Stark Law[17] allows physicians to refer patients to whole hospitals in which they have a financial interest (Blackstone & Fuhr, 2007). The effect of county physician-owned specialty hospital outpatient surgery percent **(P_POSH_OPS_C)** was significant, $t = 2.963$, $.001 < p < .01$. The estimate implies a one percent increase in county physician-owned specialty hospital outpatient surgery percent, on average and holding other variables constant, was associated with a .04131 percent *increase* in hospitals' uncompensated care expense percent. This finding suggests that general hospitals increase uncompensated care provision in counties where physician-owned specialty hospitals have larger portions of the outpatient surgery market. This finding could imply that physician-owned specialty hospitals contribute to general hospitals' bad debts (a component of uncompensated care). It may be that physician-owned specialty hospital owners refer mostly those outpatients with smaller out-of-pocket costs to their facilities, thereby minimizing their bad debts if the patient does not pay or fully pay their out-of-pocket costs. If true, then general hospitals field those outpatient surgeries with higher out-of-pocket costs, or no forms of reimbursement; they incur the associated bad debt or charity care, respectively, if the patient does not or cannot pay. This result is consistent with the finding that the presence of specialty hospitals is associated with higher general hospital operating margins (Schneider et

[17] The "Stark Law" refers to three separate provisions of federal law governing physician self-referral of Medicare and Medicaid patients. U.S. Congressman Pete Stark sponsored the initial legislation.

al., 2007) which could be used to cross-subsidize those hospitals' less profitable services through uncompensated care provision. Although this study's results provide no specific indication of the means through which general hospitals increased uncompensated care provision, it is possible that they did so in part by using their operating margins to cross-subsidize their uncompensated care provision. Schneider et al. (2007) found no evidence that general hospital operating margins were lower in markets shared with specialty hospitals. Additional research is needed to identify general hospitals' specific responses to market entry/presence of specialty hospitals. The importance of this result is the conclusion that increasing levels of county physician-owned specialty hospital outpatient surgery percent is associated with increases in Texas MSA hospitals' uncompensated care expense percent.

The effect of the county ambulatory surgery center to hospital ratio **(R_ASCHOSP_C)** was not significant, $t = 0.046$, $p = .964$. The presence of ASCs in a county is thought to affect the amount of hospitals' uncompensated care provision because better insured surgery patients may be steered to these facilities, thus, limiting other hospitals' ability to cost shift. The insignificance of this variable appears to imply that the effect of the ASC to hospital ratio represents a localized component of uncompensated care provision.

The effect of the county federally-qualified health center to hospital ratio **(R_FQHCHOSP_C)** was not significant, $t = 1.145$, $p = .254$. The availability of FQHCs in a county is thought to negatively affect the amount of hospital's uncompensated care provision due to reduced emergency room use and the shift away from hospitals. The insignificance of this variable appears to imply that the effect of the county federally qualified health center to hospital ratio represents a localized component of uncompensated care provision.

The effect of the county rural health center to hospital ratio **(R_RHCHOSP_C)** was significant, $t = -1.998$, $.01 < p < .05$. The estimate implies a one-unit increase in county rural health center to hospital ratio, on average and holding other variables constant, was associated with a .00733 percent *decrease* in hospitals' uncompensated care expense percent. Like FQHCs, the availability of RHCs in a county is thought to negatively affect the amount of hospitals' uncompensated care provision due to reduced emergency room use and the shift of care away from hospitals. The importance of this result is the conclusion that increases in the county rural health center to hospital ratio is associated with decreases in Texas MSA hospitals' uncompensated care expense percent.

The effect of county unauthorized immigration population density **(DENS_UPOP_C)** was not significant, $t = 0.592$, $p = .555$. Illegal immigration is thought to influence hospitals' uncompensated care provision. Immigrants to the U.S., both authorized and unauthorized, are less likely than their native-born counterparts to have health insurance The insignificance of this variable appears to imply that the effect of county unauthorized immigration population density represents a localized component of uncompensated care provision.

5.4.2.8 Hospital Characteristics

The effect of number of staffed beds **(LN_BEDS)** was significant, $t = -2.545$, $.01 < p < .05$. This variable is natural logarithm transformed. The estimate implies a one percent increase in the number of staffed beds, on average and holding other variables constant, was associated with a $(0.02992/100) = .000299$ percent *decrease* in hospitals' uncompensated care expense percent. The magnitude of the effect is small. Several studies have found that bed size is related to uncompensated care provision. This finding is consistent with Magnus et al. (2004) for U.S. hospitals, and McKay & Meng (2007) for Florida hospitals where they found bed size negatively influenced uncompensated care provision. This finding is inconsistent with that of Frank & Salkever (1991), Gaskin (1997), Thorpe et al. (2001), and Rosko (2004) in his adjusted uncompensated care admissions model, where they found bed size positively influenced uncompensated care provision. The importance of this result is the conclusion that increases in the number of staffed beds is associated with decreases in Texas MSA hospitals' uncompensated care expense percent. However, the magnitude of the effect is small.

The effect of occupancy percent **(P_OCCUP)** was not significant, $t = -1.359$, $p = .176$. A higher occupancy rate could be indicative of better financial performance and more discretionary income for uncompensated care provision, but higher occupancy may have increased marginal costs. Alternatively, beds occupied by paying patients could reduce or "crowd-out" the number of beds available for non-paying uncompensated care patients. This finding is consistent with Hassan et al. (2000) in a panel debt study of California hospitals. This result is inconsistent with Buczko (1994) in a cross-sectional study of Washington State hospitals. The insignificance of this variable appears to imply that the effect of occupancy percent represents a localized component of uncompensated care provision.

The effect of severity of illness **(SEV_ILL)** was significant, $t = -2.271$, $.01 < p < .05$. The estimate implies a one-unit increase in severity of illness was associated, on average and holding other variables constant, with a .02146 percent *decrease* in hospitals' uncompensated care expense percent. A hospital's higher severity of illness score could indicate elevated resource consumption and possibly less funds available for uncompensated care provision. Carpenter et al. (1999) found that severity of illness is related to resource use and Rosko & Carpenter (1994) found that resource use is related to expense per admission. The importance of this result is the conclusion that increasing severity of illness is associated with decreases in Texas MSA hospitals' uncompensated care expense percent.

The effect of births per admission **(R_BIRTHS_ADM)** was significant, $t = -2.167$, $.01 < p < .05$. The estimate implies a one-unit increase in births per admission was associated, on average and holding other variables constant, with a .07864 percent *decrease* in hospitals' uncompensated care expense percent. As previously discussed, the most common reason for U.S. uninsured hospitalizations from 1997 to 2006 was childbirth. This finding is inconsistent with Rosko (2001a) in his unadjusted uncompensated care percentage model using a similarly performing measure (i.e., bassinet days percent) that was positive and significant for uncompensated care provision. The finding in this study is counterintuitive and somewhat difficult to interpret. In the study dataset of $N = 750$: $n = 371$ (49.5 percent) of the observations are not-for-profit; $n = 371$ (39.5 percent) are for-profit; and $n = 83$ (11 percent) are local government. In addition, the mean births per admission for not-for-profit hospitals is .153; for for-profit hospitals .166; and for local government hospitals .174. The mean uncompensated care expense percent for not-for-profit hospitals is .0866; for for-profit hospitals .0651; and for local government hospitals .2179. A two-sample group mean comparison *t*-test for combined not-for-profit and for-profit hospitals' uncompensated care expense percent, compared to local government hospitals', was negative and significant, $t = -7.402$, $p < .001$. Thus, not-for-profit and for-profit hospitals together provide significantly less uncompensated care expense percent than local government hospitals. Therefore, a possible interpretation is that not-for-profit and for-profit hospitals dominate this measure because, together, they have fewer mean births per admission than do local government hospitals and their joint uncompensated care expense percent is significantly less than that of local government hospitals, which creates systematic effects on the group of study hospitals. The importance of this result is the conclusion that increasing births per admission is associated with decreases in Texas MSA hospitals' uncompensated care expense percent.

The effect of emergency room mix of outpatient visits, net of outpatient surgeries **(ERMIX_NETOPS)** was significant, $t = 1.743$, $.05 < p < .10$. The estimate implies a one-percent increase in emergency room mix of outpatient visits, net of outpatient surgeries was associated, on average and holding other variables constant, with a .01232 percent *increase* in hospitals' uncompensated care expense percent. As previously discussed, primary care-related emergency department visits are strongly correlated with the rate of uninsurance and poverty. This finding is consistent with the cross-sectional study by Rosko (2001a) and the panel study by Rosko (2004), both of which found a similar form of this measure to be significant and positively associated with uncompensated care provision in private, not-for-profit Pennsylvania hospitals. This finding is consistent with a cross-sectional study by Buczko (1994) which found a similar form of this measure to be significant and positively associated with bad debt charges, a component of uncompensated care. The importance of this result is the conclusion that increasing emergency room mix of outpatient visits, net of outpatient surgeries, is associated with increases in Texas MSA hospitals' uncompensated care expense percent.

The effect of admissions per emergency room visit **(P_ADM_ERVIS)** was not significant, $t = -0.837$, $p = .404$. As previously discussed, about 60 percent of uninsured stays begin in the emergency department compared to 44 percent of overall hospital stays. Although a recent descriptive study provides empirical support for use of this variable (Elixhauser & Owens, 2006), no comparable panel studies using this particular measure could be located. The insignificance of this variable suggests that the effect of admissions per emergency room visit represents a localized component of uncompensated care expense percent.

The effect of reciprocal physical plant age **(PLANT_AGE_R)** was not significant, $t = -0.487$, $p = .627$. Due to *TDSHS-AHA-THA Annual Survey of Hospitals* data limitations, this variable is a crude proxy for the effect of debt. If the age of a hospital's physical plant is high, capital investment in the facility may be lagging suggesting that funds may be available for uncompensated care provision. Conversely, if the age of the physical plant is low, capital investment in the facility may be ongoing suggesting that funds may not be available for uncompensated care provision. This finding is inconsistent with Magnus et al. (2004) which found debt financing was positively and significantly associated with uncompensated care provision. The insignificance of this variable appears to suggest that the effect of physical plant age (i.e., debt proxy) represents a localized component of uncompensated care provision.

The effect of other government net patient revenue percent **(P_NPREV_OGOV)** was not significant, $t = -0.598$, $p = .551$. Discounting associated with other government-funded services, other than Medicare and Medicaid (both routine and managed care), is believed to reduce funds hospitals' have available for uncompensated care provision. The insignificance of this variable appears to imply that the effect of other government net patient revenue percent represents a localized component of uncompensated care provision.

The effect of total expenses as percent of net patient revenue **(P_TEXP_NPREV)** was significant, $t = 2.945$, $.001 < p < .01$. The estimate implies a one percent increase in total expenses as percent of total net patient revenue was associated, on average and holding other variables constant, with a .10375 percent *increase* in hospitals' uncompensated care expense percent. This variable is a measure of hospitals' reliance on revenue, other than net patient revenue. Although a recent path analysis study provides empirical support for use of this variable (Trinh & O'Connor, 2002), no cross-sectional or panel studies using this particular measure could be located. If total net patient revenue is insufficient to cover total expenses, then the hospital is relying on other revenues to cover the deficit. Thus, this variable measures the degree to which the hospital relies on revenues, other than total net patient revenue (i.e. tax appropriations, other operating revenues, and/or non-operating revenue). However, it does not measure each of the other forms of revenue. In this study, the other revenues do not include Medicaid Disproportionate Share Hospital Program payments because they are already included in total net patient revenue. The significance of this result suggests that Texas MSA hospitals, on average and holding other variables constant, depend on revenues, other than total net patient revenue, to support uncompensated care expense percent. The importance of this result is the conclusion that increasing levels of total expenses percent of total net patient revenue are associated with increases in Texas MSA hospitals' uncompensated care expense percent.

The effect of network member **(D_NETWORK)** was not significant, $t = 1.316$, $p = .190$. Past studies have found that affiliation with a health system or health network was positively related to hospitals' responsiveness to community needs. This result is inconsistent with the community responsiveness notion of Lee, Alexander, & Bazzoli (2003). This result is also inconsistent with the network or system membership and financial performance support of uncompensated care provision that could be implied from Bazzoli, Chan, Shortell, & D'Aunno (2000). However, the result is consistent with Rosko (2004) who found no significance of either alliance or system membership in both models used in his real operating surplus model for not-for-profit Pennsylvania hospitals. McKay & Meng (2007) did not use a network, alliance, or system membership variable in their study of Florida hospitals. This variable appears to be inconsistently coded during the study period[18]. Thus, the insignificance of this variable should be interpreted with caution. Otherwise, the insignificance suggests that the effect of network member represents a localized component of uncompensated care expense percent.

The effect of risk-adjusted mortality reciprocal rate for acute stroke **(IQI_17_R)** was significant, $t = 1.818$, $.05 < p < .10$. The estimate implies a one-unit increase in risk-adjusted mortality reciprocal rate for acute stroke, on average and holding other variables constant, was associated with a .00014 percent *increase* in hospitals' uncompensated care expense percent. However, the magnitude of the effect is small. Recall from Section 4.4.2.8 that, in this study, higher reciprocal rates mean lower mortality rates signifying fewer deaths. This result suggests that hospitals with fewer acute stroke deaths provide more uncompensated care although the effect is small. The importance of this result is the

[18] See the mean value for this variable for 2003 in Table 5-4, compared to the other years.

conclusion that increasing risk-adjusted mortality reciprocal rates for acute stroke (fewer deaths) are associated with increases in Texas MSA hospitals' uncompensated care expense percent.

The effect of risk-adjusted mortality reciprocal rate for acute myocardial infarction, without transfer cases, **(IQI_32_R)** was not significant, $t = 0.383$, $p = .702$. This result suggests that the effect of risk-adjusted mortality reciprocal rate for acute myocardial infarction, without transfer cases, is not associated with uncompensated care provision. Although Mukamel, et al. (2002) provides empirical support for use of this measure, no studies using this particular measure were identified in the context of uncompensated care provision for comparison. As discussed previously, acute myocardial infarction has been associated with uninsured hospital admissions. The insignificance of this variable appears to suggest that the effect of risk-adjusted mortality reciprocal rate for acute myocardial infarction, without transfer cases, represents a localized component of uncompensated care provision.

The observation year variables are dummy-coded 1 if true and 0 otherwise. The omitted comparison year is 2004. The effect of the 2000 observation year **(D_YR_2000)** was significant, $t = -2.003$, $.01 < p < .05$. The coefficient implies that hospitals provided .00532 percent *less* uncompensated care expense percent in 2000, compared to the omitted comparison year 2004. However, the magnitude of the effect is small.

The effect of the 2001 observation year **(D_YR_2001)** was significant, $t = -3.417$, $p < .001$. The coefficient implies that hospitals provided .00798 percent *less* uncompensated care expense percent in 2001, compared to the omitted comparison year 2004. However, the magnitude of the effect is small.

The effect of the 2002 observation year **(D_YR_2002)** was significant, $t = -4.740$, $p < .001$. The coefficient implies that hospitals provided .00846 percent *less* uncompensated care expense percent in 2002, compared to the omitted comparison year 2004. However, the magnitude of the effect is small.

The effect of the 2003 observation year **(D_YR_2003)** was significant, $t = -3.849$, $p < .001$. The coefficient implies that hospitals provided .00698 percent less uncompensated care expense percent in 2003, compared to the omitted comparison year 2004. However, the magnitude of the effect is small.

The effect of the 2005 observation year **(D_YR_2005)** was not significant, $t = -0.674$, $p = .501$. This result implies that hospitals' uncompensated care expense percent in 2005 was not significantly different from that in the omitted comparison year 2004.

During the years 2000 through 2003, there appears to be evidence of less uncompensated care expense percent, compared to the omitted year 2004. However, the magnitude of the individual year effects are small. This result is consistent with the notion that Texas MSA hospitals provided less uncompensated care in the years preceding the Texas Legislature's reduction of Medicaid eligibility and benefits in 2004, as discussed previously. Collectively, the importance of the dummy year variables is the conclusion that, on average and holding other variables constant, Texas MSA hospitals had significantly less uncompensated care expense percent in years 2000 through 2003, compared to 2004, the omitted comparison year. Again, the magnitudes of the effects are small. The results indicate an association, but not a casual relationship, between the dummy year results for negative uncompensated care expense percent and reductions in the Texas Medicaid Program's eligibility and benefits; it is possible they are merely coincident.

5.4.3 Expected and Observed Relationships

Table 5-12 below, which presents the expected and observed relationships for the research hypotheses-related explanatory variables, shows the expected one-way fixed-effect regression coefficient sign emanating from the research hypotheses in Section 3.3 and the observed relationship with the dependent variable, uncompensated care expense percent, resulting from the regression. Although the observed one-way fixed-effect regression coefficient sign (i.e., negative) for the Medicaid managed care net patient revenue percent hypothesis was as expected (i.e., negative), the related was regression coefficient was insignificant. In addition, the observed one-way fixed-effect regression coefficient sign (i.e., negative) for the other hospitals' uncompensated care expense hypothesis was opposite that expected (i.e., positive) and the related regression coefficient was insignificant. The expected and observed one-way fixed-effect coefficient signs for Medicare managed care net patient revenue percent, Commercial managed care net patient revenue percent, and profit margin percent, net of uncompensated care expense were consistent.

Discussion of the theoretically based variables and significant variables are undertaken in the succeeding sections. The theoretical variables are discussed in Section 5.4.4.1 and the significant variables are discussed in Section 5.4.4.2.

Table 5-12. Expected and observed relationships

#	Research Hypothesis	Expected Coefficient Sign	Observed Coefficient Sign
1	Medicare managed care net revenue, as a percentage of net patient revenue, is negatively associated with uncompensated care provision.	–	– °
2	Medicaid managed care net revenue, as a percentage of net patient revenue, is negatively associated with uncompensated care provision.	–	– ns
3	Commercial managed care net revenue, as a percentage of net patient revenue, is negatively associated with uncompensated care provision.	–	– **
4	Profit margin percent is positively associated with uncompensated care provision.	+	+ ***
5	Other hospitals' uncompensated care expense percent is positively associated with uncompensated care provision.	+	– ns

Note: ° significant at alpha level .10; * significant at alpha level .05; ** significant at alpha .01; *** significant at alpha level .001; ns not significant.

5.4.4 Discussion

5.4.4.1 Theoretical Variables

The results of this study partially corroborate the Frank & Salkever (1991) and Gaskin (1997) theoretical models of uncompensated care provision as they are applied to Texas MSA hospitals during the years 2000 through 2005. According to the Frank & Salkever (1991) and Gaskin (1997) models, two key determinants of uncompensated care provision are the hospital's financial surplus, or the income effect; and the amount of uncompensated care provisioned by other hospitals in the market, or the crowd-out effect.

The results of this study confirmed the existence of a significant income effect, in which hospitals use financial surpluses to fund the provision of uncompensated care based on the profit margin percent, net of uncompensated care expenses, **(P_PRFT_NETUC)** variable. As mentioned previously, the finding here indicates a one percent increase in profit margin percent, net of uncompensated care expense, would be expected to result in a .11878 percent *increase* in uncompensated care expense percent, holding other factors constant. The finding here for the income effect is consistent with positive panel study results reported by Rosko (2004) in his adjusted uncompensated care admissions model for private, not-for-profit Pennsylvania hospitals during 1995 to 1998. The finding here for the income effect is also consistent with the positive panel study result reported by McKay & Meng (2007) for urban Florida acute care hospitals during 1998 to 2002.

However, the findings of this study did not confirm the existence of a significant crowd-out effect, in which hospitals compete for public goodwill by providing levels of uncompensated care commensurate with those of their competitors based on the other hospitals' expense percent **(P_OTHUC_C)** variable. The insignificant finding here for the crowd-out effect is inconsistent with the positive panel study result reported by Rosko (2004) in his adjusted uncompensated care admissions model for private, not-for-profit Pennsylvania hospitals during 1995 to 1998. Conversely, the insignificant finding here for the crowd-out effect is consistent with the insignificant panel study result reported by McKay & Meng (2007) for urban Florida acute care hospitals during 1998 to 2002. This study did not find support for the rivalry hypothesis of Frank, Salkever, & Mitchell (1990) and Frank & Salkever (1991) in which hospitals compete for public goodwill by providing levels of uncompensated care proportionate to those of their competitors. Also, this study did not support the impure altruism model of Frank & Salkever (1991) which suggests that a hospital's utility depends on it receiving "credit" for supplying charity care. In Texas, almost every MSA county has a mixture of local government, not-for-profit, and for-profit hospitals. Because local government hospitals, if present, bear the burden of most uncompensated care expense percent, there is no incentive for not-for-profits or for-profit hospitals to compete for uncompensated care provision, or seek credit for supplying charity care. Not-for-profit hospitals demonstrate community benefits in additional ways. Additionally, Texas had a strict charity care law applicable to not-for-profit hospitals during the study period, which mitigates their need to compete for or seek credit for uncompensated care provision.

Based on the number of natural logarithm-transformed staffed beds variable **(LN_BEDS)**, this study did not confirm institutional theory, which posits that large institutions try to appear generous to achieve legitimacy. Institutional theory suggests a positive association between hospital size and uncompensated care provision would exist because larger hospitals may be under pressure to conform to external pressures due to their higher visibility in their communities. As mentioned previously, the finding here indicates a one percent increase in number of staffed beds would be expected to result in a .0002992 percent *decrease* in uncompensated care expense percent, holding other factors constant. However, the magnitude of the effect is small. This may be because the larger hospitals (i.e., more beds) are dominated by not-for-profit and for-profit hospitals that have less uncompensated care expense percent, compared to local government hospitals. Additionally, Texas had a strict charity care law applicable to not-for-profit hospitals during the study period, which mitigates their need to appear generous.

5.4.4.2 Significant Variables

In this section, only those study variables whose significance was $p \leq .10$ are discussed.

The aim of this study was to examine the effects of government-funded managed care on hospitals' uncompensated care expense percent in Texas MSAs during the period 2000 through 2005. The two types of government-funded managed care captured in the *TDSHS-AHA-THA Annual Survey of Hospitals* are Medicare and Medicaid. Based on the **P_NPREV_MMCR** variable, this study found that higher percentages of Medicare managed care net patient revenue percent was associated with decreases in uncompensated care expense percent. The negative relationship between Medicare managed care and uncompensated care in this study is consistent with increased managed care generally affecting hospital revenues proportionately more than expenses. That is, if increased government-funded managed care leads to price discounts, one approach to maintain a given level of profit is to reduce the amount of uncompensated care provided. Even though increased Medicare managed care net patient revenue percent was associated with decreased uncompensated care expense percent, the magnitude of the effect was small. For example, in 2005, the mean levels of uncompensated care expense percent and Medicare managed care net patient revenue percent were 9.9 percent and 1.7 percent, respectively. An increase of 10 percent in Medicare managed care net patient revenue percent, which would represent a considerable increase, would be expected to be associated with a .2558 percent decrease in uncompensated care expense percent, holding other factors constant. This study's finding is consistent with previous findings that a higher level of managed care was associated with lower levels of uncompensated care[19]. More importantly, the study provides an extended test of the relationship, at the hospital-level, between managed care and uncompensated care. It

[19] See Thorpe, Seiber, & Florence (2001) and McKay & Meng (2007).

expands the managed care-uncompensated care relationship to include government-funded managed care, in addition to commercial managed care elsewhere studied[20].

Based on the Commercial managed care net patient revenue percent **(P_NPREV_MCOM)** variable, this study found that a higher percentage of Commercial managed care net patient revenue percent was associated with a decrease in uncompensated care expense percent, holding other factors constant. The negative relationship between commercial managed care and uncompensated care is consistent with increased managed care generally affecting hospital revenues proportionately more than expenses. That is, if increased Commercial managed care leads to price discounts, one approach to maintain a given level of profit is to reduce the amount of uncompensated care provided. Even though increased Commercial managed care net patient revenue percent was associated with decreased uncompensated care expense percent, the magnitude of the effect was modest. For example, in 2005, the mean levels of uncompensated care expense percent and Commercial managed care net patient revenue percent were 9.9 percent and 37.3 percent, respectively. An increase of 10 percent in Commercial managed care net patient revenue percent, which would represent a considerable increase, would be expected to be associated with a .332 percent decrease in uncompensated care expense percent, holding other factors constant. This study's finding is consistent with a previous finding, at the hospital-level, that a higher level of commercial managed care was associated with lower levels of uncompensated care[21].

Based on the profit margin percent, net of uncompensated care expense, **(P_PRFT_NETUC)** variable, this study found net profit, net of uncompensated care expense, was positively associated with uncompensated care expense percent. This particular finding

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[20] See McKay & Meng (2007)
[21] Ibid.

is important because the magnitude is large, compared to the other significant study coefficients. For example, in 2005, the mean levels of uncompensated care expense percent and profit margin percent, net of uncompensated care expense, were 9.9 percent and 14.8 percent, respectively. An increase of 10 percent in profit margin percent, net of uncompensated care expense, which would represent a considerable increase, would be expected to be associated with a substantial 1.1878 percent increase in uncompensated care expense percent, holding other factors constant. A hospital's profit is expected to influence a hospital's provision of uncompensated care. Even if uncompensated care is a fundamental element of a hospital's mission, a hospital could not provide uncompensated care unless it can earn enough on other services to cover the costs of providing such care. This result suggests that revenues, other than managed care, and expenses, other than uncompensated care, separately or interactively, support provision of uncompensated care. Other revenues, for example, may be federal supplemental payments like the DSH payments and/or other types of revenues such as tax appropriations, other operating revenues, and non-operating revenues. Lower expenses, for example, may be attributable to higher efficiency, network membership, and purchasing discounts.

Based on the for-profit hospital (**FP**) dummy variable, this study found for-profit control, compared to local government and not-for-profit control, was negatively associated to uncompensated care expense percent. Local government and not-for-profit controlled hospitals are the omitted comparison groups. It was preferable to include a second control category so that there could be only one comparison group. However, local government control was time invariant and not-for-profit control was significantly correlated with for-profit control during the study period [22]. Accordingly, the decision for this study was to proceed solely with for-profit control due its numerous dissimilarities with local government and not-for-profit controlled hospitals.

This result is consistent with earlier studies, including McKay & Meng (2007). The primary objective of for-profit hospitals is to maximize net income, which would imply little or no provision of uncompensated care. However, all hospitals must satisfy legal requirements regarding urgently needed care without consideration of ability to pay which usually results in at least some minimum level of uncompensated care in for-profit hospitals. Not-for-profit hospitals usually focus on providing services associated with its mission statement, subject to a net income constraint. Generally, provision of uncompensated care would be a major objective of not-for-profit hospitals if only due to legal considerations associated with their nonprofit status. Accordingly, not-for-profit hospitals would be expected to provide more uncompensated care than for-profit hospitals. Local government hospitals in Texas have a statutory duty to provide medical aid and hospital care for indigent county residents and receive related public funding. Because they receive significant funding from supplemental federal programs (i.e., Medicaid DSH), provision of uncompensated care is an significant objective for a local government hospital because of their safety net status, thus, local government hospitals would expected to provide more uncompensated care than either not-for-profit or for-profit hospitals.

Based on the intern and resident to staffed bed ratio **(R_INTRES_BED)** variable, this study found teaching intensity was negatively associated to uncompensated care expense percent. A 10 percent increase in the intern and resident to staffed bed ratio would decrease uncompensated care expense percent .3499 percent, holding other factors constant. An

[22] The correlation coefficient was approximately 0.8.

important mission of teaching hospitals is medical education; fulfilling this element of mission usually means that patients' ability to pay is relatively less important than it is for non-teaching hospitals. Thus, teaching hospitals would be expected to provide more uncompensated care compared to non-teaching hospitals. Not-for-profit and for-profit hospitals dominate this measure because, when combined, more of them have interns and residents than do local government hospitals and their combined uncompensated care expense percent is significantly less than that of local government hospitals, which created systematic effects on the group of study hospitals. Although local government hospitals support more interns and residents per bed per hospital, the weight of the number of not-for-profit and for-profits with lesser ratios of interns to residents to beds likely led to the significant and negative coefficient. This finding implies that patients' ability to pay is not less important for teaching hospitals than it is for non-teaching hospitals, at least for the case of Texas MSA hospitals. This finding is inconsistent with that of McKay & Meng (2007) for urban Florida hospitals; however, their measure was the more restrictive Council of Teaching Hospitals membership. This finding is also inconsistent with that of Rosko (2004), which used this exact measure; however, in his study dataset of Pennsylvania, all were private, not-for-profit hospitals.

Based on the county physician-owned specialty hospital outpatient surgery percent **(P_POSH_OPS_C)** variable, this study found that physician owned specialty hospitals' outpatient surgery percentages and uncompensated care expense percent were positively associated. Recall that two-thirds of niche hospitals were located in just seven states—Arizona, California, Kansas, Louisiana, Oklahoma, South Dakota, and Texas. Texas led the nation with the highest number of niche hospitals—almost twice as many as in California, which ranks second. Most niche hospitals are for-profit entities owned in whole or in part by physicians. Considering Texas has a sizable number of niche hospitals and continues to develop more, this study is important because its findings could add evidence to and modify existing arguments that physician-owned specialty hospitals affect general hospitals, in terms of uncompensated care provision. A recent study using a national panel of short-term acute care hospitals for the period 1997 to 2004 found that the presence of one or more new or established specialty hospitals in a market has a negative effect on general hospitals' costs and a positive effect on general hospitals' operating margins (Schneider et al., 2007).

An increase of 10 percent increase in county physician-owned specialty hospital outpatient percent[23], which would represent a considerable increase, would be associated with a .4131 percent decrease in uncompensated care expense percent, holding other factors constant. However, the magnitude of the effect is small. The sign of this coefficient could simply be an anomaly. Nevertheless, a plausible explanation may lie in the cost-sharing mechanisms of outpatient procedures. Specialty hospitals focus on "easy" cases (Skinner, 1974) because their physician owners refer less severe and therefore more profitable cases (Greenwald et al., 2006). It may be that physician-owned specialty hospital owners refer mostly those outpatients with smaller out-of-pocket costs to their facilities, thereby minimizing their potential for bad debts if the patient does not pay or fully pay their out-of-pocket costs. If true, then general hospitals likely field those outpatient surgeries with higher out-of-pocket costs, or no forms of reimbursement; they incur the associated bad debt or charity care, respectively, if the patient does not or cannot pay. This result is consistent with the finding that the presence of specialty hospitals is associated with higher general hospital

[23] On other words, the proportion of physician-owned specialty hospital outpatient surgeries to total outpatient surgeries in the county.

operating margins (Schneider et al., 2007) which could be used to cross-subsidize those hospitals' less profitable services through uncompensated care provision. Although this study's results provide no specific indication of the means through which general hospitals increased uncompensated care provision, it is possible that they did so in part by using their operating margins to cross-subsidize their uncompensated care provision.

Based on the county rural health center to hospital ratio (**R_RHCHOSP_C**), this study found that more rural health centers to hospitals are negatively associated with uncompensated care provision. However, the magnitude of the effect is very small. A 10 percent increase in the rural health center to hospital ratio would be expected to be associated with a .0733 percent decrease in uncompensated care expense percent, holding other factors constant. The availability of rural health centers in a county is believed to negatively affect the amount of hospitals' uncompensated care provision due to reduced emergency room use and the shift of care away from hospitals.

Based on the number of natural logarithm-transformed staffed beds variable **(LN_BEDS)**, this study did not confirm institutional theory, which posits that large institutions try to appear generous to achieve legitimacy. Institutional theory suggests a positive association between hospital size and uncompensated care provision would exist because larger hospitals may be under pressure to conform to external pressures due to their higher visibility. As mentioned previously, the finding here indicates a one percent increase in logarithm-transformed staffed beds would be expected to be associated with a $(0.02992/100) = .000299$ percent decrease in uncompensated care expense percent, holding other factors constant. The magnitude of the effect is small. This may be because the larger hospitals (i.e., more beds) are dominated by not-for-profit and for-profit hospitals that have less uncompensated care expense percent, compared to local government hospitals. Additionally, Texas had a strict charity care law applicable to not-for-profit hospitals during the study period, which could mitigate their need to appear generous.

This study found that the severity of illness **(SEV_ILL)** variable was associated with decreases in uncompensated care expense percent. A 10 percent increase in severity of illness results would be expected to be associated with a .2146 percent decrease in uncompensated care expense percent, holding other factors constant. Higher severities of illness scores imply more hospital resource consumption and possibly, fewer funds available for uncompensated care provision. Conversely, lower severity of illness scores could indicate less hospital resource consumption and possibly, more funds available for uncompensated care provision. It is plausible that this finding indicates that third-party payers do not reimburse proportionately for illness severity and the resulting financial pressure limits hospitals' ability to provide uncompensated care.

This study found the ratio of births to admissions **(R_BIRTHS_ADM)** was negatively associated with uncompensated care expense percent. A 10 percent increase in the ratio of births to admissions would be expected to be associated with a .7864 percent decrease in uncompensated care expense percent, holding other factors constant. This result is difficult to analyze because it is contrary to the literature. The most common reason for uninsured hospitalizations is pregnancy and childbirth and Texas has the highest uninsured rate in the nation. The number of uninsured pregnancies may be further exaggerated by Texas's adjacency to an international border with Mexico (Berk et al., 2000; Preston, 2006). So, one would expect the coefficient to have a positive sign. Nevertheless, the result suggests that hospitals with increasing ratios of births to admissions, on average, provide less uncompensated care. This may simply be a data anomaly or an imperfect measure of the effect of births on uncompensated care expense percent. Unfortunately, the study dataset does not allow one to distinguish insured from uninsured births, which tends to limit the potential for a reasoned discussion. However, it is plausible that hospitals with higher ratios of births to admissions simply provide less uncompensated care. This may be the case for not-for-profit and for-profit hospitals due, possibly, to managed care contracting. It may also be that deliveries simply crowd out uncompensated care, although this is not likely because deliveries typically have the shortest length of stays. It is also reasonable that certain hospitals either do not provide or provide limited obstetrical services. It is also plausible that hospitals under common control have downsized their obstetrical services into single facility.

This study found the emergency room mix of outpatient visits, net of outpatient surgeries **(ERMIX_NETOPS)** was positively associated with uncompensated care expense percent. A 10 percent increase in emergency room mix of outpatient visits, net of outpatient surgeries results would be expected to be associated with a .1232 percent increase in uncompensated care expense percent, holding other factors constant. This result is sensible. Many of the uninsured seek primary care in hospital emergency rooms. The literature has shown that primary care-related emergency department visits are strongly correlated with the rate of uninsurance and poverty, particularly in Texas (Begley et al., 2006). Texas has the highest rate of uninsurance in the nation.

This study found that total expenses, as a percent of net patient revenue **(P_TEXP_NPREV)** was positively associated with uncompensated care expense percent. This particular finding is important because the magnitude is large, compared to the other significant study coefficients. This measure is the proportion of total expenses to total net patient revenue. Unfortunately, the *TDSHS-AHA-THA Annual Survey of Hospitals* does not capture information on operating expenses. Assuming a hospital prefers breaking even (i.e., revenues match expenses), if total expenses are not entirely supported by net patient revenue, then the hospital must rely on additional forms of revenue to cover the difference. Thus, this variable measures the degree to which the hospital relies on forms of revenue, other than net patient revenue. Again, the magnitude of this effect is large. For example, in 2005, the mean levels of uncompensated care expense percent and total expenses, as a percent of net patient revenue, were 9.9 percent and 100.1 percent, respectively. An increase of 10 percent in total expenses, as a percent of net patient revenue, which would represent a considerable increase, would be expected to be associated with a substantial 1.0375 percent increase in uncompensated care, holding other factors constant. Although a hospital would not increase total expenses to provide more uncompensated care, this result demonstrates that revenues, other than net patient revenue (i.e., tax appropriations, other operating revenues, and/or non-operating revenue), act as revenue subsidies. This would the case for local government hospitals (total expenses are 126.63 percent of net patient revenue), more so than for not-for-profit hospitals (total expenses are 100.97 percent of net patient revenue) and for-profit hospitals (total expenses are 89.83 percent of net patient revenue) hospitals, which seem to rely less on non-net patient revenues, on average. This result could also suggest that local government hospitals use revenues, other than total net patient revenue, to discount patient charges, or strive to keep their charges as low as practicable. In turn, this result suggests that local government hospitals, in addition to their reliance upon total net patient revenues and compared to not-for-profit and for-profit hospitals, generate substantial non-patient revenues.

This study found that risk-adjusted mortality reciprocal rate for acute stroke **(IQI_17_R)** was positively associated with uncompensated care expense percent. An increase of 10 percent in risk-adjusted mortality reciprocal rate for acute stroke which would represent a considerable increase, would be expected to be associated with a .0014 percent increase in uncompensated care, holding other factors constant. Acute stroke has been associated with uninsured hospital admissions. Recall from Section 4.4.2.8 that, in this study, higher reciprocal rates mean lower mortality rates signifying fewer deaths. This result is somewhat difficult to assess because health outcome measures have yet to be introduced to studies of hospitals' uncompensated care provision. However, the following logic is plausible. Primarily, acute hospital care is intended to prevent death and hospitals expend considerable resources doing so. This may be because third-party financial incentives for hospitals are increasingly being linked to health outcome measures. Thus, to the degree hospitals become more efficient at improving their health outcomes (i.e., fewer deaths and less expense), their otherwise (inefficient) committed resources could be re-directed toward their uncompensated care provision.

This study found that years 2000 **(D_YR_2000)**, 2001 **(D_YR_2001)**, 2002 **(D_YR_2002)**, and 2003 **(D_YR_2003)**, compared to year 2004 **(D_YR_2004)**, were negatively associated with uncompensated care expense percent. During the years 2000 through 2003, there is a consistent pattern among hospitals of less uncompensated care expense percent, compared to 2004, the omitted year. This result is consistent with the notion that Texas MSA hospitals provided less uncompensated care in the years preceding 2004, which coincides with implementation of the Texas Legislature's reduction of Medicaid eligibility and benefits in 2004, as previously discussed. This is not saying the Medicaid reductions caused an increase in uncompensated care provision in 2004, but the significant results are associated with the periods prior to the reductions occurring. Because the results provide no specific indication of a relationship between the dummy year results for negative uncompensated care expense percent and reductions in the Texas Medicaid Program's eligibility and benefits, it is possible they are merely coincident.

Chapter 6 – Conclusions

6.1 Summary

This study examined the effects of government-funded managed care on hospitals' provision of uncompensated care using a panel data set of Texas MSA hospitals for the period 2000 through 2005. The level of uncompensated care provided by hospitals is considered a measure of access to care for the low-income, uninsured, and under-insured populations. Texas hospitals are of particular interest given that the state has the highest rate of uninsurance in the nation; more than one-fourth of the state's population is uninsured. Additionally, Texas has the most stringent prescriptive charity care law for not-for-profit hospitals among all states. These uncompensated care demand factors, when combined with the revenue reduction and cost pressure effects of managed care, represent challenges to Texas hospitals' ability to continue providing uncompensated care. The objective of this study was to examine the effects of Medicare and Medicaid managed care on Texas hospitals' uncompensated care provision, controlling for other managed care provision, profit, mission, demand for uncompensated care, other hospitals' supply of uncompensated care, market characteristics, and hospital characteristics. This study was limited to non-federal, non-state, short-term acute care medical-surgical hospitals with at least 25 beds located in counties within the MSAs of Texas $(N = 750)$. The unit of analysis was the hospital. This study used a one-way fixed-effects panel regression model with robust standard errors. The significance criterion used was $p \leq .10$. For the key variables, this study found that Medicare managed care was negatively associated with hospitals' uncompensated care provision. Among the other variables, the study results show that profit net of uncompensated care expense, physician-owned specialty hospital outpatient surgeries, outpatient mix, total expenses as a percent of net revenue, and risk-adjusted mortality for acute stroke were positively associated with hospitals' provision of uncompensated care. The study results also show that commercial managed care, for-profit hospitals, teaching intensity, rural health centers, number of beds, severity of illness, births per admission, and the years 2000 through 2003, compared to 2004, were negatively associated with hospitals' uncompensated care provision. This study's main results suggest that Texas MSA hospitals should consider their uncompensated care provision when negotiating Medicare managed care payments. This study expands and diversifies the pool of existing state-level hospital uncompensated care studies in two significant ways. First, it broadens existing literature concerning the effects of managed care with its examination of the specific effects of government-funded managed care on hospitals' uncompensated care provision. Second, it diversifies the present physician-owned specialty hospital literature with its findings on the effects of these hospitals' outpatient surgeries on general hospitals' uncompensated care provision. The study's findings will benefit hospital administrators, trustees, industry leadership, policy makers, regulators, advocacy groups, and others at the local, state, and national levels that are interested in and concerned about managed care and other factors that influence hospitals' provision of uncompensated care at the state level.

6.2 Disposition of Research Hypotheses

The five research hypotheses are in Section 3.3. The one-way fixed-effects (within) estimates using robust standard errors clustered on hospital (i.e., ID) are in Section 5.4.3. A summary disposition of the individual research hypotheses is in Table 6-1 below. With the exception of the hypotheses relating to Medicaid managed care net revenue, as a percentage of net patient revenue; and other hospitals' uncompensated care expense percent, the remaining research hypotheses were accepted. Although the observed one-way fixed-effect regression coefficient sign (negative) for the Medicaid managed care net patient revenue percent hypothesis was as expected (negative), the related regression coefficient was insignificant. In addition, the observed one-way fixed-effect regression coefficient sign (negative) for the other hospitals' uncompensated care expense hypothesis was opposite that expected (positive) and the related regression coefficient was insignificant. The expected and observed one-way fixed-effect coefficient signs for Medicare managed care net patient revenue percent, Commercial managed care net patient revenue percent, and profit margin percent, net of uncompensated care expense were consistent.

Table 6-1. Disposition of research hypotheses

#	Research Hypothesis	Accept/Reject
1	Medicare managed care net revenue, as a percentage of net patient revenue, is negatively associated with uncompensated care provision.	Accept
2	Medicaid managed care net revenue, as a percentage of net patient revenue, is negatively associated with uncompensated care provision.	Reject
3	Commercial managed care net revenue, as a percentage of net patient revenue, is negatively associated with uncompensated care provision.	Accept
4	Profit margin percent is positively associated with uncompensated care provision.	Accept
5	Other hospitals' uncompensated care expense percent is positively associated with uncompensated care provision.	Reject

6.3 Policy Implications

Uncompensated care is a significant national and health care industry policy issue. This is particularly true in Texas where the health care uninsured rate is the highest in the nation. Texas hospitals devote substantial resources to uncompensated care. In this study, uncompensated care accounted for 9.3 percent, on average, of total expenses for Texas MSA hospitals on average over the period 2000 through 2005. Although hospitals have been questioned and criticized about the manner in which the value of uncompensated care services are calculated, the results of this study show that hospitals continue to incur considerable unpaid costs for providing services to patients who cannot or do not completely pay.

From a public policy perspective, the current system of reliance on hospitals to provide free care is a poor substitute for expanding coverage to the uninsured and improving coverage for the underinsured.

The major policy implication of this study is that, increases in Medicare-funded managed care could produce unanticipated, albeit modest according to this study, negative spillover effects on the provision of uncompensated care by hospitals.

Although all hospitals have a legal duty to treat urgent medical conditions without consideration of ability to pay, many uncompensated care services currently provided are not vital. Thus, any changes that reduce uncompensated care provision could result in a reduction in access to hospital services for those who cannot or do not completely pay.

Finally, the findings from this study suggest that higher numbers of interns and residents per bed has negative spillover effect hospitals' uncompensated care provision.

Policies regarding reimbursement for graduate medical education should consider hospitals' uncompensated care provision.

6.4 Management Implications

The findings from this study suggest that hospitals with more Medicare managed care provide less uncompensated care. This implies that it will be important for hospital management to monitor future adjustments in Medicare-funded managed care contracts and payments for hospital services.

The findings from this study suggest that hospitals with more Commercial managed care (i.e., HMO and PPO) provide less uncompensated care. This implies that it will be important for hospital management to monitor future Commercial managed care contracts and payments for hospital services.

The findings from this study also suggest that profitable hospitals provide more uncompensated care. This implies that it is important to maintain profitability. It is also important monitor the level of uncompensated care provision if profitability decreases. This is particularly important in Texas where strict not-for-profit hospital charity care requirements are in place.

The findings from this study suggest that for-profit hospitals provide less uncompensated care, compared to local government hospitals. This implies that is important to monitor the number of for-profit hospitals in the market.

The findings from this study additionally suggest that the proportion of physician-owned outpatient surgical procedures to total outpatient surgical procedures in the county positively influences uncompensated care provision. This implies that it is important to monitor the number of physician-owned specialty hospitals in the market and changes in the proportions of county-level outpatient surgical procedures.

The findings of this study additionally suggest that rural health centers influence uncompensated care provision. This implies that it could be useful for hospital management to investigate the need for additional rural health centers.

The findings of this study also suggest that severity of illness influences uncompensated care provision. This implies that it is important for hospital management to monitor their levels of uncompensated care provision if severity of illness levels increase.

The findings of this study also suggest revenues, other than net patient revenues influence uncompensated care provision. This implies that it is important for hospital management to monitor the source and flow of non-patient revenues, particularly for not-for-profit and local government hospitals.

Finally, the findings of this study suggest that state legislative adjustments to Medicaid eligibility and enrollment could affect (i.e., increase) hospitals' uncompensated care provision. This suggests that hospital management should be vigilant to legislative process and educate regulators and policy makers as necessary.

6.5 Study Limitations

Application and interpretation of this study is subject to several limitations. The study was limited to a single state. Although this allowed a more consistent measure of uncompensated care and avoided interstate policy variations that could have confounded results, it precludes generalization of the findings to other states and the nation. Several factors that are unique to Texas limit the transferability of this study's findings. Texas has the highest health care uninsured rate in the nation and a long-standing prescriptive charity care law for not-for-profit hospitals. Counties in Texas are required by law to appropriate funds for care of their local indigent residents. Additionally, the state adjoins an international border with Mexico, has a large undocumented resident population, and has one of the least generous Medicaid programs in the nation.

This study assumed that the costs incurred by a hospital in providing uncompensated care were consistent with the hospital's overall expense-to-charge ratio. This is a broad assumption motivated by data limitations; information on operating costs is not available from the *TDSHS-AHA-THA Annual Survey of Hospitals*.

The *TDSHS-AHA-THA Annual Survey of Hospitals* does not capture information on Medicaid UPL payments made to hospitals. As a result, this information is not included per se in the study dataset. The UPL program is a variant of the DSH program and provides supplemental payments to offset the difference between what Medicaid and Medicare pay for covered hospital services. The UPL program was activated in Texas in 2002 for local government hospitals, but was soon made available to not-for-profit and for-profit hospitals. Hospital-specific UPL program payment histories are not publicly available. Hospitals' receipt of these supplemental UPL payments could substantially influence their uncompensated care policies.

The goal of this analysis was to determine if government-sponsored managed care and other factors influence hospital's provision of uncompensated care. Therefore, the dependent variable employed in this study was uncompensated care. Uncompensated care was used due to the definitional issues involved in distinguishing charity care from bad debt due to classification inconsistencies and the related data limitations that arise. Aggregating charity care and bad debt is common in empirical work (Atkinson et al., 1997; LoSasso & Seamster, 2007; McKay & Meng, 2007; Rosko, 2001a, 2004) and tracks an earlier recommendation that charity care and bad debt should be reported separately, though their sum (uncompensated care) should be used for policy purposes (Hoerger & Waters, 1993).

Another limitation of this study is the nature of the data collected for uncompensated care charges and other study variables. The data from the *TDSHS-AHA-THA Annual Survey of Hospitals* are self-reported and not routinely audited by regulators. Although responses to the *Annual Survey of Hospitals* are required to be based on hospitals' audited financial statements, survey responses are often times submitted prior to audit completion. Initial survey responses are not always updated following conclusion of hospitals' financial audits. There is a perception that self-reported data on uncompensated care are often inflated. Particularly, there is the suspicion that some hospitals have an incentive to embellish the amount of uncompensated care provided to satisfy regulators and potentially qualify for or continue receiving funding from the Medicaid DSH program.

The expense-to-charge ratio used in this study is based, in part, on hospital charges. Hospital charges are similar to listed prices and they can deviate significantly from the real transaction prices. Hospital charges are subject to intense bargaining and typically are discounted when there is a third-party insurance payer. Levels of hospital charity care and bad debt among hospitals may be determined by different environmental and policy factors.

Finally, like all empirical studies, this one may be subject to omitted variable bias, although the employment of fixed-effects modeling sought to minimize this. Several independent variables that could have contributed substantially to the analysis were simply not available. These include, for example, a direct measure of the uninsured population in each county, a direct measure of the number of unauthorized residents in each county, direct data on hospitals' long-term debt obligations, and direct data on UPL program payments.

6.6 Future Research

This study provides new knowledge about the effects of government-sponsored managed care on Texas MSA hospitals' uncompensated care provision and other important effect information for 2000 through 2005. Like most significant research, this study stimulates new questions and presents fresh possibilities for subsequent research.

Notwithstanding this study's focus on the effects of government-sponsored managed care on hospitals' uncompensated care provision, this study particularly found the proportion of physician-owned specialty hospital outpatient surgeries to total outpatient surgeries in a county positively influenced hospitals' provision of uncompensated care. A comprehensive understanding of that relationship could be useful to policy makers and health care management, particularly considering the current controversies surrounding physician control of specialty hospitals and the resource demands of uncompensated care provision on general hospitals.

In this study, Medicaid enrollment reductions appeared to increase hospitals' uncompensated care provision. It could be useful to examine the effects of state-level policy decisions regarding Medicaid enrollments.

Finally, additional, subsequent study year's data are now available. This study could be expanded to include additional, subsequent years, in part, to determine if the initial findings of this study are sustained.

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Appendix A: STATA Panel Estimating Commands

Estimating Method	STATA Commands
One-way, fixed-effects	xtreg,fe areg, abs(id)
One-way, fixed-effects with robust standard errors	xtreg,fe vce(robust or cluster id) areg, abs vce(robust or cluster id)
One-way, random-effects	xtreg,re xtreg,mle
One-way, random-effects with robust standard errors	xtreg,re vce(robust or cluster id) xtreg,mle vce(bootstrap)

Appendix B: STATA Poolability, Spherical, and Model Selection Commands

Testing For	Null Hypothesis	STATA Commands
Poolability, group effects	$u_i = 0$, for $i = 1,\dots,N$	Included in standard FEM output
Cross-sectional dependence	$E[\varepsilon_{it},\varepsilon_{is}] = 0$, for all $s \neq t$	xtcsd xtserial xttest2
Groupwise heteroskedasticity	$\sigma_i^2 = \sigma^2$, for $i = 1,\dots,N_g$	xttest3
Random-effects	$\sigma_u^2 = 0$	xttest0
Joint random-effects and first-order serial correlation	$\sigma_u^2 = 0$ $\lambda = 0$	xttest1
Fixed-Effects Model vs. Random-Effects Model	$\text{Var}(\beta_{FEM} - \beta_{REM}) = 0$	hausman hausman, sigmamore hausman, sigmaless xtoverid

Appendix C: STATA Panel Post-Estimation Commands

STATA Command	Use After	Description
hausman	xtreg,fe and xtreg,re	Hausman (1978) specification test for REM after FEM estimation
xtcsd,frees	xtreg,fe or xtreg,re	Frees (1995) *Q* distribution test of cross-sectional independence
xtcsd,friedman	xtreg,fe or xtreg,re	Friedman (1937) non-parametric test of cross-sectional independence
xtcsd,pesaran	xtreg,fe or xtreg,re	Pesaran (2004) CD test of cross-sectional independence
xtoverid	xtreg,re	Arellano (1993), Wooldridge (2002, pp. 290-291), and Hayashi (2000, pp. 227-228) Wald test for significance of additional regressors
xtserial	xtreg,fe or xtreg,re	Wooldridge (2002, pp. 282-283) test for serial correlation in panel data
xttest0	xtreg,re	Breusch & Pagan (1980), modified by Baltagi & Li (1990), LM test for random-effects
xttest1 (test 1 of 7)	xtreg,re	Breusch & Pagan (1980) two-sided LM test for random-effects, assuming no serial correlation
xttest1 (test 2 of 7)	xtreg,re	Breusch & Pagan (1980), modified by Baltagi & Li (1995), two-sided LM test for random-effects, which works even under serial correlation
xttest1 (test 3 of 7)	xtreg,re	Breusch & Pagan (1980) one-sided LM test for random-effects, assuming no serial correlation
xttest1 (test 4 of 7)	xtreg,re	Breusch & Pagan (1980), modified by Baltagi & Li (1995), one-sided LM test for random-effects, which works even under serial correlation
xttest1 (test 5 of 7)	xtreg,re	Breusch & Pagan (1980), modified by Baltagi & Li (1995), LM test for first-order serial correlation, assuming no random-effects
xttest1 (test 6 of 7)	xtreg,re	Breusch & Pagan (1980), modified by Baltagi & Li (1995), LM test for first-order serial correlation, which works even under random-effects
xttest1 (test 7 of 7)	xtreg,re	Baltagi & Li (1991) LM joint test for random-effects and serial correlation
xttest2	xtreg,fe	Breusch & Pagan (1980) LM test statistic for contemporaneous correlation
xttest3	xtreg,fe	Greene (2008, pp. 172-175) modified Wald statistic for groupwise heteroskedasticity

Appendix D: STATA Multicollinearity Test Commands

Multicollinearity Tests	STATA Commands
Variance inflation factors	estat vif collin
Correlation coefficients	corr pwcorr

Appendix E: Observation Patterns

```
. xtdescribe if e(sample), patterns(100)

      ID:  1, 2, ..., 155                                   n =         155
    YEAR:  1, 2, ..., 6                                     T =           6
           Delta(YEAR) = 1 unit
           Span(YEAR)  = 6 periods
           (ID*YEAR uniquely identifies each observation)

Distribution of T_i:   min      5%     25%       50%       75%     95%     max
                         2       2       4         5         6       6       6

     Freq.  Percent    Cum. |  Pattern
 ---------------------------+---------
       71     45.81   45.81 |  111111
       12      7.74   53.55 |  .11111
       10      6.45   60.00 |  ..1111
        6      3.87   63.87 |  11111.
        5      3.23   67.10 |  1111.1
        4      2.58   69.68 |  ...111
        4      2.58   72.26 |  11....
        4      2.58   74.84 |  111.11
        3      1.94   76.77 |  ...1.1
        3      1.94   78.71 |  .111.1
        3      1.94   80.65 |  .1111.
        3      1.94   82.58 |  1.1111
        3      1.94   84.52 |  1111..
        2      1.29   85.81 |  ..111.
        2      1.29   87.10 |  .1.1..
        2      1.29   88.39 |  .11.1.
        2      1.29   89.68 |  .11.11
        2      1.29   90.97 |  1..111
        2      1.29   92.26 |  11.111
        1      0.65   92.90 |  ....11
        1      0.65   93.55 |  ...11.
        1      0.65   94.19 |  ..1..1
        1      0.65   94.84 |  .1...1
        1      0.65   95.48 |  .1..11
        1      0.65   96.13 |  .11...
        1      0.65   96.77 |  .111..
        1      0.65   97.42 |  1....1
        1      0.65   98.06 |  1..1..
        1      0.65   98.71 |  1..1.1
        1      0.65   99.35 |  1.11.1
        1      0.65  100.00 |  111...
 ---------------------------+---------
      155    100.00         |  XXXXXX
```

Appendix F: Long Form Data Organization

```
. list ID YEAR NFP FP BEDS P_OCCUP SEV_ILL if ID==9, table separator(6) nolabel
```

	ID	YEAR	NFP	FP	BEDS	P_OCCUP	SEV_ILL
34.	9	1	0	0	472	.726145	1.846627
35.	9	2	0	0	339	.9656201	1.88538
36.	9	3	0	0	355	.9795485	1.891131
37.	9	4	0	0	367	.9324176	1.930986
38.	9	5	0	0	484	.7065099	1.706619
39.	9	6	0	0	369	.9386865	1.172705

Appendix G: Panel and Time Identifiers

```
. xtset ID YEAR
       panel variable:  ID (unbalanced)
        time variable:  YEAR, 1 to 6, but with gaps
                delta:  1 unit
```

Appendix H: Variance Inflation Factors

```
. qui reg `dvar' `ivars'

. estat vif

    Variable |       VIF       1/VIF
-------------+----------------------
 DENS_UPOP_C |      3.34    0.299315
P_TEXP_NPREV |      3.12    0.320809
R_INTRES_BED |      3.06    0.327251
   P_OTHUC_C |      2.51    0.397835
   D_YR_2003 |      2.21    0.452602
     SEV_ILL |      2.15    0.465516
R_BIRTHS_ADM |      2.15    0.465545
P_NPREV_MCOM |      2.09    0.478758
   D_YR_2000 |      2.05    0.488887
     LN_BEDS |      2.04    0.489265
   D_YR_2001 |      2.00    0.499226
   D_YR_2002 |      1.86    0.537705
 R_ADM_ERVIS |      1.77    0.566249
   D_YR_2005 |      1.76    0.568590
P_PRFT_NETUC |      1.67    0.599196
   P_UNEMP_C |      1.66    0.603969
ERMIX_NETOPS |      1.65    0.606356
P_NPREV_MMCD |      1.61    0.622517
          FP |      1.60    0.624035
 R_ASCHOSP_C |      1.49    0.670488
P_NPREV_MMCR |      1.49    0.670684
   D_NETWORK |      1.48    0.675865
R_FQHCHOSP_C |      1.46    0.682665
     P_OCCUP |      1.42    0.701919
P_POSH_OPS_C |      1.42    0.703611
 R_RHCHOSP_C |      1.30    0.770101
 PLANT_AGE_R |      1.22    0.820266
P_NPREV_OGOV |      1.22    0.821341
    IQI_32_R |      1.19    0.843522
    IQI_17_R |      1.14    0.875644
-------------+----------------------
    Mean VIF |      1.84
```

Appendix I: Correlation Coefficients

```
. corr `ivars'
(obs=750)
```

	P_NPRE~R	P_NPRE~D	P_NPRE~M	P_PRFT~C	FP	R_INTR~D	P_UNEM~C
P_NPREV_MMCR	1.0000						
P_NPREV_MMCD	0.2021	1.0000					
P_NPREV_MCOM	0.0534	-0.1532	1.0000				
P_PRFT_NETUC	-0.0893	0.0644	-0.1531	1.0000			
FP	0.1423	0.1380	-0.0242	0.1465	1.0000		
R_INTRES_BED	-0.0540	0.1560	-0.2569	0.3449	-0.2649	1.0000	
P_UNEMP_C	-0.1736	0.0706	-0.1928	0.0622	0.0922	-0.0415	1.0000
P_OTHUC_C	0.2965	0.2499	0.2950	-0.1575	0.1173	-0.1251	0.0875
P_POSH_OPS_C	0.1312	0.3163	-0.0972	0.0415	0.1480	0.1450	0.1045
R_ASCHOSP_C	0.0606	-0.0169	0.1191	0.0608	-0.0218	0.0471	-0.0841
R_FQHCHOSP_C	-0.1345	0.0992	-0.2021	0.0833	0.0165	0.0609	0.1535
R_RHCHOSP_C	-0.1469	-0.0954	-0.2166	0.0044	0.0063	-0.0905	0.2099
DENS_UPOP_C	0.3322	0.2897	0.3049	0.0246	0.0145	0.1668	0.0186
LN_BEDS	-0.0217	0.0562	-0.1193	0.1791	-0.1115	0.3847	0.0109
P_OCCUP	0.0256	-0.0340	-0.0087	0.1826	-0.1830	0.3079	0.0947
SEV_ILL	0.0637	-0.0156	-0.1162	-0.1091	-0.0274	0.0429	0.0541
R_BIRTHS_ADM	-0.0509	0.2436	0.0593	0.2036	0.0559	0.1521	0.0811
ERMIX_NETOPS	0.2226	0.1442	0.2342	-0.1132	0.1932	-0.3292	-0.0578
R_ADM_ERVIS	0.0659	-0.0539	-0.0620	-0.0121	0.0394	0.0738	0.1198
PLANT_AGE_R	0.0460	0.1070	-0.0042	-0.0387	0.2842	-0.0939	0.0416
P_NPREV_OGOV	-0.1620	0.0412	-0.2062	0.0242	-0.0528	0.0092	0.0790
P_TEXP_NPREV	-0.1119	0.1179	-0.3525	-0.0467	-0.4078	0.6545	-0.0466
D_NETWORK	-0.1434	0.0037	0.0224	-0.0085	-0.1712	-0.0843	0.1766
IQI_17_R	-0.0623	0.1088	0.0556	-0.0825	-0.0052	-0.0472	0.0251
IQI_32_R	0.0266	0.0100	0.0414	0.0131	-0.0482	0.1450	0.0044
D_YR_2000	0.1356	-0.1325	-0.0760	-0.0187	0.0280	-0.0104	-0.2683
D_YR_2001	0.1896	-0.0254	-0.0359	0.0315	0.0151	-0.0130	-0.1778
D_YR_2002	-0.0260	-0.0185	-0.0112	0.0596	-0.0050	0.0052	0.1559
D_YR_2003	-0.1395	0.0212	0.0313	-0.0579	-0.0119	0.0079	0.2769
D_YR_2005	-0.0677	0.0518	0.0311	-0.0126	-0.0255	0.0021	-0.0991

	P_OTHU~C	P_POSH~C	R_ASCH~C	R_FQHC~C	R_RHCH~C	DENS_U~C	LN_BEDS
P_OTHUC_C	1.0000						
P_POSH_OPS_C	0.2717	1.0000					
R_ASCHOSP_C	0.1956	-0.0562	1.0000				
R_FQHCHOSP_C	-0.1098	0.1115	0.0254	1.0000			
R_RHCHOSP_C	-0.2768	-0.0598	-0.1464	0.2214	1.0000		
DENS_UPOP_C	0.6764	0.2603	0.3264	-0.2712	-0.2874	1.0000	
LN_BEDS	0.1884	0.2135	0.2854	0.1409	-0.1674	0.2427	1.0000
P_OCCUP	0.0865	0.0666	0.2759	0.1209	-0.0175	0.2554	0.3381
SEV_ILL	0.1088	-0.0015	0.0859	-0.0873	-0.0645	0.1274	0.2166
R_BIRTHS_ADM	0.0342	0.0770	0.0263	0.1498	-0.0030	0.0996	0.0096
ERMIX_NETOPS	0.1244	0.0678	0.0521	-0.0210	-0.0520	0.0476	-0.3171
R_ADM_ERVIS	0.2235	0.1855	0.0780	0.1274	-0.0138	0.1348	0.4791
PLANT_AGE_R	0.0081	0.0193	-0.0567	0.0453	0.0382	-0.0010	-0.1920
P_NPREV_OGOV	-0.1500	0.0452	-0.1049	0.1557	0.0448	-0.2360	-0.0401
P_TEXP_NPREV	-0.1645	0.0654	0.0168	-0.0128	-0.0308	0.0871	0.1394
D_NETWORK	-0.0282	0.0100	0.0389	0.1472	0.0090	-0.0448	0.0084
IQI_17_R	0.0527	0.0403	-0.0586	-0.0203	-0.0518	0.0478	-0.0353
IQI_32_R	0.0519	0.0792	-0.0011	-0.0195	-0.0433	0.1242	0.0358
D_YR_2000	-0.0051	-0.0390	-0.0959	-0.0520	0.0079	-0.0052	0.0158
D_YR_2001	-0.0205	-0.0853	-0.0950	-0.0641	0.0339	0.0006	-0.0146
D_YR_2002	-0.0323	-0.0682	-0.0616	-0.0358	-0.0100	-0.0347	-0.0109
D_YR_2003	-0.0279	0.0549	0.0081	-0.0324	-0.0024	0.0072	-0.0190
D_YR_2005	0.0221	0.0424	0.1514	0.1132	0.0062	0.0032	0.0241

	P_OCCUP	SEV_ILL	R_BIRT~M	ERMIX_~S	R_ADM_~S	PLANT_~R	P_NPRE~V
P_OCCUP	1.0000						
SEV_ILL	0.1216	1.0000					
R_BIRTHS_ADM	0.0139	-0.5972	1.0000				
ERMIX_NETOPS	-0.1608	-0.0694	0.0931	1.0000			
R_ADM_ERVIS	0.1685	0.1959	-0.1170	-0.3503	1.0000		
PLANT_AGE_R	-0.0812	-0.0646	0.1263	0.1504	-0.0148	1.0000	
P_NPREV_OGOV	-0.1091	-0.1057	0.0473	-0.1214	-0.0858	-0.0307	1.0000
P_TEXP_NPREV	0.1292	-0.0380	0.1233	-0.2953	-0.0619	-0.1051	-0.0185
D_NETWORK	0.1010	0.0252	0.0036	0.0199	-0.1149	-0.1021	0.0884
IQI_17_R	-0.0028	0.0780	0.0331	0.0873	0.0429	0.1121	0.0334
IQI_32_R	0.0725	0.1089	0.1143	0.0574	-0.0228	0.1395	-0.0715
D_YR_2000	-0.0439	-0.0583	0.0191	-0.0463	0.0575	0.0526	-0.0484
D_YR_2001	-0.0582	-0.0027	-0.0156	-0.0318	0.0657	0.0081	-0.0209
D_YR_2002	0.0479	0.0508	-0.0019	-0.0164	-0.0057	-0.0000	-0.0171
D_YR_2003	0.0660	0.1578	-0.0136	0.0336	-0.0505	-0.0245	0.0203
D_YR_2005	-0.0140	-0.0064	0.0063	0.0195	-0.0434	-0.0187	0.0305

	P_TEXP~V	D_NETW~K	IQI_17_R	IQI_32_R	D_Y~2000	D_Y~2001	D_Y~2002
P_TEXP_NPREV	1.0000						
D_NETWORK	-0.0222	1.0000					
IQI_17_R	-0.0148	-0.0097	1.0000				
IQI_32_R	0.1130	-0.0569	0.1582	1.0000			
D_YR_2000	-0.0319	-0.1033	-0.0974	-0.0715	1.0000		
D_YR_2001	-0.0041	-0.1033	-0.0185	-0.0317	-0.1796	1.0000	
D_YR_2002	-0.0393	-0.0891	-0.1098	-0.0131	-0.1856	-0.2047	1.0000
D_YR_2003	0.0377	0.4506	0.0914	0.0712	-0.1899	-0.2095	-0.2165
D_YR_2005	0.0174	-0.0940	0.0770	0.0825	-0.1830	-0.2019	-0.2087

	D_Y~2003	D_Y~2005
D_YR_2003	1.0000	
D_YR_2005	-0.2135	1.0000

Appendix J: Wooldridge Autocorrelation Test

```
. xtserial `dvar' `ivars'

Wooldridge test for autocorrelation in panel data
H0: no first order autocorrelation
    F(  1,     131) =     12.434
           Prob > F =      0.0006
```

Appendix K: Bhargava, et al., Panel Durbin-Watson Correlation Test

```
. xtdurbin

Tests for First-order Serial Correlation in a Fixed Effects Model:

    P_UC_TEXP[ID,YEAR] = Xb + u[ID] + v[ID,YEAR]

         AR(1): v[ID,YEAR] = rho v[ID,YEAR-1] + e[ID,YEAR], or

         MA(1): v[ID,YEAR] =  e[ID,YEAR] + lamba e[ID,YEAR-1]

    Tests:

           LM(rho=0 or lamba = 0)     =   0.012   Pr>chi2(1) =  0.9118

           LM5(rho=0 or lamba = 0)    =   0.111   Pr>N(0,1)  =  0.4559

Bhargava, Franzini and Narendranathan DW Statistic = 1.2611592
```

Appendix L: Greene Groupwise Heteroskedasticity Test

```
. xttest3

Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (155)  =    4.0e+31
Prob>chi2 =      0.0000
```

Appendix M: Bickel Version of Breusch-Pagan Heteroskedasticity Test

```
. qui xtreg `dvar' `ivars', fe

. bickel_bp

 ( 1)  yhat1 = 0
 ( 2)  yhat2 = 0
 ( 3)  yhat3 = 0
 ( 4)  yhat4 = 0
 ( 5)  yhat5 = 0
 ( 6)  yhat6 = 0
 ( 7)  yhat7 = 0

       F(  7,   742) =   45.40
            Prob > F =    0.0000



Bickel (1978) version of B-P Test for Heteroskedasticity in FE Model:
Test for within and between heteroskedasticity for small T
Highest power used in calculation =  7
Constraints dropped code = 0  (1 if yes, 0 otherwise)

    Wald F statistic =   45.400  Prob > F(7,742) =   0.0000
```

Appendix N: Chow Poolability Test

```
Chow (1960) F-test for fixed effects:

    H0: all u_i=0  Source: Baltagi (2008), p. 15

         F ( 154 , 565 ) =   17.094  Prob > F =   0.0000
```

Appendix O: Robust Hausman Specification Test

```
. qui xtreg `dvar' `ivars', fe vce(cluster ID)

. r_hausman

 ( 1)  P_NPREV_MMCR_fe = 0
 ( 2)  P_NPREV_MMCD_fe = 0
 ( 3)  P_NPREV_MCOM_fe = 0
 ( 4)  P_PRFT_NETUC_fe = 0
 ( 5)  FP_fe = 0
 ( 6)  R_INTRES_BED_fe = 0
 ( 7)  P_UNEMP_C_fe = 0
 ( 8)  P_OTHUC_C_fe = 0
 ( 9)  P_POSH_OPS_C_fe = 0
 (10)  R_ASCHOSP_C_fe = 0
 (11)  R_FQHCHOSP_C_fe = 0
 (12)  R_RHCHOSP_C_fe = 0
 (13)  DENS_UPOP_C_fe = 0
 (14)  LN_BEDS_fe = 0
 (15)  P_OCCUP_fe = 0
 (16)  SEV_ILL_fe = 0
 (17)  R_BIRTHS_ADM_fe = 0
 (18)  ERMIX_NETOPS_fe = 0
 (19)  R_ADM_ERVIS_fe = 0
 (20)  PLANT_AGE_R_fe = 0
 (21)  P_NPREV_OGOV_fe = 0
 (22)  P_TEXP_NPREV_fe = 0
 (23)  D_NETWORK_fe = 0
 (24)  IQI_17_R_fe = 0
 (25)  IQI_32_R_fe = 0
 (26)  D_YR_2000_fe = 0
 (27)  D_YR_2001_fe = 0
 (28)  D_YR_2002_fe = 0
 (29)  D_YR_2003_fe = 0
 (30)  D_YR_2005_fe = 0

       F( 30,   154) =    4.01
            Prob > F =    0.0000

Robust Hausman (1978) Test

  Ho: Gamma = 0

     Wald F(30,154) =    4.008

     Prob > F =    0.0000
```

Appendix P: Standard Hausman Specification Test

```
. *based on (co)variance matrices on disturbance from consistent estimator (FE)
. hausman FE RE, sigmaless
```

	Coefficients (b) FE	(B) RE	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
P_NPREV_MMCR	-.0255817	-.0515481	.0259664	.0075555
P_NPREV_MMCD	-.0763501	-.0369478	-.0394023	.0211703
P_NPREV_MCOM	-.0331952	-.0631309	.0299357	.0050853
P_PRFT_NETUC	.1187787	.2489977	-.130219	.0089643
FP	-.0098704	-.014408	.0045377	.0033184
R_INTRES_BED	-.0349937	.0290254	-.0640191	.0091117
P_UNEMP_C	.1224344	.1199073	.0025271	.0456369
P_OTHUC_C	-.0048153	-.0852299	.0804146	.0216282
P_POSH_OPS_C	.0413105	.0201977	.0211128	.0047659
R_ASCHOSP_C	.0000859	-.003222	.0033079	.0014185
R_FQHCHOSP_C	.0024878	.0017323	.0007556	.0012918
R_RHCHOSP_C	-.007331	-.0060676	-.0012634	.0021786
DENS_UPOP_C	.0002271	.0001478	.0000793	.0002344
LN_BEDS	-.0299234	-.0011428	-.0287806	.0046902
P_OCCUP	-.0218749	.0071751	-.02905	.0070731
SEV_ILL	-.0214649	-.0221382	.0006732	.0057225
R_BIRTHS_ADM	-.0786375	-.0084621	-.0701754	.0180274
ERMIX_NETOPS	.0123228	-.0034666	.0157893	.0039527
R_ADM_ERVIS	-.0157328	-.06066	.0449272	.0064777
PLANT_AGE_R	-.0032632	.0043433	-.0076066	.0018916
P_NPREV_OGOV	-.0400494	-.0797569	.0397075	.0198491
P_TEXP_NPREV	.1037523	.2046582	-.1009059	.0070032
D_NETWORK	.002282	.0015726	.0007094	.0008154
IQI_17_R	.0001418	.0000876	.0000542	.0000225
IQI_32_R	.000056	-.0000389	.0000949	.0000327
D_YR_2000	-.0053204	-.0051378	-.0001826	.0015734
D_YR_2001	-.0079766	-.0106976	.002721	.0011832
D_YR_2002	-.0084593	-.0098736	.0014143	.0009759
D_YR_2003	-.0069776	-.0072022	.0002246	.0008872
D_YR_2005	-.0011851	.0000697	-.0012548	.0007356

```
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(30) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                           =       300.49
                Prob>chi2 =       0.0000
```

```
.*based on (co)variance matrices on disturbance from efficient estimator (RE)
. hausman FE RE, sigmamore
```

	---- Coefficients ---- (b) FE	(B) RE	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
P_NPREV_MMCR	-.0255817	-.0515481	.0259664	.0088671
P_NPREV_MMCD	-.0763501	-.0369478	-.0394023	.0248453
P_NPREV_MCOM	-.0331952	-.0631309	.0299357	.0059681
P_PRFT_NETUC	.1187787	.2489977	-.130219	.0105205
FP	-.0098704	-.014408	.0045377	.0038944
R_INTRES_BED	-.0349937	.0290254	-.0640191	.0106934
P_UNEMP_C	.1224344	.1199073	.0025271	.0535592
P_OTHUC_C	-.0048153	-.0852299	.0804146	.0253828
P_POSH_OPS_C	.0413105	.0201977	.0211128	.0055932
R_ASCHOSP_C	.0000859	-.003222	.0033079	.0016647
R_FQHCHOSP_C	.0024878	.0017323	.0007556	.0015161
R_RHCHOSP_C	-.007331	-.0060676	-.0012634	.0025568
DENS_UPOP_C	.0002271	.0001478	.0000793	.000275
LN_BEDS	-.0299234	-.0011428	-.0287806	.0055044
P_OCCUP	-.0218749	.0071751	-.02905	.008301
SEV_ILL	-.0214649	-.0221382	.0006732	.0067158
R_BIRTHS_ADM	-.0786375	-.0084621	-.0701754	.0211568
ERMIX_NETOPS	.0123228	-.0034666	.0157893	.0046389
R_ADM_ERVIS	-.0157328	-.06066	.0449272	.0076022
PLANT_AGE_R	-.0032632	.0043433	-.0076066	.00222
P_NPREV_OGOV	-.0400494	-.0797569	.0397075	.0232948
P_TEXP_NPREV	.1037523	.2046582	-.1009059	.0082189
D_NETWORK	.002282	.0015726	.0007094	.000957
IQI_17_R	.0001418	.0000876	.0000542	.0000264
IQI_32_R	.000056	-.0000389	.0000949	.0000384
D_YR_2000	-.0053204	-.0051378	-.0001826	.0018465
D_YR_2001	-.0079766	-.0106976	.002721	.0013886
D_YR_2002	-.0084593	-.0098736	.0014143	.0011453
D_YR_2003	-.0069776	-.0072022	.0002246	.0010412
D_YR_2005	-.0011851	.0000697	-.0012548	.0008632

```
                          b = consistent under Ho and Ha; obtained from xtreg
           B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(30) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                           =      218.17
                Prob>chi2 =      0.0000
```

Appendix Q: Overidentifying Restrictions Test

```
. xtoverid

Test of overidentifying restrictions: fixed vs random effects
Cross-section time-series model: xtreg re
Sargan-Hansen statistic 300.134  Chi-sq(30)   P-value = 0.0000

.
. xtoverid, cluster(ID)

Test of overidentifying restrictions: fixed vs random effects
Cross-section time-series model: xtreg re  robust cluster(ID)
Sargan-Hansen statistic 116.201  Chi-sq(30)   P-value = 0.0000
```

Appendix R: Data Description

```
. sum `dvar' `ivars'
```

Variable	Obs	Mean	Std. Dev.	Min	Max
P_UC_TEXP	750	.0926402	.0786626	.0083867	.6345191
P_NPREV_MMCR	750	.0229305	.0401193	0	.436737
P_NPREV_MMCD	750	.0308125	.0351732	0	.2427338
P_NPREV_MCOM	750	.3613935	.1740386	0	.8142762
P_PRFT_NETUC	750	.1508031	.1133939	-.6686003	.6428116
FP	750	.3946667	.4891052	0	1
R_INTRES_BED	750	.0523568	.1351602	0	.9353982
P_UNEMP_C	750	.0578267	.0200385	.01518	.135911
P_OTHUC_C	750	.1086244	.0512171	0	.255092
P_POSH_OPS_C	750	.0338209	.0607957	0	.366471
R_ASCHOSP_C	750	1.368017	.8349389	0	4.5
R_FQHCHOSP_C	750	.4671282	.7424229	0	4.666667
R_RHCHOSP_C	750	.206181	.5811902	0	6
DENS_UPOP_C	750	57.98985	48.98992	1.797882	148.5248
LN_BEDS	750	5.399755	.6689198	3.218876	7.239933
P_OCCUP	750	.6295134	.1291941	.2149842	.9825865
SEV_ILL	750	1.803432	.137883	1.037944	2.258527
R_BIRTHS_ADM	750	.1602719	.0814668	0	.4043494
ERMIX_NETOPS	750	.4026634	.1638055	.0192781	1
R_ADM_ERVIS	750	.3377257	.1874226	.0809814	2.269971
PLANT_AGE_R	750	.159649	.1326889	.0460171	.9939959
P_NPREV_OGOV	750	.0253164	.035573	0	.2596893
P_TEXP_NPREV	750	.9941432	.1898253	.5063032	2.213627
D_NETWORK	750	.4706667	.4994719	0	1
IQI_17_R	750	11.13961	5.36884	2.468929	61.80088
IQI_32_R	750	11.65337	4.454461	1.377891	43.85196
D_YR_2000	750	.14	.3472186	0	1
D_YR_2001	750	.1653333	.371729	0	1
D_YR_2002	750	.1746667	.3799351	0	1
D_YR_2003	750	.1813333	.3855512	0	1
D_YR_2005	750	.1706667	.3764685	0	1

Appendix S: Fixed-Effects Estimates Using Robust Standard Errors

```
. xtreg `dvar' `ivars', fe vce(cluster ID)

Fixed-effects (within) regression               Number of obs      =       750
Group variable: ID                              Number of groups   =       155

R-sq:  within  = 0.3308                         Obs per group: min =         2
       between = 0.3264                                        avg =       4.8
       overall = 0.3826                                        max =         6

                                                F(30,154)          =      8.30
corr(u_i, Xb)  = 0.2997                         Prob > F           =    0.0000

                               (Std. Err. adjusted for 155 clusters in ID)
------------------------------------------------------------------------------
             |               Robust
   P_UC_TEXP |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
P_NPREV_MMCR |  -.0255817   .0149098    -1.72   0.088    -.0550358    .0038725
P_NPREV_MMCD |  -.0763501   .0558204    -1.37   0.173    -.1866226    .0339224
P_NPREV_MCOM |  -.0331952   .0102355    -3.24   0.001    -.0534153   -.0129751
P_PRFT_NETUC |   .1187787   .0328577     3.61   0.000     .0538687    .1836888
          FP |  -.0098704   .0059595    -1.66   0.100    -.0216434    .0019027
R_INTRES_BED |  -.0349937   .0184859    -1.89   0.060    -.0715123     .001525
  P_UNEMP_C  |   .1224344   .0783148     1.56   0.120    -.0322755    .2771443
  P_OTHUC_C  |  -.0048153   .0345915    -0.14   0.889    -.0731503    .0635197
P_POSH_OPS_C |   .0413105    .013941     2.96   0.004     .0137703    .0688507
 R_ASCHOSP_C |   .0000859    .001879     0.05   0.964    -.0036261     .003798
R_FQHCHOSP_C |   .0024878   .0021721     1.15   0.254     -.001803    .0067787
 R_RHCHOSP_C |   -.007331   .0036699    -2.00   0.048    -.0145809   -.0000812
 DENS_UPOP_C |   .0002271   .0003838     0.59   0.555     -.000531    .0009853
     LN_BEDS |  -.0299234   .0117587    -2.54   0.012    -.0531525   -.0066943
     P_OCCUP |  -.0218749   .0161003    -1.36   0.176    -.0536809     .009931
     SEV_ILL |  -.0214649   .0094505    -2.27   0.025    -.0401344   -.0027955
R_BIRTHS_ADM |  -.0786375   .0362911    -2.17   0.032    -.1503301   -.0069449
ERMIX_NETOPS |   .0123228    .007071     1.74   0.083    -.0016459    .0262914
  R_ADM_ERVIS |  -.0157328   .0188035    -0.84   0.404     -.052879    .0214134
 PLANT_AGE_R |  -.0032632   .0067002    -0.49   0.627    -.0164995     .009973
P_NPREV_OGOV |  -.0400494   .0669706    -0.60   0.551    -.1723489    .0922501
P_TEXP_NPREV |   .1037523    .035224     2.95   0.004     .0341677    .1733369
   D_NETWORK |    .002282   .0017335     1.32   0.190    -.0011426    .0057066
    IQI_17_R |   .0001418    .000078     1.82   0.071    -.0000123    .0002959
    IQI_32_R |    .000056   .0001464     0.38   0.702    -.0002331    .0003451
   D_YR_2000 |  -.0053204   .0026557    -2.00   0.047    -.0105667   -.0000742
   D_YR_2001 |  -.0079766   .0023347    -3.42   0.001    -.0125887   -.0033645
   D_YR_2002 |  -.0084593   .0017847    -4.74   0.000    -.0119849   -.0049337
   D_YR_2003 |  -.0069776   .0018127    -3.85   0.000    -.0105585   -.0033967
   D_YR_2005 |  -.0011851   .0017584    -0.67   0.501    -.0046588    .0022886
       _cons |   .2016057   .0795724     2.53   0.012     .0444113    .3588001
-------------+----------------------------------------------------------------
     sigma_u |  .06209168
     sigma_e |   .0122769
         rho |  .96237681   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Appendix T: Fixed-Effects Estimates Using Standard Errors

```
. xtreg `dvar' `ivars', fe

Fixed-effects (within) regression               Number of obs      =       750
Group variable: ID                              Number of groups   =       155

R-sq:  within  = 0.3308                         Obs per group: min =         2
       between = 0.3264                                        avg =       4.8
       overall = 0.3826                                        max =         6

                                                F(30,565)          =      9.31
corr(u_i, Xb)  = 0.2997                         Prob > F           =    0.0000

------------------------------------------------------------------------------
   P_UC_TEXP |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
P_NPREV_MMCR |  -.0255817   .0200584    -1.28   0.203    -.0649798    .0138165
P_NPREV_MMCD |  -.0763501   .0392005    -1.95   0.052    -.1533466    .0006464
P_NPREV_MCOM |  -.0331952   .0089987    -3.69   0.000    -.0508702   -.0155202
P_PRFT_NETUC |   .1187787    .013571     8.75   0.000     .0921229    .1454346
          FP |  -.0098704   .0044726    -2.21   0.028    -.0186553   -.0010854
R_INTRES_BED |  -.0349937   .0150556    -2.32   0.020    -.0645654    -.005422
  P_UNEMP_C  |   .1224344   .0754054     1.62   0.105    -.0256748    .2705435
  P_OTHUC_C  |  -.0048153    .036344    -0.13   0.895    -.0762012    .0665706
P_POSH_OPS_C |   .0413105   .0138696     2.98   0.003     .0140683    .0685527
R_ASCHOSP_C  |   .0000859   .0021339     0.04   0.968    -.0041053    .0042772
R_FQHCHOSP_C |   .0024878   .0021052     1.18   0.238     -.001647    .0066227
R_RHCHOSP_C  |   -.007331   .0030697    -2.39   0.017    -.0133604   -.0013017
DENS_UPOP_C  |   .0002271   .0002389     0.95   0.342    -.0002422    .0006964
    LN_BEDS  |  -.0299234   .0053233    -5.62   0.000    -.0403793   -.0194675
    P_OCCUP  |  -.0218749   .0105546    -2.07   0.039    -.0426059    -.001144
    SEV_ILL  |  -.0214649    .010447    -2.05   0.040    -.0419846   -.0009452
R_BIRTHS_ADM |  -.0786375   .0255015    -3.08   0.002    -.1287269   -.0285482
ERMIX_NETOPS |   .0123228   .0075368     1.64   0.103    -.0024808    .0271263
R_ADM_ERVIS  |  -.0157328   .0094937    -1.66   0.098    -.0343801    .0029144
PLANT_AGE_R  |  -.0032632   .0056307    -0.58   0.562    -.0143229    .0077964
P_NPREV_OGOV |  -.0400494    .035843    -1.12   0.264    -.1104512    .0303524
P_TEXP_NPREV |   .1037523   .0106923     9.70   0.000     .0827508    .1247537
  D_NETWORK  |    .002282   .0020285     1.12   0.261    -.0017023    .0062663
   IQI_17_R  |   .0001418   .0001072     1.32   0.186    -.0000687    .0003523
   IQI_32_R  |    .000056   .0001342     0.42   0.677    -.0002076    .0003197
  D_YR_2000  |  -.0053204   .0028218    -1.89   0.060     -.010863    .0002221
  D_YR_2001  |  -.0079766   .0023476    -3.40   0.001    -.0125878   -.0033655
  D_YR_2002  |  -.0084593   .0020451    -4.14   0.000    -.0124762   -.0044425
  D_YR_2003  |  -.0069776   .0022949    -3.04   0.002    -.0114852     -.00247
  D_YR_2005  |  -.0011851   .0018722    -0.63   0.527    -.0048624    .0024922
       _cons |   .2016057   .0423006     4.77   0.000     .1185201    .2846913
-------------+----------------------------------------------------------------
     sigma_u |  .06209168
     sigma_e |   .0122769
         rho |  .96237681   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0:     F(154, 565) =    17.09            Prob > F = 0.0000
```

Appendix U: MSAs, Counties, and Observations by MSA and Counties

MSA CODE	MSA NAME	COUNTIES	# OBS
10180	Abilene	Callahan	0
		Jones	0
		Taylor	12
11100	Amarillo	Armstrong	0
		Carson	0
		Potter	10
		Randall	0
12420	Austin-Round Rock	Bastrop	0
		Caldwell	2
		Hays	5
		Travis	27
		Williamson	13
13140	Beaumont-Port Arthur	Hardin	0
		Jefferson	23
		Orange	0
15180	Brownsville-Harlingen	Cameron	17
17780	College Station-Bryan	Brazos	6
		Burleson	0
		Robertson	0
18580	Corpus Christi	Aransas	0
		Nueces	14
		San Patricio	0
19100	Dallas-Fort Worth-Arlington	Collin	17
		Dallas	84
		Delta	0
		Denton	19
		Ellis	5
		Hunt	6
		Johnson	4
		Kaufman	11
		Parker	0
		Rockwall	5
		Tarrant	70
		Wise	0
21340	El Paso	El Paso	28

MSA CODE	MSA NAME	COUNTIES	# OBS
26420	Houston-Sugar Land-Baytown	Austin	0
		Brazoria	10
		Chambers	0
		Fort Bend	13
		Galveston	4
		Harris	125
		Liberty	5
		Montgomery	16
		San Jacinto	0
		Waller	0
28660	Killeen-Temple-Fort Hood	Bell	17
		Coryell	2
		Lampasas	0
29700	Laredo	Webb	11
30980	Longview	Gregg	8
		Rusk	3
		Upshur	0
31180	Lubbock	Crosby	0
		Lubbock	9
32580	McAllen-Edinburg-Mission	Hidalgo	21
33260	Midland	Midland	3
36220	Odessa	Ector	6
41660	San Angelo	Irion	0
		Tom Green	10
41700	San Antonio	Atascosa	4
		Bandera	0
		Bexar	46
		Comal	2
		Guadalupe	4
		Kendall	0
		Medina	0
		Wilson	0
43300	Sherman-Denison	Grayson	6
45500	Texarkana	Bowie	12
46340	Tyler	Smith	10
47020	Victoria	Calhoun	0
		Goliad	0
		Victoria	9
47380	Waco	McLennan	12
48660	Wichita Falls	Archer	0
		Clay	0
		Wichita	4
		Total	750