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UNCOMPENSATED CARE PROVISION AND THE ECONOMIC BEHAVIOR OF HOSPITALS: THE INFLUENCE OF THE REGULATORY ENVIRONMENT

A Dissertation
Presented to
The Academic Faculty

by

Lei Zhang

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
School of Public Policy/Andrew Young School of Policy Studies

Georgia Institute of Technology/Georgia State University
DECEMBER, 2008

UNCOMPENSATED CARE PROVISON AND THE ECONOMIC BEHAVIOR OF HOSPITALS: THE INFLUENCE OF THE REGULATORY ENVIRONMENT

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THIS DISSERTATION IS DEDICATED TO MY FAMILY…

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SUMMARY

This dissertation project examines the effect of various state regulations such as Certificate-of-Need (CON) regulation, uncompensated care pools and community benefit requirement laws on hospital provision of uncompensated care and analyzes both for-profit and non-profit hospitals' responsiveness to the regulatory environment. The analysis of these regulations uses panel data econometric methods for a sample of hospitals in 17 states from 2002 to 2004. This study overcomes the limits of previous research that focused primarily on the effect of a single regulation in a given state. It uses three estimation methods: pooled Ordinary Least Squares (pooled OLS), random effects generalized least squares (GLS) and Hausman Taylor instrumental variable (HTIV) to obtain the parameter estimates. Weighing the advantages and disadvantages of each method, we interpret results based on the cross-validation of the GLS and HTIV estimates. Findings suggest that nonprofit and for-profit hospitals respond to some policy instruments similarly and others differently. For example, both nonprofit and for-profit hospitals respond to CON laws by increasing their uncompensated care provision. However, they respond to policy incentives such as community benefit requirement laws differently. Furthermore, regulatory interactions are found to significantly influence the uncompensated care provision by both nonprofit and for-profit hospitals. The dissertation helps policy makers formulate strategies to create incentives to enhance access to care for the economically disadvantaged. For example, implementing CON and providing public subsidies at the same time may offer better access to care for the uninsured than

implementing either regulation alone. However, community benefit requirement laws do not appear to expand the amount of uncompensated care provided by nonprofit hospitals.

CHAPTER ONE

INTRODUCTION

A continued decline in the share of the population with health insurance coverage combined with movement to decreased reimbursement for hospitals have caused renewed concern about access to health care for the underinsured and uninsured. Hospital uncompensated care, a primary source of care for the indigent, has been declining even though the demand for such care continues to grow. According to a Census Bureau report, the number of uninsured has risen considerably over the years. In less than a decade, the percentage of people without health insurance coverage rose from 14.2 percent in 2000 to 15.8 percent in 2006, that is, 47 million people (DeNavas-Walt, Proctor et al. 2006; Census 2008). This trend has resulted in substantial stress for public and nonprofit teaching hospitals that have played a central role in providing access to care for the indigent. American Hospital Association (AHA) statistics show that hospitals provided almost $29 billion in uncompensated care in 2005, which comprised about six percent of U.S. acute care hospitals' revenue (AHA 2006). In the face of growing fiscal pressures, this burden has started to jeopardize the financial solvency of some hospitals, and has consequently exerted significant impact on access to care for those who need it the most.

Because state regulatory policies have greatly influenced the level of uncompensated care and the ability of hospitals to finance such care, this study examines the impact of such policies on hospital provision of uncompensated care and analyzes

hospitals' relative responsiveness to the regulatory environment[*]. Specifically, the study will seek to answer the following research questions: (1) How do regulatory environments affect hospitals that differ by type of ownership? (2) Do regulatory interactions make individual regulations more or less effective?

Answers to these research questions are important because they will help policy makers formulate strategies to improve hospital financing of uncompensated care and create incentives to enhance access to care for the uninsured. For instance, in light of the recent debate over the new Internal Revenue Service (IRS) ruling requiring nonprofit hospitals to report community benefits, it is crucial for the policy makers to understand the intended or unintended consequences of the existing state community benefit requirement laws and whether they influence other similar regulations. In addition, alternative interventions might be developed to protect the safety net hospitals[†], which are often the last resort for care for the uninsured and underinsured, by redistributing the burden of uncompensated care to financially relieve these providers. Furthermore, if regulations are jointly effective in increasing hospital provision of uncompensated care, policy makers targeting at expanding access to care for the uninsured should consider designing more complex regulatory strategies. If interaction among regulations reduces the effectiveness of an individual regulation, the existing regulatory environment should

---

[*] Note that we are not including federal regulations in the current study due to a lack of variation across states. Our main interest lies in state's regulatory variations.

[†] These are hospitals, either public or private, that have a legal obligation or a commitment to provide direct health care services to the uninsured or underinsured Dalton, et al. (2005). "Survival strategies for Michigan's health care safety net providers." Health Serv Res **40**(3): 923-40..

be carefully examined when new regulations are designed. Thus, the investigation of multiple regulations is crucial to policy design (Antel, Ohsfeldt and Becker, 1995).

We adopt panel data econometric methods for a sample of 2,235 nonprofit and 295 for-profit hospitals in 17 states from 2002 to 2004. This study uses a comprehensive dataset that includes information obtained from three major data sources: the American Hospital Association (AHA) annual survey of hospitals, the Area Resource File (ARF) and the State Inpatient Database (SID) of the Health Care Utilization Project (HCUP). It overcomes the limits of previous research that focused primarily on the effect of a single regulation in a given state. It uses three estimation methods: pooled Ordinary Least Squares (pooled OLS), random effects generalized least squares (GLS) and Hausman Taylor instrumental variable (HTIV) to obtain the parameter estimates. Weighing the advantages and disadvantages of each method, we interpret results based on the cross-validation of the GLS and HTIV estimates.

Our findings suggest that nonprofit and for-profit hospitals respond to some policy instruments similarly and others differently. In addition, we find significant regulatory interactions. Sometimes the effect of a regulation bundle differs from that of individual regulations. This result indicates that previous studies that failed to include regulatory interactions tend to overestimate or misestimate the effect of single regulations. Some important limitations need to be noted. Due to data unavailability, we do not have real changes over time for some key variables that the HTIV model uses to construct robust internal instruments. Additionally, our population adjustment of these variables, though introducing within group variation, creates measurement errors that could bias our estimates. Future research should focus on obtaining more data on these variables so that

we could improve the HTIV estimations. Enhanced measures of regulatory intensity using data that include information on primary/preventive care should also be used improve our understanding of the mechanism by which these regulations affect hospital uncompensated care provision.

Scope of the Research

In the current research, we focus on nonfederal, short-term general medical and surgical hospitals. We exclude nursing homes, hospices, and home health care agencies because they compete in a different market and are typically treated separately. We further exclude federal hospitals for similar reasons.

We focus on differences in state regulatory environments for three reasons. First and foremost, states are playing an increasingly significant role in regulating their marketplaces. With the recent shifts toward a more state-centered form of federalism, states have been encouraged to formulate and implement their own regulations to reflect regional dynamics (Turnock and Atchison 2002). Second, failure to recognize regulatory variations among states would lead to an incomplete understanding of regulation's impact on organizational behaviors (Anderson, Heyssel et al. 1993). Third, states have always been an ideal laboratory for "natural experiments". With the variation in the regulatory environment among states, we are able to test theoretical models in a more scientific and rigorous fashion, using a near-natural experiment approach (i.e., comparisons of outcomes under different regulatory environments). To capture a state's regulatory environment, we include in our analysis a much broader scope of regulations than many existing studies. These regulations include Certificate-of-Need (CON) laws, Any-Willing-Provider (AWP) or Freedom-of-Choice (FOC) regulation, rate-setting/uncompensated care pool regulation, state hospital conversion regulation, and community benefit mandates.[‡]

[‡] Due to a lack of variations on AWP/FOC and state hospital conversion regulations in our data sample, we do not empirically test the impact of these two regulations.

Dissertation Overview

This dissertation is organized as follows. Chapter Two first reviews literature on hospital regulation and behavior, as well as hospital provision of uncompensated care. It then summarizes the empirical studies and identifies gaps in the research.

Chapter Three discusses theoretical models of hospital behavior and uncompensated care provision. The first section develops models of hospital behaviors in response to exogenous changes. The next section presents hypotheses to be tested.

Chapter Four presents the methodology, empirical model, and data to be used in the analysis. Chapter Five describes the estimation methodology and presents findings, while Chapter Six concludes, discusses policy implications and study limitations, and suggests directions for future research.

CHAPTER TWO

LITERATURE REVIEW

Previous literature analyzing regulation's impact on uncompensated care provision largely emphasizes the effect of a single regulation without much focus on sectoral differences or policy interactions. This chapter first reviews literature on uncompensated care trends. It then explores motivations for government intervention and the regulation of the hospital industry. This chapter then describes the specific regulations under investigation and reviews relevant empirical studies. It concludes with a summary of the literature and an evaluation of the gaps in prior research.

Trends in Uncompensated Care Provision

Health services researchers have been closely monitoring uncompensated care trends since the early 1980s. They have generally found that between 1980 and 1990, the relative cost of uncompensated care as a percentage of total revenue for all non-federal acute care hospitals increased by about 20 percent, with much of the increase occurring in the first half of the 1980s. The 1990s saw a reversed trend. Despite the fact that the demand for uncompensated care continued to increase, the level of uncompensated care generally declined throughout the 1990s (Atkinson, Helms et al. 1997; Cunningham and Tu 1997; Mann, Melnick et al. 1997; GAO 2006). These studies also find that uncompensated care has not been evenly distributed across hospitals and in fact has been increasingly concentrated among a small number of hospitals. Public and nonprofit teaching hospitals bear much of the uncompensated care burden. Some studies report a

lower level of uncompensated care supply by for-profit hospitals when compared with nonprofit and public/nonprofit teaching hospitals (Rosenau 2003). Some others fail to show that there is significant performance difference between for-profit and nonprofit hospitals on this criterion[§] (Rosenau 2003; Rosenau and Linder 2003).

For example, a 2006 General Accounting Office report (GAO 2006) reviewed hospital uncompensated care provision by nonprofit, for-profit and government hospitals in five states (California, Florida, Georgia, Indiana, and Texas). Their statistics show that government hospitals generally devoted the largest share of patient operating expenses to uncompensated care. The nonprofit hospitals' average percentages of uncompensated care expenses were greater than for-profit hospitals in four of the five study states (Florida, Georgia, Texas, and Indiana). In California, the report did not find significant differences among the two hospital groups. In addition, within each hospital group, the uncompensated care burden was generally concentrated in a small number of hospitals. The authors of the report did not, however, control for any hospital or market characteristics that might influence hospital provision of uncompensated care.

Another study released by the Congressional Budget Office (CBO) expands on the GAO's findings (CBO, 2006). Using the same dataset, the CBO adopted multiple regression techniques to adjust the differences between nonprofit and for-profit hospitals

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[§] The empirical literature examining other performance criteria such as cost, efficiency, diffusion of technology, or quality of care among hospitals of different ownership types is not discussed here. For a systematic evaluation of nonprofit vs. for-profit performance, please see Rosenau, P. V. (2003). "Performance Evaluations of For-profit U.S. Hospitals Since 1980." Nonprofit Management and Leadership **13**(4): 401-423, Rosenau, P. V. and S. H. Linder (2003). "Two Decades of Research Comparing For-profit and Nonprofit Health Provider Performance in the United States." Social Science Quarterly **84**(2): 219-241..

in uncompensated care provision due to hospital and market characteristics. They report an adjusted difference of 0.6 percentage points in uncompensated care as a share of operating expenses, with nonprofit hospitals slightly leading for-profit hospitals.

Schlesinger et al. (1997) used data from a 1987-1988 national survey of 915 psychiatric specialty and general hospitals to examine the impact of hospital ownership and competition, as well as the interaction of these variables on access to hospital care for the uninsured. Results from their Ordinary Least Squares (OLS) regressions show that controlling for some confounding covariates, nonprofit hospitals operating in 1988 provided significantly more uncompensated care than their for-profit counterparts. However, when competition intensifies, such difference in the provision of uncompensated care tends to disappear.

Another study by Norton and Staiger (1994) used the 1981 American Hospital Association (AHA) annual survey of hospitals to compare the volume of uninsured patients treated in nonprofit and for-profit hospitals. Employing an instrumental variable approach, their study failed to find any significant ownership-related difference in the number of uninsured patients served by nonprofit and for-profit hospitals when they are located in the same market. However, they also found that for-profit hospitals often self-select into better-insured markets to avoid those in need of charity care.

Banks, Paterson and Wendel (1997) examined nonprofit vs. for-profit hospital response to exogenous shocks in term of their uncompensated care provision. They used an unbalanced panel of non-Kaiser acute care hospitals in California from 1981-1989 to test the hypotheses that nonprofit and for-profit hospitals react differently to exogenous

shocks in the market when they make decisions to supply uncompensated care measured as bad debt and charity care expenditures. The study results show that decreased demand for hospital services is associated with an increase in the for-profit hospital supply of uncompensated care, and a negative but insignificant change in the nonprofit hospital supply of such care. Reduced community expectations as measured by the percent of public hospitals in the market are negatively related to for-profit hospital uncompensated care provision.

Using discharge data from California's short-term acute care hospitals that were operating from 1982-1988, Gruber (1994) investigates the impact of market concentration on hospital provision of uncompensated care measured as bad debt and charity care charges. Results show that hospitals in less concentrated areas reduced their uncompensated care, relative to those in more concentrated areas. However, this study did not directly test whether hospitals of different ownership types respond to market concentration differently in terms of their uncompensated care provision due to limited sample size (398 hospitals including public, for-profits and nonprofits). Instead, the study shows that controlling for market concentration and other covariates, for-profit and nonprofit hospitals' supply of uncompensated care did not differ significantly.

In summary, the literature provides some evidence that nonprofit and for-profit hospitals might behave differently in terms of their uncompensated care provision as well as responses to the exogenous environment. This is relevant to our analysis of regulation because if hospitals of different ownership types respond in different ways with regard to their uncompensated care provision, they ought to be modeled differently and tested in separate equations.

Theory of Regulation

In order to predict hospital responses to regulation or in other words, the impact of regulation on hospital provision of uncompensated care, it is important to understand motivations for states to intervene in private activities. There are mainly three lines of theory that provides reasons for government interventions: the public interest theory, the private interest theory and regulation for taxation.

The prevailing theory of regulation since Adam Smith has been known as the "normative analysis as a positive theory" or NPT (Joskow and Noll 1981). It regarded market failure as the motivating reason for the entry of regulation. Once established, regulatory bodies were supposed to lessen or eliminate the inefficiencies engendered by the market failure (Peltzman 1989). Since this theory is based on traditional welfare economics, it implies that regulations are implemented to serve the public interest. However, the weakness of this theory is its assumption that perfectly informed social welfare maximizers are either managing the regulation or running the regulated organizations (Winston 1993).

Private interest theory of regulation starts with the capture theory or CT. It states that over time regulatory agencies are controlled by the industry pressing to pass supportive regulations (Stigler 1971). In other words, regulation is designed to protect the regulated firms from competition. It was later developed by Pelzman (1976) and Becker (1983) into a general line of theory called the Chicago theory of regulation or the economic theory of regulation (ET). Taken together, the private interest theory implies that members of the regulated industry often form effective advocacy coalitions that are able to influence policy making for their own protection.

The taxation by regulation theory is developed mainly because neither public interest theory or private interest theory is able to adequately explain the deliberate and continued provision of many services by the regulated industry at lower rates and in larger quantities than would be offered in an unregulated competitive or monopolistic market (Posner 1971). This theory hence maintains that regulation is designed to realize cross-subsidization. That is regulatory authorities may use cross-subsidization (or taxation) as a means to regulate the activity of a monopoly by limiting monopoly rents and improving consumer welfare.

Hospital Regulation

Scholars have provided a variety of reasons for government intervention in the hospital industry (Salkever 2000). Early discussion focused on health care market failures. In line with the public interest theory, supporters of this argument posit that regulatory agencies act to improve economic performance of hospitals since the market itself fails to achieve an efficient allocation of resources. Indeed, the hospital industry is replete with market failures. First, consumers typically lack perfect information about the prices and technical aspects of many medical devices. This lack of information places physicians in a strong position to practice opportunistic behavior; second, most health care providers (hospitals, clinics, physicians) face portions of downward sloping demand curves (i.e., they have some degree of monopoly power); third, there is a lack of incentives for both patients and providers to shop around and conserve resources. Particularly, there is a problem of moral hazard as a result of traditional forms of health insurance; fourth, hospitals tend to compete over quality because consumers are less sensitive to prices. It is frequently argued that hospitals often engage in a "medical arms

race" and compete through the provision of medically unnecessary services (Feldstein 1971; Robinson and Luft 1987; Kessler and McClellan 2000). However, some scholars argue that correcting market failure and enhancing efficiency as objectives of regulatory agencies are more normative than descriptive. In other words, in principle, government should regulate the hospital industry only because public interventions maximize social welfare. In practice, the entry of government regulations often cannot be solely explained by the public interest theory.

With the development of more positive theories such as private interest theory and taxation by regulation, scholars started to offer additional explanations to hospital regulation. McDonough (1997) examined the regulation and deregulation of hospital rate settings in four states: New York, New Jersey, Massachusetts, and Maryland. He found that key at-stake interest groups were able to manipulate regulation to their own advantage. After investigating the Certificate-of-Need (CON) law in all 50 states, Teske (2004) concluded that CON has increased hospital revenue, evidence of regulation serving the interest of the regulated.

Paralleling the taxation by regulation or consumer subsidy rationales explained by Posner (1971) and others, this line of argument for direct regulation of hospitals posit that public interventions such as rate settings and CON offer some protection to hospitals that provide charity or uncompensated care. For example, Salkever (2000) noted that as managed care plans promote price competition in markets for hospital services, hospital profit margins will be squeezed and the willingness of hospitals to supply charity care will diminish. Price regulation in this case is able to pressure major payers to cover a portion of the hospital's uncompensated care costs.

The next section examines the adoption, implementation and impact of specific regulations such as Certificate-of-Need (CON) laws, Any-Willing-Provider (AWP) or Freedom-of-Choice (FOC) regulation, rate-setting/uncompensated care pool regulation, state hospital conversion regulation, and community benefit mandates which are the focus of this study.

Certificate-of-Need

Certificate-of-Need (CON) laws require that hospitals obtain approval from health planning agencies for investment related to new buildings or expansion of services in excess of certain dollar thresholds. The original rationale of this regulatory intervention, which is to control escalating hospital costs, is embedded in views that hospitals will duplicate services and invest in costly excess capacity because they tend to compete on a non-price basis (Folland, Stano et al. 2004). In the hospital industry, consumers are believed to be largely insensitive to the price of care due to moral hazard resulting from the proliferation of health insurance. Left unchecked, unnecessary duplication of facilities as well as the mere availability of facilities leads to higher cost of care.

CON regulation began when New York became the first state instituting the law in 1964. In 1972, the federal government enacted investment regulation with the passage of Section 1122 of the Social Security Act Amendments. Section 1122 provided for the denial of Medicare and Medicaid cost reimbursement to hospitals expanding capacity without prior approval by local planning agencies. In 1974, the federal government passed the National Health Planning and Resource Development Act (§P.L.93-641) which provided federal funds for states to implement investment laws. As a consequence,

CON soon gained in popularity among states. Most states adopted CON regulations in the mid-1970s. By 1980 all 50 states had some form of CON or Section 1122 agreement.

In 1984, Section 1122 expired with the implementation of Medicare's prospective payment system. In 1986, the federal government ended its National Health Planning and Resource Development Act that supported the development of CON programs (Santerre, 2005). Absent federal support, 14 states completely repealed CON regulation. However, six states (Arkansas, Nebraska, Louisiana, Ohio, Oregon, and Wisconsin) retained their CON regulation for nursing homes and long term care services, and as many as 31 states maintained their complete CON laws.

CON laws may improve access to care for the indigent and uninsured in many ways. Regulators may use CON to prevent entry of potential competitors who may "cherry-pick" profitable services, hence undermining the ability of existing providers to sustain money-losing services such as care for the indigent (Alpha-Center, 1999; Conover & Sloan, 2003). CON may also be used to give providers incentives to build facilities in underserved areas that have a greater demand for services such as uncompensated care (Lewin-ICF & Center, 1991). CON is further used to protect safety net providers who form the backbone of uncompensated care provision by increasing their financing margin (Mendelson & Arnold, 1993). CON may explicitly require providers to supply certain level of uncompensated care as a condition of obtaining CON approval. Lastly, some states use CON to encourage development of nonprofit hospitals that are supposed to provide more uncompensated care than for-profit hospitals (Alpha Center, 1999).

Few studies provide a direct link between CON and hospital uncompensated care provision. Mendelson and Arnold (1993) found that regulators in Ohio used CON to

protect access to care for the disadvantaged by denying applications that could have adverse effects on the financial viability of safety net hospitals in inner cities. Lewin and Alpha Center's report (1991) to the Ohio Department of Health provided similar evidence. In Pennsylvania, the CON program also tended to reward providers who agreed to supply more uncompensated care (Alpha-Center 1999). However, an evaluation of the CON program in Michigan yielded only minimal support for a moderate beneficial effect of CON on serving the uninsured (Conover and Sloan 2003).

Linkages between CON and uncompensated care were most thoroughly investigated in studies in Florida and California. Using a unique Florida data set on CON rulings from 1983 to 1986, Fournier and Campbell (1997) examined the relationship between CON licenses and uncompensated care provision (measured by the dollar amount of indigent care provided by the hospital and a relative measure constructed by dividing the dollar amount of indigent care by hospital bed size). They found that, controlling for the endogeneity of indigent care, regulators in Florida systematically awarded CON licenses to hospitals providing greater amount of care to the poor. Although the validity of their instrument, hospital teaching status, is questionable, the study offers some evidence of the impact of CON on the provision of indigent hospital care. Similar results were reported in their earlier, more descriptive study of Florida's CON (Campbell and Fournier 1993).

Campbell and Ahern (1993) used two-period California data to explore the effect of CON on uncompensated care provision. Specifically, they run separate multivariate regressions for California hospitals in 1963 and 1987 to examine the determinants of hospital provision of uncompensated care. They found a positive relationship between

net profitability of private nonprofit hospitals and the amount of uncompensated care they provide. They argue that this finding suggests government regulators reward heavily burdened uncompensated care providers with profitable CON licenses. Since no CON variables are actually used in estimating the amount of uncompensated care given by providers, this study fails to demonstrate a direct connection between CON activities and actual provision of indigent care (Conover and Sloan 1998).

Any-Willing-Provider and Freedom-of-Choice Law

The Any-Willing-Provider (AWP) law requires that managed care organizations accept any provider willing to abide by the plans' terms and conditions as well as their payment rates. The Freedom-of-Choice (FOC) law requires that a managed care enrollee be reimbursed for health care services outside of the managed care plan networks.

The arguments for the adoption of AWP/FOC are threefold. AWP increases access to care and, at the same time, improves quality of care. Many proponents of AWP believe that AWP promotes health care continuity by allowing patients to maintain relations with providers who have been their regular source of care. These laws also resulted from the negative consumer reactions to the restrictions of managed care although they may increase the costs of health care by relaxing these restrictions.

There are wide variations among states instituting AWP/FOC laws. Some laws affect virtually all providers (e.g., hospitals, physicians, pharmacies) whereas others only restrict pharmacies. As our study examines the effect of regulations on hospitals, we include only AWP/FOC laws relating to hospitals. AWP laws applying to hospitals were enacted as early as 1984 in Georgia. However, since the 1990s, the laws gained popularity from concerns about potential adverse effects of managed care selective

contracting. Thirty states had enacted either AWP or FOC, or both, for pharmacies by 1996. Thirteen states have laws relating to hospitals, and 17 have laws covering physician services (Ohsfeldt, Morrisey et al. 1998).

Although there is no direct evidence that AWP/FOC laws influence hospital provision of uncompensated care, some studies argue that such laws stifle competition among hospitals, which may in turn affect their financial ability to provide uncompensated care (Gruber 1994; Hellinger 1995). Gruber (1994) used hospital panel data from 1984 to1988 to examine the effect of managed care selective contracting on uncompensated care provision in California. He found that there was a large fall in net revenue and net income in more competitive hospital markets after the advent of selective contracting by managed care organizations. This result suggests that when competitive pressure from selective contracting increased, uncompensated care to the uninsured declined because hospitals are less capable of cross-subsidizing such care. Since AWP/FOC laws restrict the extent to which managed care organizations selectively contract with hospitals, the competitiveness of hospital markets might have decreased. One plausible explanation is that with AWP/FOC laws, hospitals no longer enjoy guaranteed volume of patients when all hospitals that agree to the terms set by managed care organization are able to contract with them. As a result, hospitals do not have the incentive to lower their cost in order to compete for managed care contracts, and hence lower levels of competition.

Hospital Rate Settings and Uncompensated Care Pools

These two regulations are discussed together because empirical studies of the impact of rate setting programs on uncompensated care focus exclusively on its mandated uncompensated pools.

Rate setting programs were widely believed to be designed to alleviate the perceived problem of rapidly growing hospital expenditures (Cone and Dranove, 1988). New York was the first state to enact a mandatory rate setting law in 1969 (Salkever, 2000). Rate setting soon spread to other states with some variations. However, in a typical rate setting program, a legal authority is established for approving the rates that hospitals charge. With Medicare's shift to a perspective payment system in the early 1980s and the emergence of managed care and capitation as viable cost-control mechanisms in the late 1980s, states started terminating their rate setting programs. In the early 1980s, about 30 states employed some form of hospital rate-setting as a cost-containment device, but today none of these states except Maryland still use hospital rate-setting (McDonough 1997; Volpp, Ketcham et al. 2005).

In the early 1980s, some states started to mandate hospital uncompensated care pools as part of their rate setting programs. Although all but one of these states eliminated their rate setting programs, some kept the uncompensated pools requirement. New mandates replaced the old hospital-specific add-on to rates and applied a uniform surcharge. The resulting funds were then pooled and redistributed to hospitals according to their amounts of uncompensated care. Hospitals with low loads of uncompensated care were net contributors, while those with high levels were net recipients. The goals of pooling were to improve the financial condition of hospitals with high uninsured care

loads, more equitably fund uncompensated care, and improve access for the uninsured by removing disincentives for hospitals, particularly private hospitals, to treat uninsured patients (Bovbjerg, Cuellar et al. 2000). In the 1990s, Florida, Indiana, Massachusetts, New Jersey, New York, South Carolina and Virginia all had such pools. Since Maryland still maintains its rate setting system, hospitals are reimbursed for their uncompensated care as part of the rate setting program (Fraser 1990).

Using data from a sample of New Jersey short-term, acute care hospitals from 1979 to 1987, Dunn and Chen (1994) employed a pre- and post-design to assess the impacts of the introduction of uncompensated care payment on the overall level of uncompensated care provision as well as the distribution of uncompensated care across hospitals. Their study shows that hospitals in New Jersey did not significantly increase their uncompensated care after the implementation of this new regulation. However, there is evidence that this regulation has resulted in a more even distribution of uncompensated care burden across hospitals as indicated by a positive effect on the financial condition of hospitals providing a disproportionately larger share of this care.

Using an updated New Jersey data from 1986 to1990, Gaskin (1997) estimated the impact of the uncompensated care pool on both inpatient and outpatient uncompensated care. He further investigated how uncompensated care pools affect hospitals' collection efforts. Evidence from this study suggests that such pools have actually induced hospitals to increase their inpatient uncompensated care by an average of 14.8% and statewide uncompensated care by $360 million during 1987-1990. This study did not find evidence that uncompensated care pools created a moral hazard problem by decreasing the state's collection efforts.

Spencer (1998) examined the redistributive effect of the uncompensated care pool across hospitals in New York. Using data from 1981 to 1987, the author found that such pools did result in routine care being redistributed away from hospitals that traditionally provided a disproportionate share of uncompensated care to the uninsured, whereas highly technological care was not significantly redistributed.

Earlier studies using New York hospital data all found that levels of uncompensated care increased due to changes in regulation. Thorpe (1988) found that during the post-regulation period from 1983 to 1985, uncompensated care increased significantly. Similar results were found in another study by Thorpe and Phelps (1991). However, they further argued that hospitals in New York did not increase charity care in proportion to the amount of the grant received. Thorpe and Spencer (1991) later used a longer panel (1981-1987) and found that pools have led to increased access for the uninsured with public hospitals leading private hospitals in the amount of care provided.

Hospital Conversion Regulations

These state regulations impose state oversight on the process of converting public or non-profit facilities to for-profit status through requiring attorney general approval, advance notification, and community involvement. This state intervention was partly motivated by the concern that conversions from public or non-profit hospitals to for-profit status might harm access to care for the low income uninsured and underinsured population by reducing the amount of charity care provided. Stricter oversight (i.e., state monitoring in addition to federal oversight) might protect the community's charitable interests. As of 1997, 24 states and District of Columbia have enacted such laws to affect conversions from nonprofit/public hospital to for-profit status (GAO 1997).

Little evidence exists concerning the effect of hospital conversion regulation on conversions or uncompensated care, although a number of studies have examined the impact of actual conversions on the provision of uncompensated care. These studies noted either insignificant differences in the level of uncompensated care provision in nonprofit to for-profit conversions (Young, Desai et al. 1997; Needleman, Lamphere et al. 1999; Young and Desai 1999) or significantly less uncompensated care provided to the indigent when such conversions occur (Thorpe, Florence et al. 2000). This literature implies that if the presence of conversion regulations successfully inhibits or stimulates conversion activity, these regulations may have profound impact on hospital provision of uncompensated care.

Community Benefit Mandates

Community benefit mandates require that nonprofit hospitals provide a sufficient amount of community benefit[**] to justify their tax exempt status (Noble, Hyams et al. 1998). Prior to the mid-1980s, most states used a broad community benefit approach in defining tax exempt status for health care providers (Noble, Hyams et al. 1998; Colombo 2006). However, during the 1980s and early 1990s, motivated by the escalating concerns that the line between nonprofit and for-profit was blurring, several states began to question the tax exemption status for nonprofit hospitals (Potter and Longest, 1994; Noble, Hyams, and Kane, 1998). As a result, some states adopted explicit charity care

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[**] Community benefit commonly include uncompensated care, health promotion services, research and education, open access to services and community health orientation. Please see Ginn, G. O. and C. B. Moseley (2006). "The impact of state community benefit laws on the community health orientation and health promotion services of hospitals." J Health Polit Policy Law **31**(2): 321-44..

tests in defining tax exempt status. In 1993, Texas became the first state to pass legislation that requires hospitals to provide a specific percentage of hospital net patient revenues for charity care and other community benefits. Other states have adopted a broader community benefit test and required public reporting for a variety of community benefits, including charity care (Noble, Hyams, and Kane 1998).

We did not find studies that explicitly examined the effect of these mandates on hospital uncompensated care provision. Only one study indirectly investigated the effect of state community benefit laws and guidelines on community health orientation and the provision of hospital-based health orientation activities including uncompensated care provision. Using a sample that included all not-for-profit and investor-owned acute-care hospitals in the United States during the year 2000, Ginn and Moseley (2006) used multiple regressions to test the effect of community benefit laws and type of ownership while controlling for organizational and environmental variables. The results indicated that, on average, nonprofit hospitals in the ten states with community benefit laws/guidelines reported significantly more community health orientation activities than did nonprofit hospitals in the forty other states. In addition, on average, for-profit hospitals in the ten states with laws/guidelines reported significantly more community health orientation activities than did comparable hospitals in the forty other states. The study also found that community benefit laws had the effect of decreasing ownership-related differences in reported community health orientation activities.

Summary of Literature Review

The literature provides some evidence that nonprofit and for-profit hospitals might behave differently in terms of their uncompensated care provision as well as responses to the exogenous environment. This suggests that they ought to be examined in separate models. Furthermore, much of the research on regulation and hospital provision of uncompensated care has focused on uncompensated care pools (and pools as part of hospital rate setting programs). A majority of studies found that such subsidies have successfully increased the level of uncompensated care provision in the market (Thorpe 1988; Thorpe and Spencer 1991; Gaskin 1997; Spencer 1998). Two other studies provided additional evidence that uncompensated care pools redistributed provision of such care among hospitals (Dunn and Chen 1994; Spencer 1998). However, one of them fails to find that uncompensated care pool increases the level of uncompensated care provided in New Jersey (Dunn and Chen 1994).

Although researchers have also examined the impact of CON on hospital behavior, few studies provide a direct link between CON and hospital uncompensated care provision. Most studies presented descriptive evidence from evaluation reports of state CON programs (Lewin-ICF and Center 1991; Mendelson and Arnold 1993; Alpha-Center 1999; Conover and Sloan 2003). They found that CON has been used by regulators to increase access to care for the vulnerable population. Only two studies provided some limited empirical evidence on this question (Campbell and Ahern 1993; Campbell and Fournier 1993; Fournier and Campbell 1997). Their studies show that in Florida and California, hospitals that provide more uncompensated care are systematically rewarded under CON legislation.

The impact of other regulatory programs on hospital provision of uncompensated care is inadequately explored. Only one study indirectly examined the effect of a community benefit requirement on uncompensated care provision (Ginn and Moseley 2006). Their results supported the hypothesis that nonprofit hospitals offer significantly more community health-oriented services (which include uncompensated care) in the presence of community benefit mandates.

The review of the literature on regulatory environment and hospital supply of uncompensated care also revealed some shortcomings. First, most previous studies have examined hospitals' uncompensated care provision and regulatory environment by focusing on a single regulation such as hospital uncompensated pool or certificate-of-need (CON) regulation. Recent studies have indicated that regulatory programs should be analyzed in the context of the larger regulatory environment (Sloan, Morrisey et al. 1988; Antel, Ohsfeldt et al. 1995). The interplay of incentives offered by different regulatory programs may have resulted in unexpected consequences that cannot be predicted by analyzing a single regulation. In addition, due to interactions among different regulations, the combined effects of a regulation bundle may be different from a regulation acting alone. Evidence from other industry studies further suggest that regulations, particularly of different parts of an industry, should be viewed as a system because, for instance, when regulation controls price, firms will find other ways to compete (i.e., engaging in non-price competition) (Viscusi, Harrington et al. 2005).

Second, early works have predominately used data from a single state (e.g., New Jersey, New York, California or Florida). Although some CON studies have used a dichotomous variable to compare regulatory effects in markets with and without

regulation using data from all 50 states, none has investigated the effect of CON on uncompensated care provision using national data. The shortcoming of employing data from a single state is the inability to compare differences in regulations among the states. Further, even if studies have used national data, the comparison states are not completely free of similar regulations if they fail to take into account a broader scope of regulations. Regulations other than the one under investigation might have confounded the results if researchers are not cautious about their comparison groups.

Finally, existing studies need to be updated. An overwhelming number of studies used data in the 1980s and early 1990s, a period which is no longer of current policy interest. There have been dramatic changes in the health care marketplace during the late 1990s and early 2000s (e.g., increased competition and cost control and reduced support for care of the uninsured). These major changes in the health care market may be altering the effectiveness of existing programs. Results obtained from recent data will prove to be more relevant to formulate policies for the current health care system.

CHAPTER THREE

THEORETICAL FRAMEWORK, TYPOLOGY AND HYPOTHESES

Theoretical Framework

As suggested by previous literature, hospitals of different ownership types differ in term of their uncompensated care provision and their different responses might be influenced by the regulatory environment. Theoretical models of hospital uncompensated care supply are useful in examining hospital response to and the impact of different policy options since these frameworks help illuminate determinants of hospital uncompensated care provision. We draw on the work of Frank and Salkever (1991), Gruber (1994), and Banks, Paterson and Wendel (1997) and simplify their models to investigate equilibrium hospital behavior when the regulatory environment changes.

In these models, nonprofit hospitals are assumed to be concerned about the health of the entire community, including the economically disadvantaged. Their supply of uncompensated care is believed to be socially motivated, subject to financial resource constraints. In contrast, for-profit hospitals are hypothesized to supply uncompensated care to the extent that doing so maximizes profits because they are concerned that they might incur costs if the community perceives that they under-produce uncompensated care. For-profit hospitals' supply of uncompensated care therefore is a business strategy that may enhance a hospital's reputation and reduce the expected penalty of under-producing such care.

Frank and Salkever (1991) focus on the supply of charity services by nonprofit hospitals. They argue that price-taking private nonprofit hospitals seek to maximize utility (U) which is a function[††] of net revenue *R* and unmet indigent care need *N*.

$$U = U\,(R, N) \quad \text{or}$$

$$U = U\,[(QP + rD + E - C(Q + D)), (T\text{-}D\text{-}H\text{-}G)]$$

where

QP = the average revenue for compensated care;

Q = the number of paying patients

r = revenue per indigent patient;

D = the number of indigent patients;

E = sum of endowment income;

C = hospital's cost function

T = total indigent care need;

H = other private hospitals

G = public hospitals

In this model, nonprofit hospitals earn net revenue to subsidize uncompensated care. It also predicts that increases in the supply of charity care by other hospitals in the market crowds out indigent care in the nonprofit hospital. A slight variation, the "impure

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[††] It should be noted that the argument *R* in the nonprofit utility function may be viewed as a proxy representing "profits" spent to pursue all objectives perceived by the hospital's managers or trustees other than uncompensated care provision. For example, Newhouse proposed a utility function with quality and quantity as arguments subject to a breakeven constraint (please refer to Newhouse, J. (1970). "Toward a theory of nonprofit institutions: an economic model of a hospital." American Economic Review **60**(1): 64-74.) The model offered by Pauly suggests that hospitals seek to maximize income of physicians or decision makers. The specification of the arguments does not however alter the results (see Pauly, M. V. (1987). "Nonprofit firms in medical markets." American Economic Review **77**(2): 257-262.)

altruism" model (Frank and Salkever 1991), was proposed to account for nonprofit hospital's rivalry motivation, which leads to a potential smaller crowd-out effect by other hospitals in the market. In this model, a third argument (*Z*) indicating the hospital's performance in supplying charity care relative to its rivals was added to the utility function so that nonprofit hospitals are assumed to compete with other private hospitals by providing uncompensated care.

Gruber (1994) simplified the above model as nonprofit hospitals maximizing a utility function $V[R, U]$, subject to $R = pq - c(q) - U$

where

R = net revenue,

U= uncompensated care,

p = price per unit of service,

q = quantity of services,

$c(q)$ = hospital cost function; $c_q > 0$, $c_{qq} > 0$.

In contrast to Frank and Salkever's framework which takes price as exogenous, this model assumes a monopolistic hospital market, or in other words, prices charged to private paying patients are endogenous. This assumption was supported by literature arguing that the medical market place can be best described as monopolistically competitive, due to the presence of imperfect, costly price and quality information (Dranove, Satterthwaite et al. 1986; Dranove and Satterthwaite 1992). However, the difference in assumptions does not change the predictions drawn from these models.

The model developed by Banks, Paterson and Wendel (1997) was motivated by Gray (1991) to explain uncompensated care provision by for-profit hospitals. This model

assumes that for-profit hospitals provide charity care because they are concerned that they might incur costs if the community perceives that they under-produce uncompensated care. These costs might take the form of penalties such as failure to be granted a CON or loss of state Disproportionate Share Hospital (DSH) payments. For-profit hospitals are hence assumed to maximize the profit function[‡‡] (Π) with:

$$\Pi = QP\ (Q;d) - C(Q,\ U) - F - L(e - U)$$

where

U = uncompensated care;

$QP\ (Q;d)$ = the average revenue for compensated care;

Q = the patient days of compensated care;

d = demand curve shift parameter;

$C\ (Q,\ U)$ = variable cost of producing Q and U;

F = fixed cost

$L(e - U)$ = expected penalty cost.

Based on previous research and given different motivations between nonprofit and for-profit hospitals, a nonprofit hospital's utility function (V) can be mathematically expressed as:

Nonprofit: $V \equiv \max\ [R,\ U]$; subject to[§§] $R = QP\ (Q;d) + rU - C(Q,\ U)$

[‡‡] For derivations of the for-profit model, please refer to Banks, et al. (1997). "Uncompensated hospital care: charitable mission or profitable business decision?" Health Econ **6**(2): 133-43..

[§§] Nonprofit organizations face a non-distribution constraint, which means they cannot legally distribute any of their residual earnings to stakeholders. Santerre, R. E. and J. A. Vernon (2006). "The consumer welfare implications of the hospital ownership mix in the US: an exploratory study." Ibid. **15**(11): 1187-99.

To simplify the derivations, we follow Banks et al (1997) and assume a special case where hospitals earn net revenue to subsidize uncompensated care. In other words, we assume that nonprofit hospitals maximize uncompensated care:

$$V' \equiv \max [U]; \text{ subject to } F = QP(Q;d) + rU - C(Q, U) = 0$$

whereas a for-profit hospital's objective is to maximize profit (Π):

$$\textit{For-profit: } \Pi \equiv \max [QP(Q;d) + rU] - C(Q, U) - L(e - U)$$

where

R = net revenue

U = uncompensated care;

$QP(Q;d)$ = the average revenue for compensated care;

Q = the patient days of compensated care;

d = demand curve shift parameter such as competition;

r = revenue per indigent care patient[***]

$C(Q, U)$ = variable cost of producing Q and U;

$L(e - U)$ = expected penalty cost.

These theoretical models assume that hospitals are price setters and they exercise control over the amount of uncompensated care supplied. In addition, the medically indigent demand for uncompensated care is assumed to exceed hospital desired supply.

For nonprofit hospitals, solving for their constraint:

$$F = QP(Q;d) + rU - C(Q, U) = 0$$

[***] r theoretically is zero for indigent care as this care is uncompensated. However, with various subsidies this care can be compensated at a rate that equals to r ($0 \leqslant r \leqslant p$).

$QP(Q;d)+rU = C(Q, U)$

This equation implies that nonprofit hospitals supply uncompensated care to the point when marginal revenue equals marginal cost (i.e., MR = MC)[†††].

For for-profit hospitals: the first order conditions (FOC) are

$\pi_Q = QP_Q + P - C_Q = 0$

$\pi_U = r - C_U + L' = 0$

These FOCs imply that for-profit hospitals supply uncompensated care to the point when marginal benefit equals marginal cost (i.e., MB = MC).

Solving for the constraint and the FOCs, we obtain the following comparative statics for nonprofit and for-profit hospitals respectively (Table 1[‡‡‡]).

[†††] Given that net revenue is modeled as a proxy for "activities" that produce utilities/benefits, the marginal revenue really is another way of labeling marginal utility/benefits.

[‡‡‡] D is the determinant of matrix $\begin{vmatrix} \frac{\partial \pi_Q}{\partial Q} & \frac{\partial \pi_Q}{\partial U} \\ \frac{\partial \pi_U}{\partial Q} & \frac{\partial \pi_U}{\partial U} \end{vmatrix}$.

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Table 1: Comparative Static Results for Nonprofit and For-profit Model

Nonprofit		*For-profit*	
$U_d = P_dQ/C_U$	<0	$U_d = [-C_{QU}P_{Qd}]/D$	>0
$U_r = -U/-C_U$	>0	$U_r = -[2P_Q + QP_{QQ} - C_{QQ}]/D$	>0
		$U_e = [(QP_{QQ} + 2P_Q - C_{QQ})(-L'')]/D$	>0

These results delineate the differences between nonprofit and for-profit hospital supply of uncompensated care. Nonprofit hospitals provide uncompensated care because supplying such care increases their utility. They produce uncompensated care to the point where the marginal revenue is balanced by the marginal cost of uncompensated care provision. However, for-profit hospitals provide uncompensated care because they are concerned that they might incur costs if the community perceives that they under-produce uncompensated care. Unlike their nonprofit counterparts, for-profit hospitals treat uncompensated care provision as a profit maximizing strategy. Producing such care does not add utility to for-profit hospitals but it maximizes their profits by lowering their penalty costs. The optimum level of uncompensated care supplied by for-profit hospitals is achieved by equating marginal cost with the hospital's marginal benefit of producing such care.

These differences indicate that nonprofit hospitals and for-profit hospitals would respond to different incentives and environmental changes differently. Nonprofit hospitals respond to a downward shift in demand by reducing the amount of uncompensated care provision because decreased demand for paid care implies decreased profits available for financing uncompensated care. An increase in the marginal revenue

that results from an increased number of paying patients will increase supply of uncompensated care. Similarly, an increase in the revenue per indigent patient (usually in the form of subsidies) increases uncompensated care. Nonprofit hospitals will also respond to increased competition by reducing their charity care output. This is because when competition intensifies, the price for paying patients goes down. As a result, nonprofit hospitals have less revenue from the paying patients to cross-subsidize uncompensated care. They therefore have to decrease the amount of uncompensated care in order to survive the fierce competition. On the contrary, for-profit hospitals may increase the supply of uncompensated care when market demand for compensated care decreases since the concurrent decrease in paid care reduces the marginal cost of producing uncompensated care. They would respond to competition by increasing their uncompensated care supply. One explanation is that the price for paying patients decreases as competition increases. Consequently, the decrease in the price of paid care lowers the marginal cost of providing uncompensated care. For-profit hospitals therefore supply more uncompensated care as the marginal cost of providing such care decreases. On the other hand, the for-profit model also predicts that for-profit hospitals will respond to the level of community expectation or will incur penalties resulting from failure to meet community expectation.

Typology

Before we generate any predictions regarding the impact of regulatory environment on hospital's provision of uncompensated care, it is crucial that we develop a typology so that regulations can be grouped and examined in meaningful ways. The comparative static analysis represents a convenient tool for this categorization. The

analysis illuminates different mechanisms through which regulations exert an impact on hospital behavior. We hence categorize different regulatory environment on this basis. Since both CON and AWP/FOC affect hospital supply of uncompensated care by either increasing or decreasing competition *d*, we label these regulations as competition regulations. Uncompensated care pools and pools as part of the rate setting programs increase revenue per indigent care patient *r,* and we classify this type of regulation as subsidies. Because states use requirements such as conversion oversight and community benefit requirements to explicitly communicate expectations for community services such as uncompensated care, we categorize these regulations as mandates. This taxonomy provides us a framework to organize seemingly complicated regulatory environments so as to improve our understanding of the different mechanisms through which regulations can affect hospital behavior. The next section uses CON, uncompensated care pool, and community benefit requirement regulations as examples to illustrate how hypotheses can be developed for each type and/or individual regulation.

Hypotheses

Previous research shows that CON, as an entry barrier, has reduced competition by maintaining high levels of industry concentration and restricting supply of services. After analyzing the impact of CON on entry of new firms into the dialysis industry, Ford and Kaserman (1993) found that the presence of CON laws significantly reduced the entry and expansion of dialysis firms. Gruber (1994) studied the effect of competitive pressure on hospital provision of uncompensated care. He found that nonprofit hospitals provide more uncompensated care in more concentrated markets. These findings, in conjunction with predicted effect of competition on hospital provision of uncompensated

care discussed in the previous section, led us to conclude that nonprofit hospitals may increase their uncompensated care supply in response to CON laws.

For-profit hospitals may respond to CON by either decreasing or increasing their uncompensated care supply. This is because on the one hand, CON has constrained market competition and promoted profits generated by private paying patients. When paid care becomes more profitable, the opportunity cost of providing uncompensated care (i.e., cost of forgoing paid care) rises. For-profit hospitals therefore would reduce their uncompensated care supply when CON increases industry concentration. On the other hand, for-profit hospitals may also perceive the failure to obtain CON as a profit loss, and hence increase their uncompensated care provision in states with such a regulation. The resulting direction of CON's impact on for-profit hospitals remains undetermined.

H1: ceteris paribus, nonprofit hospitals in states with CON laws will provide more uncompensated care than their counterparts in states without such a regulation.

H2: ceteris paribus, for-profit hospitals in states with CON laws will provide less or more uncompensated care than their counterparts in states without such a regulation.

With increasing direct subsidies such as reimbursement from uncompensated care pools, both nonprofit and for-profit hospitals should increase their uncompensated care supply. Intuitively, this happens because reimbursing hospitals based on their uncompensated care cost increases the revenue per indigent patient. Therefore, we expect to see hospitals increase their uncompensated care supply when provided such a subsidy. Profit maximizing for-profit hospitals might also perceive the loss of pool subsidies as

penalties resulting from failure to meet the health care needs of the community. In this case, they will increase their supply of uncompensated care when such subsidies raise their expected penalty cost. Therefore, the direction of the signs on nonprofit and for-profit hospital uncompensated care provision is expected to be the same.

H3: ceteris paribus, both nonprofit and for-profit hospitals in states with uncompensated care pool regulation or subsidy regulation will provide more uncompensated care than their counterparts in states without such regulations.

The responses of nonprofit and for-profit hospitals under community benefit requirement regulations are rather ambiguous. Given the mandate for nonprofit hospitals, we expect that they comply with the regulations by increasing their uncompensated care supply (if they had not provided the desired level). However, if community benefit requirement regulations help to improve the overall health of the community, given that hospitals in states with such laws typically provide better access to primary/preventive care (Ginn and Moseley 2006), we might see a decrease in uncompensated inpatient care as a result of a decline in the demand for inpatient care. We might also see such a negative relationship between community benefit requirement laws and nonprofit hospitals' provision of uncompensated care if the community benefit requirement is set below the level at which hospitals actually provide uncompensated care. These laws could provide a signal to reduce nonprofit hospitals' provision of care by suggesting that their prior levels of such care are above the levels expected by the community.

Although these mandates are not intended to be binding for the for-profit hospitals, they send a signal to health care providers of what is expected by the community. Since for-profit hospitals perceive that they could incur costs if they fail to meet community expectation, we might expect to see a significant increase in the level of uncompensated care provided by for-profit hospitals.

However, there might be a "crowd-out" effect as a result of these mandates as Frank and Salkever (1991) predict. If for-profit hospitals increase their uncompensated care supply, nonprofits serving the same market will tend to reduce their provision of uncompensated care. A number of empirical studies supported this argument (Horwitz 2005; Schlesinger and Gray 2006). The extended "impure altruism" model adds to this prediction by arguing that this effect is likely to be moderate or weak if we further assume that a nonprofit hospital maximizes performance in supplying charity care relative to its rivals. If an increase in for-profit hospital's uncompensated care provision results in a decrease of supply from its rivalry nonprofit hospital, the mandates could lead to a different distribution of uncompensated care supply in the market.

Another piece of evidence complicates this prediction even further. Some studies have shown that in mixed ownership markets, for-profit hospitals provide significantly less charity care when nonprofit hospitals provide high level of uncompensated care (Clement, White et al. 2002). This phenomenon represents a reversed crowd-out effect: for-profit crowd-out by nonprofit hospitals. This means if nonprofit hospitals respond to mandates by increasing their supply of care, for-profit hospitals will decrease their supply. After all, these mandates are not legally intended for for-profit hospitals and might not be binding for them. The final direction of the signs therefore remains an empirical matter.

H4: ceteris paribus, both nonprofit and for-profit hospitals in states with community benefit requirement laws will provide more/less uncompensated care than their counterparts in states without such regulations.

In addition to behavioral differences between hospitals, we are also interested in regulatory interactions. A few studies suggest that regulations working together may in some cases enhance the effectiveness of one another. For example, Antel et al. (1995) examined the effects of various regulation (e.g., rate setting, CON, Medicare perspective payment and Nixon-era Economic Stabilization Program) on hospital costs. Using a two-decade-long panel dataset of the 48 continental states, they found that although few regulations under investigation have had a significant effect on controlling hospital costs, rate regulation, interacting with Medicare perspective payment, has successfully limited the cost increase. We therefore predict that there might be interaction effects in the sense that an individual regulation will be more/less effective in the presence of other regulations.

CON, interacting with uncompensated care pools may complement each other and increase the uncompensated care provision by nonprofit hospitals. This is expected because both CON and pool are predicted to be positively related to nonprofit hospital supply of uncompensated care. CON improves nonprofit hospital's ability to cross-subsidize care for the uninsured. When given extra incentive by public subsidies such as uncompensated care pools, nonprofit hospitals will provide more uncompensated care

comparing with comparable hospitals in states that do not have both regulations. For for-profit hospitals, the sign on the interaction term between CON and uncompensated care pool is undetermined. CON is expected to decrease uncompensated care provision by for-profit hospitals since the cost of providing unpaid care increases when CON stifles competition. However, uncompensated care pool gives for-profit hospitals incentive to increase their uncompensated care provision. Which impact dominates when states implement both regulations remains an empirical issue.

The evaluation of interaction effects between CON and community benefit requirement laws is another empirical issue because the impact of community benefit requirement laws can be either positive or negative for both types of hospitals. The sign on the interaction between community benefit requirement and uncompensated care pool as well as the interaction of all three regulations remain uncertain for similar reasons.

CHAPTER FOUR

DATA AND EMPIRICAL MODEL SPECIFICATION

Empirical Specification

Our model specification follows the theoretical framework described in the previous section. A hospital's provision of uncompensated care is influenced by the regulatory environment, institutional/market factors that affect the hospital's capacity to supply uncompensated care, and demand for uncompensated care.

We treat nonfederal, short-term hospitals as our study unit to examine different organizational responses to the regulatory environment and possible policy interactions. A general specification of our empirical model is:

$$UC_{it} = \beta_0 + \beta_1 Hospital_{it} + \beta_2 Market_{it} + \beta_3 Regulation_{it} + \beta_4 Year + \beta_5 State + \varepsilon_{it}$$

where i = 1 to N, t = 1 to T; UC_{it} is our measure for hospital i uncompensated care provision by services in year t; *Hospital* is a vector of hospital organizational characteristics to measure a hospital's capacity to provide uncompensated care; *Market* is a vector of market variables that can affect the supply of, or demand for, uncompensated care in a market; *Regulation*, our key focus, is a vector of regulatory variables that measures states' different regulatory environments; *Year* represents year dummies; *State* represents a vector of states dummies, capturing state specific trends; ε_{it} is a composite error term that can be expressed as $\varepsilon_{it} = \alpha_i + \eta_{it}$, where α_i is a hospital specific error component term; and η_{it} represents the idiosyncratic error term.

Data

We rely on three primary data sources for the period 2002 – 2004 for the current research. (1) The American Hospital Association (AHA) Annual Survey of Hospitals (2002, 2003, and 2004) collects data from all U.S. hospitals and includes a variety of organizational and operational characteristics such as availability of services, utilization, personnel, finances and governance; (2) The Area Resource File (ARF) (2005) contains information on market characteristics as well as community demographics that may affect demand for uncompensated care. Compiled by the Health Resources and Services Administration (HRSA), ARF is a national county-level collection of datasets from more than 50 sources including the Current Population Survey (CPS), InterStudy, and the Bureau of Labor Statistics. It includes information on healthcare professionals, health professions training, health facilities, hospital utilization, hospital expenditures, county population and economics, as well as county-level socioeconomic and geographic codes that allow us to merge these data with other files; (3) The State Inpatient Database (SID) from the Healthcare Cost and Utilization Project (HCUP) (2002, 2003, and 2004) contains detailed information on over 90 percent of inpatient discharges from all community hospitals in 20 states. Since hospital discharge data include zip code information on patient residence, we are able to define markets using patient flows and test if differences in market definition will affect study results.

Construction of the Sample

We used HCUP SID data for seventeen states (AZ, CO, FL, IA, KY, MA, MD, NV, NJ, NY, OR, RI, UT, WA, WV, WI and NC) for information on the total number of admissions and payer types to obtain the percentage of admissions for the uninsured. These states are selected based on their geographical representativeness and diverse regulatory environments.

Geographically, our study states are distributed across the five U.S. regions (as shown by Figure 1): West (WA, OR, NV, UT, CO), Southwest (AZ), Midwest (IA, WI), Southeast (FL, NC, KY, WV), and Northeast (MD, NY, NJ, RI, MA) with Southwest and Midwest slightly under-represented.

When examining individual regulations, we observe some variation except in AWP/FOC laws. Table 2 shows that among all 17 states, five are non-CON states (AZ, CO, OR, UT and WI). Five states have community benefit requirement regulations (MA, MD, NY, RI and UT)[§§§], and eight states fund an uncompensated care pool (AZ, CO, MA, MD, NJ, NV, NY and WV). Additional evidence for variations in policy interactions can be found in Appendix A.

[§§§] NC and NV enacted community benefit requirement laws in 2005.

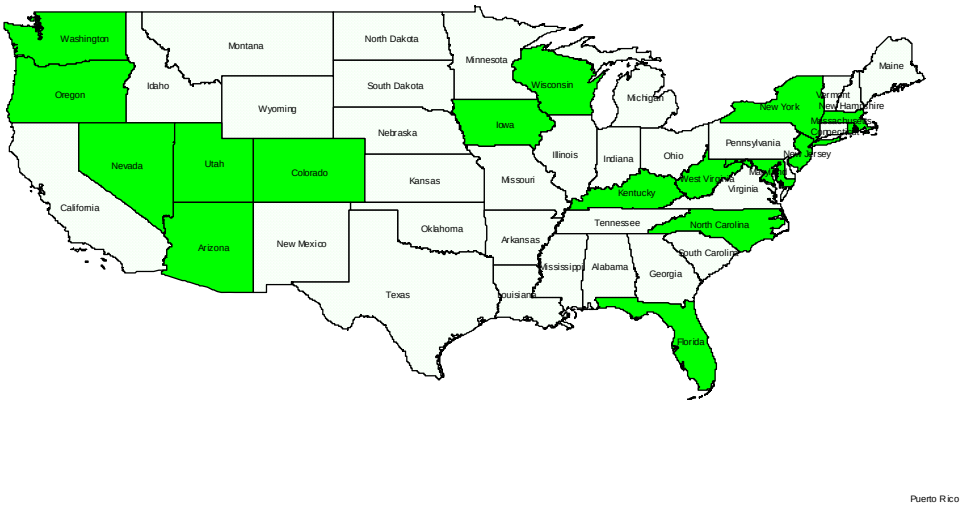

Figure 1: Study States vs. Non-study States

Table 2: Variations of Regulations by Study States

States	*CON*	*REQUIREMENT*	*POOL*	*CONVERSION*	*AWP/FOC*
Arizona			X	X	
Colorado			X	X	
Florida	X				
Iowa	X				
Kentucky	X				X
Maryland	X	X	X	X	
Massachusetts	X	X	X		
Nevada	X	X	X		
New Jersey	X		X		
New York	X	X	X		
North Carolina	X	X			
Oregon†	X			X	
Rhode Island	X	X		X	
Utah		X			
Washington	X			X	
West Virginia	X		X		
Wisconsin†	X				X
Total	12	7	8	6	2

† Long-term care facility only

The HCUP SID data assign a unique data source hospital identifier which can be matched with the AHA identifier provided by a link file in the HCUP SID data. The AHA identifier then serves as the distinguishing identifier in the linked dataset, which uses the AHA data for information on hospital characteristics such as hospital size and ownership status. Data from the Area Resource Files on market and community characteristics are merged using county codes.

The sample for this study consists of hospital-level data for nonfederal, short-term, general hospitals in the 17 states. All specialty, psychiatric, and long-term care hospitals are excluded. The original dataset for analysis comprised 4,324 hospital-years for the study period 2002-2004. This excludes 2004 data for Utah and New York as these states did not report to the HCUP for those years. After hospitals with only one year of observations are excluded, we are left with a study sample of 2,625 nonprofit and 500 for-profit hospital-year observations. In the nonprofit sample, about 78 percent (779 hospitals) have all three years of observations and the remaining 22 percent (204 hospitals) have two years of observations. In the for-profit sample, about 84 percent (148 hospitals) have three years of observations and the remaining 16 percent (28 hospitals) have two years of observations. In addition, we have missing values on two important control variables, the technology intensity variable and the ER variable measuring whether a hospital has an emergency department. We imputed values for the technology intensity variable for 2002, the year we have missing values. Our final sample therefore contains 2,322 nonprofit and 295 for-profit observations. In our final sample, 76 percent (613 nonprofit hospitals) and 24 percent (198 nonprofit hospitals) have three and two

years of observations respectively. 48 percent (57 for-profit hospitals) and 52 percent (62 for-profit hospitals) have three and two years of observations respectively.

We carefully examined whether there might be sample selection bias due to our choice of the states as well as to the pattern of the missing values. Since it is reasonable to assume that a state's decision to participate in HCUP reporting during certain time periods is independent of hospital supply of uncompensated care, we are confident that states are excluded randomly.

We also lost a significant number of observations due to missing values on the technology intensity and ER variable. Table 3.1 shows that none of the hospitals in our study states reported on the technology intensity variable in 2002. The remaining states/years have missing values that range from 1% to 42%. In 2003 and 2004, those hospitals that did not respond to the technology intensity variable did not respond to the ER variable, either. Most hospitals reported on the ER variable in 2002 (Table 3.2). In order to utilize the 2002 data, we imputed values for the 2002 technology intensity variable. We replaced missing values on this variable in 2002 by values the same hospitals reported in 2003, assuming that the number of hi-tech services did not change from 2002 to 2003 for these hospitals. Sensitivity analyses are conducted to examine whenever our results are significantly affected by excluding/including these two variables.

Table 3.1: Percent of Missing Values for Technology Intensity by State/Year

State	*2002*	*2003*	*2004*
Arizona	X	26%	24%
Colorado	X	22%	13%
Florida	X	27%	29%
Iowa	X	0	0
Kentucky	X	5%	19%
Maryland	X	0	4%
Massachusetts	X	0	1%
Nevada	X	27%	42%
New Jersey	X	13%	13%
New York	X	24%	N/A
North Carolina	X	15%	14%
Oregon	X	0	0
Rhode Island	X	20%	20%
Utah	X	13%	N/A
Washington	X	15%	22%
West Virginia	X	0	0
Wisconsin	X	2%	7%

Table 3.2: Percent of Missing Values for ER by State/Year

State	*2002*	*2003*	*2004*
Arizona	22%	26%	24%
Colorado	21%	22%	13%
Florida	33%	27%	29%
Iowa	0	0	0
Kentucky	13%	5%	19%
Maryland	9%	0	4%
Massachusetts	1%	0	1%
Nevada	23%	27%	42%
New Jersey	6%	13%	13%
New York	25%	24%	N/A
North Carolina	17%	15%	14%
Oregon	3%	0	0
Rhode Island	10%	20%	20%
Utah	18%	13%	N/A
Washington	12%	15%	22%
West Virginia	0	0	0
Wisconsin	7%	2%	7%

Dependent Variable

Uncompensated care is widely used to capture hospital provision of care to the uninsured. In many prior studies, it is measured as charity care and bad debt. Charity care includes care provided to the indigent who are not expected to pay, whereas bad debt is accrued by someone who is expected to pay but does not pay at all or fails to pay the full amount of their medical bills. There are three problems with this definition. Some scholars argue that including bad debt as part of the measure would overstate a hospital's uncompensated care provision. This is because the amount of bad debt also reflects a hospital's debt collection efforts (Gaskin 1997; Thorpe, Florence et al. 2000; Rosko 2004). For example, Gaskin (1997) argues that the implementation of an uncompensated care pool in Massachusetts could potentially create a moral hazard problem in that the pool reduced the marginal cost of debt collection. As a result, without proper monitoring of the hospitals' debt collection efforts, their bad debt portion of the uncompensated care could increase in response to the Trust Fund. A second disadvantage of lumping charity care and bad debt under the same uncompensated care umbrella is that the distinction between charity care and bad debt is unclear. Some hospitals use a formal process in advance of billing to identify those who are unable to pay, while others use the billing and collection process. Consequently, care delivered to patients may be classified as charity care by one hospital but bad debt by another (AHA 2005). Lastly, using uncompensated care data for comparisons among different types of hospitals or hospitals with mixed payer types can be problematic because uncompensated care data, generally expressed as charges, are usually sensitive to different hospital accounting practices (AHA 2005). Despite these concerns, studies continue to use both charity care and bad

debt to measure hospital provision of uncompensated care due to the fact that existing data sets do not make meaningful distinctions between the two concepts (Rundall, Sofaer et al. 1988).

We improve upon measures of uncompensated care used in previous studies by focusing on the actual hospital services delivered to the uninsured. In our analysis, uncompensated care is measured as number/percent of admissions per hospital that are for the uninsured. This dependent variable is constructed as (1) number of all admissions for self-pay/charity patients in a hospital; (2) percent of admissions for self-pay/charity patients by dividing the number of admissions for self-pay and charity patients in a hospital by all the admissions in that hospital. Although this measure could slightly overstate the amount of hospital care that is indeed uncompensated since some of these uninsured patients may pay in-part or in-full and some may qualify for coverage after they have been admitted, this still represents an improvement over previous measures for the following reasons. Our measure directly captures care provided to the uninsured. Therefore, it represents a better indicator of access to care for the uninsured than financial measures of uncompensated care. In addition, it is not influenced by individual hospital accounting practices. As argued by Gruber (1994), changes in uncompensated care measured as charges may not be directly interpretable as changes in the level of care delivered to the uninsured because these changes in charges are likely to reflect shifts in hospital pricing policy and debt collection efforts.

One earlier study that used the same measure to capture hospitals services to the uninsured, Frank and Salkever (1991), developed a theoretical model of indigent care supply by nonprofit hospitals. They tested the model using 40 nonprofit general hospitals

in Maryland during the period of 1980-1984. Three regression analyses were conducted with three different dependent variables: the number of equivalent admissions accounted for by uncompensated care in the hospital (calculated by dividing the dollar amount of uncompensated care by the hospital's gross inpatient revenue per admission), the same measure adjusted by case-mix costliness, and number of discharges of inpatients classified at admission as either self-pay or charity cases. Their study found few differences across the three measures, which provides validation for our alternative measure of uncompensated care.

Regulatory Variables

The literature on regulations suggests that variations in regulatory intensity affect the financial resources of hospitals and hence have direct and indirect effects on hospital responses to their regulatory environment (Cook, Shortell et al. 1983). Cook, Shortell et al. (1983) also argue that dimensions of regulations, such as scope, restrictiveness, uncertainty, and duration, need to be considered when examining regulatory impacts. We therefore include these specific dimensions proposed by Cook et al. in our regulatory measures to capture the intensity of the regulations.

Researchers argue that the structure and scope of CON regulations have led to variations in the effectiveness of this program (Salkever 2000). Variables such as dollar thresholds and scope of services are indicative of intensity variations of CON programs with lower dollar thresholds and broader scope of control predictive of stricter regulatory control. We therefore adopt the index developed by the American Health Planning Association (2005) to measure the presence and intensity of CON programs. This index is constructed as a weighted number of covered services, with the weights capturing the

review thresholds[****] of different CON programs. Specifically, state CON programs are first weighted by their capital, equipment and new service review dollar thresholds. Assigning a weight to each state's CON programs represents a way to reflect the restrictiveness of the program. These weights are then multiplied by the number of services, which captures the scope of the program, to obtain the intensity index. States with a higher index have more restrictive CON control, while states without CON programs are assigned a score of zero. Although this index has been adopted by many earlier studies, it has some limitations. This index does not reflect the duration of the program, which is argued to affect the intensity of the programs. However, this will not affect our estimates because all the study states adopted their CON regulation in the late 1960s or early 1970s. Another problem with this index, as is true with all indices, is the assumption that each unit on the intensity scale exerts the same impact on the dependent variable, which tends to limit our interpretation of marginal effects. However, our ability to determine the direction of the impacts is not compromised by this problem.

POOL is an interval level variable measuring variations of the restrictiveness of state uncompensated care pool regulations. States without a pool regulation are assigned a value of zero, states with a voluntary pool regulation, such as West Virginia and Nevada, are accorded a value of one, and states with mandatory pools are assigned a value of two.

[****] Review threshold refers to the threshold for expenditure of the new service/capital/equipment that exceeds certain dollar amount. Hospital expenditures have to be reviewed if they exceed a certain threshold.

REQUIREMENT represents an index that takes values of zero, one, two and three. It captures the duration, restrictiveness and scope of community benefit requirement laws. Duration is measured by the length of time community benefit requirement laws have been in effect. Consistent with Ginn and Moseley (2006) and given our study period, we argue that laws that are proposed and implemented before year 2000 are more mature, have a longer duration and stronger impact than laws that were instituted after year 2000. We measure restrictiveness by whether community benefit requirement laws are mandatory or voluntary. Some states such as Massachusetts have laws that are largely voluntary, making them less restrictive than those that are mandatory. Lastly, we posit that laws that are broader in scope, such as those mandating both public reporting of community benefits and a specific percentage of hospital net patient revenues be devoted to charity care, are more intense than laws that require either public reporting or a proportionate amount of contribution. The index is developed by summing the numbers across three dimensions (see Table 4). States without community benefit requirement laws are assigned a value of zero. By construction, a state with a voluntary community benefit requirement law implemented prior to 2000 and with either public reporting or a percent requirement would also assume a value of zero, which makes it indistinguishable from states without such a regulation. This, however, is not a concern for the current study because none of our study states fits the above profile.

Table 4: Intensity Index: Dimensions for Community Benefit Requirement Laws

Dimensions	*Duration*	*Restrictiveness*	*Scope*
Before 2000	0		
After 2000	1		
Voluntary		0	
Mandatory		1	
Public Reporting OR Percentage Requirement			0
Public Reporting AND Percentage Requirement			1

We also create interactions of regulatory variables to test if there are any interaction effects among different regulatory programs. We test nonprofit and for-profit hospitals in separate models, as suggested by previous literatures as well as the theoretical framework. We exclude AWP/FOC and state conversion laws from our final analysis due to a lack of variation on both regulations. Only two states (KY and WI) have AWP/FOC laws. Although six states have conversion regulations, limited information on regulatory intensity prohibits us from separating the effects of locating in a given state (or states effects) from the effects of state conversion regulations.

Control Variables

We control for a series of hospital characteristics that could affect its capacity to provide uncompensated care. To be consistent with other studies of hospital uncompensated care provision, we controlled for teaching status, the number of high-technology services offered by the hospital, hospital size, public hospital, whether a hospital has an emergency department, and hospital system/network membership. These variables are all extracted from the AHA (2002, 2003, and 2004) data.

We include hospital teaching status coded one as teaching and zero otherwise to capture uncompensated care provision by teaching hospitals. We define a teaching hospital as one approved to participate in residency training by the Accreditation Council for Graduate Medical Education, affiliated with a medical school, or a member of the Council of Teaching Hospitals (COTH). Studies have shown that teaching hospitals bear a disproportionate share of the uncompensated care burden. In their five-state analysis of uncompensated care distribution among U.S. hospitals, the General Accounting Office (GAO) found that major teaching hospitals accounted for a large percentage of the total uncompensated care cost compared with other nonprofit or for-profit hospitals (GAO 2006). We hence expect that hospital teaching status is positively associated with uncompensated care provision.

Following previous studies, we also control for hospital characteristics that would affect the shape of the cost curve. Such measures include technology intensity, hospital size, and whether the hospital has an emergency department. Since larger and more technology-intense hospitals have more capacity to provide uncompensated care, we expect that hospital size (as measured by number of beds), technology intensity (as measured by the number of high-technology services offered by the hospital in the following areas: neonatal intensive care, open heart surgery, cardiac catheterization, CT and Positron Emission Tomography or PET[††††]), are positively related to uncompensated

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[††††] As suggested by previous studies, Dranove, D. and M. Shanley (1995). "Cost Reductions or Reputation Enhancement as Motives for Mergers: the Logic of Multihosipital Systems." Strategic Management Journal **16**(1): 55-74, Davidoff, A. J., A. T. LoSasso, et al. (2000). "The effect of changing state health policy on hospital uncompensated care." Inquiry **37**(3): 253-67, Bazzoli, G. J., R. C. Lindrooth, et al. (2006). "The influence of health policy and market factors on the hospital safety net." Health Serv Res **41**(4 Pt 1): 1159-

care provision. Whether a hospital has an emergency department is a dummy variable measure indicating the presence of an ER. Since hospitals with an ER are more likely to encounter uninsured patients (given that the uninsured often wait to seek care until symptoms worsen), we expect that having an emergency department is also positively associated with uncompensated care provision.

Research suggests that multiunit system affiliations promote hospital provision of community benefits including uncompensated care (Proenca, Rosko et al. 2000; Lee, Alexander et al. 2003). This is because, on the one hand, hospitals belonging to a system/network have more resources or excess capacity to deal with exogenous pressures, such as financial stress from various cost containment efforts, without compromising their community orientation (Cook, Shortell et al. 1983). On the other hand, institutional theory indicates that larger organizations attract more attention and therefore may be under more pressure to conform to community expectations (Rosko 2004). We therefore expect that the network/system affiliation be positively related to hospital uncompensated care provision. Because we have missing values for 51 percent of the hospital-years, we replace the network dummy variable with the prevalence of a network/system (measured as percent of hospitals that belong to a network/system in the market). We hypothesize that this variable will be positively associated with uncompensated care provision, given that network/system hospitals tend to provide more uncompensated care than non-network/system hospitals.

80.), these services tend to require higher technological investment and hence represent a good measure of technological sophistication.

We also control for major market area characteristics that affect hospital provision of uncompensated care. A growing body of literature suggests that the level of hospital competition and health maintenance organization (HMO) penetration greatly influence hospitals' ability to provide uncompensated care (Gruber 1994; Bazzoli, Lindrooth et al. 2006). Price shopping and cost control strategies adopted by managed care organizations have increased price competition among hospitals. As market competition intensifies, nonprofit hospitals' ability to cross-subsidize uncompensated care decreases. However, such care becomes more attractive for for-profit hospitals because the opportunity cost of providing uncompensated care decreases. We therefore expect to see different behavioral responses from hospitals of different ownerships in markets with various levels of HMO penetration and market competition. We also include an interaction term between HMO penetration and market competition to test if there are any interaction effects. As suggested by previous studies, in markets where competition is already intense, HMO penetration could reduce nonprofit hospitals' capacity to provide uncompensated care even further by shrinking their paying patient base (Mann, Melnick et al. 1997; Davidoff, LoSasso et al. 2000). In addition, Davidoff et al. (2000) found that although market competition has no effect on nonprofit hospitals at any level of HMO penetration, for-profit hospitals show a negative effect of competition on uncompensated care at all but the highest level of penetration.

The key issue in measuring market competition and HMO penetration is defining the appropriate hospital market area. Prior research suggests a number of ways to define relevant hospital markets. Some studies choose geographic measures such as counties, Metropolitan Statistical Areas (MSAs), or Health Service Areas (HSAs) (Dranove,

Shanley et al. 1992; Gaynor and Vogt 2000). Other studies define a fixed or variable radius from each hospital as the relevant market area (Luft, Robinson et al. 1986; Gresenz, Rogowski et al. 2004). Although these measures have the advantage of computational ease, they are often considered to be arbitrary and sometimes underestimate the amount of competition facing a hospital (Wong, Zhan et al. 2005). Another commonly used method is to examine patient flows and define markets as consisting of geographic areas (typically zip codes) that send a nontrivial number of patients to a given hospital. This approach overcomes the disadvantages inherited in previous measures. However, using patient flows has the potential for endogeneity bias when used to investigate the effects of competition on hospital cost and quality (Wong, Zhan et al. 2005). Given the relative merits and drawbacks of each approach, the current study defines hospital markets using an exogenous measure - counties and a potential endogenous measure - patient flows (please see Appendix B for a detailed account of this construction). We performed a sensitivity analysis to select a superior measure between markets defined by counties and markets defined by patient flows. The test did not, however, reveal significant differences between these two measures (see Appendix C for detailed results from the sensitivity analysis). We therefore use the market measure defined by patient flows in our final analysis to avoid the arbitrariness of the county measure.

Once the relevant geographic market is defined, we are able to control for the market competition by computing a Hirschman-Herfindahl Index (HHI) using hospital market shares. HHI is a commonly used index to measure the degree of competition in a given market area. It is derived by summing the squared market shares of each hospital in the relevant market area:

$$HHI = \sum_{i=1}^{N} S_i^2$$

where S_i is the percentage of hospital beds the ith hospital has. HHI ranges from 0 to 10,000 with 10,000 representing a monopoly and 0 being a hospital in a near perfectly competitive market. As HHI increases, the competitiveness in the market decreases. The U.S. Department of Justice (1992) considers a market with a HHI of less than 1,000 to be a competitive marketplace. This index is calculated for each year, using the full sample of hospitals. It is then rescaled to a range of 0 to 1.

HMO penetration is measured by the percentage of county population enrolled in HMOs in 1998. This measure was extracted from the 2005 ARF data. Unfortunately, this dataset does not give us access to the updated numbers for our study period. Since studies have suggested an increasing trend for managed care enrollment (Bian and Morrisey 2006), we expect that our measure will likely underestimate the effect of managed care organizations on the level of uncompensated care provision.

Socioeconomic characteristics of the surrounding community also affect hospital provision of uncompensated care. The demand for uncompensated care is much greater in communities with a large number of uninsured, lower income individuals and lower percentage of elderly population. We therefore control for insurance coverage, per capita income and percentage of population aged 65 or above. We obtain insurance coverage information from the 2000 Census Small Area Health Insurance Estimates for Counties and States (SAHIE). This measure is calculated as the percentage of county population without health insurance. We generate comparable numbers for markets defined by patient flows. However, with the steadily growing number of uninsured over the years,

our year 2000 data will likely understate the demand for uncompensated care due to lack of insurance. Per capita income for county markets is calculated by dividing the total income by county population for each year. The same measure for markets based on patient flows is calculated by adding all the income by market groups and total population by market groups respectively, and then dividing total income by market groups by total population by market groups. We use 2003 per capita income to replace the 2004 numbers as the 2004 data are not available from the 2005 ARF. Percent of population over age 65 is calculated using similar method for both county markets and markets based on patient flows. As we only have the 2002 data on this variable, we use the 2002 numbers for 2003 and 2004. We do expect that percentage of population over 65 is relatively stable over these three years.

We also control for whether a hospital is located in rural or urban areas. We define rural/urban status using the Department of Agriculture's rural-urban continuum codes for metro and non-metro counties provided by the ARF data. These codes range from one to nine, with one representing metro areas with a million population or more and nine being completely rural with less than 2,500 urban population, and not adjacent to a metro area. Appendix D provides a complete list of rural-urban continuum codes.

Tables 5 presents the independent variables and the expected sign of their effects on uncompensated care based on the above discussion.

Table 5: Predicted Effects on Uncompensated Care Provision

	Uncompensated Care	
Variables	**Nonprofit**	**For-profit**
Regulatory Measures		
CON	+	+/-
POOL	+	+
REQUIREMENT	+	+/-
CON*POOL	+	+/-
CON* REQUIREMENT	+/-	+/-
POOL*REQUIREMENT	+/-	+/-
CON*POOL* REQUIREMENT	+/-	+/-
Hospital Characteristics		
Teaching hospital status	+	+
Proportion public hospital	-	-
Technology intensity	+	+
Hospital size	+	+
ER	+	+
Proportion network/system	-	-
Market Characteristics		
HHI	+	-
HMO penetration	-	+
Percentage of population aged 65 or above	-	-
Per capita income	-	-
Percentage of population that are uninsured	+	+
Rural	-	-

Descriptive Statistics

Table 6 defines each variable and Table 7 presents the descriptive statistics for our full sample. These data represent means across three years, treating each hospital-year combination as a separate observation.

Over the three year period, our full sample has 4,324 hospital-year observations, which includes 1,552 hospitals in 2002, 1,508 hospitals in 2003, as well as 1,264 hospitals in 2004. The figures show that, for example, in 2003, there are about 69% nonprofit hospitals in our sample, as compared to 62 percent nationally; 19% public hospitals, as compared to 20% nationally; and 12 percent for-profit hospitals, as compared to 18 percent nationally. We slightly over-sampled nonprofit hospitals and under-sampled for-profit hospitals. For all hospital-year observations, we have about 19 percent public hospitals, 70 percent nonprofits and 11 percent for-profit hospitals, with nonprofit hospitals slightly over-represented. Also note that public hospitals are included in the full sample for the purpose of comparison among different types of hospitals. They are however excluded from the analytical sample because we use percent of public hospitals in the market as a control variable.

Table 6: Variables and Their Definitions

Variables	*Definition*
Dependent Variables	
Selfpay/Charity	Number of admissions that are for self-pay/charity care patients
Percent Selfpay/Charity	Percentage of admissions that are for self-pay/charity care patients
Regulatory Measures	
CON	Certificate of Need
REQUIREMENT	Community benefit requirement
POOL	Uncompensated care pool
Hospital Characteristics	
Teaching hospital status	Dummy variable representing teaching hospital status
Public Hospital_county	Proportion of public hospitals in the market (by counties)
Public Hospital_market	Proportion of public hospitals in the market (by patient flows)
Technology intensity	Number of hi-tech services offered
Hospital size	Hospital bed size
ER	Dummy variable indicating whether a hospital has an Emergency Department
Network/system_county	Proportion of system/network members in markets defined by counties
Network/system_market	Proportion of system/network members in markets defined by patient flows
Market Characteristics	
HHI_county	Herfindahl-Hirschman Index (based on county)
HHI_market	Herfindahl-Hirschman Index (based on patient flows)
HMO penetration_county	Proportion of population in the market (based on county) enrolled in HMO
HMO penetration_market	Proportion of population in the market (based on patient flows)enrolled in HMO
Percentage of population 65+_county	Percentage of population aged 65 or above
Percentage of population 65+_market	Percentage of population aged 65 or above
Per capita income_county	Per capita income (1,000)
Per capita income_market	Per capita income (1,000)
Percent uninsured_county	Percentage of population that are uninsured
Percent uninsured_market	Percentage of population that are uninsured
Rural	Rural/Urban continuum

Table 7: Descriptive Statistics for the Full Sample

Variables	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
Dependent Variables					
Selfpay/Charity	4324	443.37	805.14	0	14215
Percent Selfpay/Charity	4324	5	6	0	100[‡‡‡‡]
Regulatory Measures					
CON	4324	9.31	6.64	0	21.60
REQUIREMENT	4324	0.35	0.75	0	3
POOL	4324	0.70	0.93	0	2
Hospital Characteristics					
Teaching hospital status	4324	0.26	0.44	0	1
Public Hospital_county	4324	3	8	0	29
Public Hospital_market	4324	3	6	0	76
Technology intensity	2385	2.10	1.41	0	5
Hospital size	4324	220.99	265.32	0[§§§§]	2163
ER	3706	0.98	0.13	0	1
Network/system_county	4324	10	39	0	87
Network/system_market	4324	10	30	0	41
Market Characteristics					
HHI_county	4324	0.50	0.35	0	1
HHI_market	4324	0.31	0.29	0.05	1
HMO penetration_county	4324	0.25	0.18	3.8	0.96
HMO penetration_market	4324	0.28	0.17	0	0.96
Percentage of population 65+_county	4324	14	4	6.54	34
Percentage of population 65+_market	4324	13.97	3.94	6.53	34.24
Per capita income_county	4324	29.64	9.51	14.80	84.59
Per capita income_market	4324	30.63	9.03	14.80	84.59
Percent uninsured_county	4324	13.65	4.12	5.4	29.50
Percent uninsured_market	4324	13.44	3.77	13.52	25.70
Rural	4324	3.24	2.41	1	9

[‡‡‡‡] A nonprofit hospital that is excluded later in the analysis because of possible reporting error from the hospital.
[§§§§] A public hospital that reported zero beds. Public hospitals are excluded in the analysis.

The next set of tables (Tables 8.1 – 8.3) report full sample summary statistics by hospital status: public, nonprofit, and for-profit. It shows that on average, a slightly higher percentage (6%) of admissions in public and for-profit hospitals are for the uninsured patients than those in nonprofit hospitals (5%). Figure 2 and 3 further illustrate the distribution of total number of admissions for the uninsured by ownership types in 2002. This pattern remains largely unchanged for 2003 and 2004 (Appendix E). In the aggregate, nonprofit hospitals consistently have the most uninsured admissions (68-70 percent) compared with public (11-14 percent) and for-profit hospitals (16-21 percent). This is partly because the majority of U.S. hospitals are nonprofits.

The summary tables also show that on average, nonprofit hospitals tend to be larger (as measured in number of beds) and are more technologically sophisticated than public or for-profit hospitals.

Table 8.1: Descriptive Statistics for the Full Sample by Hospital Ownership Status (Public)

Variables	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
Number of Self-pay/Charity	826	495.77	1350.11	0	14215
Percent of Self-pay/Charity	826	6	7	0	71
CON	826	9.92	6.21	0	21.6
REQUIREMENT	826	0.16	0.57	0	3
POOL	826	0.42	0.77	0	2
Teaching hospital status	826	0.16	0.37	0	1
Technology intensity	461	1.58	1.27	0	5
Hospital size	826	143.69	224.77	0	1839
ER	715	0.98	0.13	0	1
Network/system_county	826	5	15	0	36
Network/system_market	826	6	21	0	41
HHI_county	826	0.64	0.36	0.05	1
HHI_market	826	0.36	0.33	0.03	1
HMO penetration_county	826	0.13	0.13	0	0.66
HMO penetration_market	826	0.21	0.15	0	0.66
Percentage of population 65+_county	826	15	4	7	30
Percentage of population 65+_market	826	13.92	3.58	6.54	31.58
Per capita income_county	826	26.52	7.71	14.30	84.59
Per capita income_market	826	28.90	8.04	16.05	84.59
Percent uninsured_county	826	14.80	4.54	4.4	26.9
Percent uninsured_market	826	14.11	4.21	5.5	24.76
Rural	826	4.85	2.57	1	9
2002	826	0.35	0.48	0	1
2003	826	0.34	0.47	0	1
2004	826	0.31	0.46	0	1

Table 8.2: Descriptive Statistics for the Full Sample by Hospital Ownership Status (Nonprofit)

Variables	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
Number of Self-pay/Charity	2962	434.68	636.01	0	5844
Percent of Self-pay/Charity	2962	5	5	0	100
CON	2962	9.50	6.81	0	21.6
REQUIREMENT	2962	0.44	0.78	0	3
POOL	2962	0.83	0.97	0	2
Teaching hospital status	2962	0.31	0.46	0	1
Public Hospital_county	2962	1	7	0	29.4
Public Hospital_market	2962	2	6	0	76
Technology intensity	1674	2.26	1.44	0	5
Hospital size	2962	251.38	288.31	6	2163
ER	2634	0.99	0.12	0	1
Network/system_county	2962	13	46	0	87
Network/system_market	2962	12	34	0	41
HHI_county	2962	0.48	0.34	0.05	1
HHI_market	2962	0.30	0.28	0.03	1
HMO penetration_county	2962	0.27	0.18	0	0.96
HMO penetration_market	2962	0.30	0.17	0	0.96
Percentage of population 65+_county	2962	14	4	0.03	0.34
Percentage of population 65+_market	2962	13.69	3.48	7.15	34.24
Per capita income_county	2962	30.64	10.12	14.80	84.59
Per capita income_market	2962	31.35	9.62	14.80	84.59
Percent uninsured_county	2962	13.01	3.97	3.8	29.5
Percent uninsured_market	2962	12.89	3.59	5.4	25.7
Rural	2962	2.94	2.25	1	9
2002	2962	0.37	0.48	0	1
2003	2962	0.35	0.48	0	1
2004	2962	0.28	0.45	0	1

Table 8.3: Descriptive Statistics for the Full Sample by Hospital Ownership Status (For-profit)

Variables	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
Number of Self-pay/Charity	536	410.70	427.47	0	4070
Percent of Self-pay/Charity	536	6	6	0	55
CON	536	7.35	5.95	0	20.7
REQUIREMENT	536	0.19	0.68	0	3
POOL	536	0.44	0.76	0	2
Teaching hospital status	536	0.11	0.32	0	1
Public Hospital_county	536	1	0.02	0	12
Public Hospital_market	536	1	0.02	0	9
Technology intensity	250	2.02	1.19	0	5
Hospital size	536	172.18	118.89	6	655
ER	357	0.96	0.20	0	1
Network/system_county	536	4	0.10	0	84
Network/system_market	536	4	0.07	0	49
HHI_county	536	0.40	0.33	0.05	1
HHI_market	536	0.24	0.24	0.03	1
HMO penetration_county	536	0.29	0.19	0	0.64
HMO penetration_market	536	0.30	0.18	0.01	0.61
Percentage of population 65+_county	536	15	6	4	34
Percentage of population 65+_market	536	15.55	5.97	8.15	34.24
Per capita income_county	536	28.93	7.14	13.52	49.54
Per capita income_market	536	29.28	6.12	17.56	49.54
Percent uninsured_county	536	15.39	3.33	6.5	25.3
Percent uninsured_market	536	15.44	3.16	8.27	24.76
Rural	536	2.43	1.88	1	9
2002	536	0.33	0.47	0	1
2003	536	0.34	0.47	0	1
2004	536	0.34	0.47	0	1

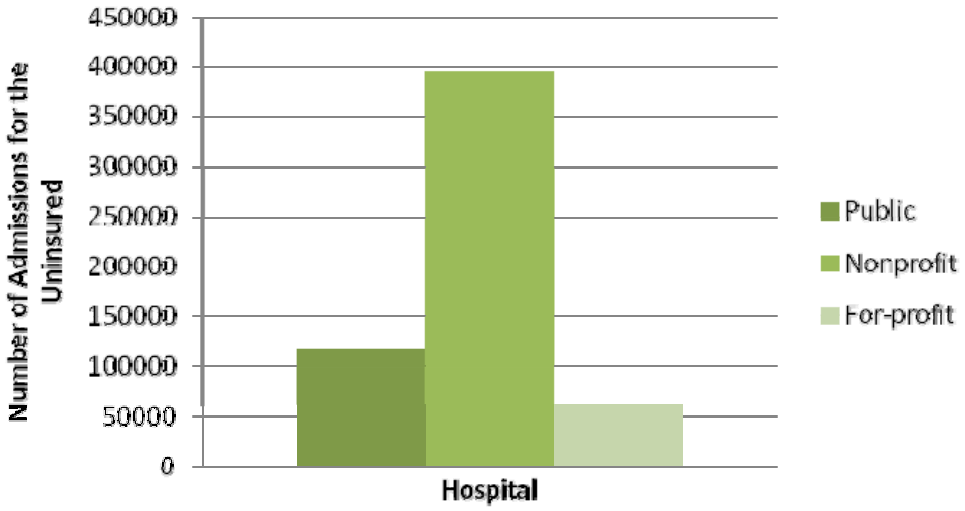

Figure 2: Hospital Provision of Uncompensated Care 2002

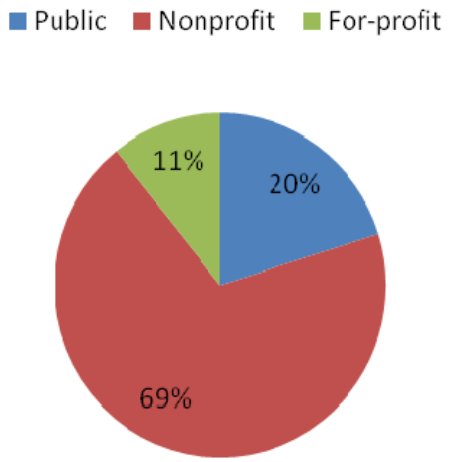

Figure 3: Percent of Uncompensated Care Admissions by Ownership Types 2002

Table 9 presents summary statistics for the final study sample by nonprofit/for-profit status, after all the missing values for technology intensity variable and ER variable are excluded. This sample has 2,235 nonprofit observations and 295 for-profit observations that are representative of nonprofit and for-profit hospitals of all sizes in the U.S. Table 10 compares hospitals in our study sample in 2003 with those nationally with regard to size (as measured in number of beds) and location (as indicated by rural/urban). Our two-sample paired *t* test fails to find any significant differences between the study sample and national statistics, indicating that our nonprofit and for-profit samples mirror the U.S. hospitals of all sizes and in rural/urban areas (test results are reported in Appendix F). Additionally, the summary statistics are not significantly different from the full sample statistics. Nonprofit hospitals are still found to provide, on average, a higher volume of admissions for the uninsured but a slightly lower percentage than their for-profit counterparts. They tend to be larger, more technologically sophisticated and more likely to have an Emergency Department.

We further examined the regulatory variations by ownership status. Tables 11.1 – 11.3 and 12.1 – 12.3 represent intensity variations of each regulation across all hospitals by ownership types. In the nonprofit sample, 28.9 percent of the hospitals are located in non-CON states and the remaining 71.1 percent in states with CON of varying intensities. 74.5 percent of the nonprofit hospitals are in states without a community benefit requirement regulation. More than half of the nonprofit hospitals are found in states that do not have an uncompensated care pool. In the for-profit sample, 20.7 percent of the hospitals are located in non-CON states. 88.1 percent of the for-profit hospitals are in

states without a community benefit requirement regulation. 71 percent of the for-profit hospitals are found in states without an uncompensated care pool.

Table 9: Descriptive Statistics for the Final Study Sample by Nonprofit/For-profit Status

	Nonprofit				*For-profit*			
Variables	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Number of Self-pay/Charity	476.98	705.25	0	9370	395.11	346.24	0	1613
Percent of Self-pay/Charity	4.62	4.90	0	100	5.19	3.94	0	25.66
CON	8.91	7.01	0	20.7	7.90	6.53	0	20.7
REQUIREMENT	0.39	0.74	0	3	0.26	0.78	0	3
POOL	0.80	0.95	0	2	0.45	0.75	0	2
Teaching hospital status	0.30	0.46	0	1	0.09	0.29	0	1
Public Hospital_county	0.90	2.78	0	19.63	0.75	2.10	0	12.22
Public Hospital_market	1.51	2.61	0	19.63	1.34	2.05	0	8.83
Technology intensity	2.15	1.37	0	5.00	2.11	1.18	0	5.00
Hospital size	216.86	215.09	6	2163	159.02	104.71	6	655
ER	0.99	0.12	0	1	0.97	0.18	0	1
Network/system_county	9.50	15.80	0	109.90	5.21	11.23	0	84.39
Network/system_market	9.36	12.78	0	90.91	4.70	8.12	0	49.07
HHI_county	0.52	0.34	0.05	1	0.44	0.32	0.05	1
HHI_market	0.32	0.30	0.03	1	0.26	0.24	0.03	1
HMO penetration_county	0.26	0.18	0	0.8	0.27	0.19	0.01	0.64
HMO penetration_market	0.29	0.18	0	0.8	0.29	0.18	0.01	0.61
Percentage of population 65+_county	13.84	3.62	3.00	32.02	15.50	6.00	6.40	33.77
Percentage of population 65+_market	13.70	3.34	7.15	34.24	15.94	6.28	8.15	34.24
Per capita income_county	30.26	9.22	14.80	84.59	28.45	6.91	17.56	47.45
Per capita income_market	30.98	8.66	14.80	84.59	28.83	6.05	17.56	44.12
Percent uninsured_county	12.70	3.93	3.8	29.5	14.85	3.11	7.8	23.5
Percent uninsured_market	12.60	3.48	5.4	25.3	14.97	2.98	8.90	23.32
Rural	3.09	2.29	1	9	2.56	1.87	1	9
2002	0.35	0.48	0	1	0.31	0.46	0	1
2003	0.36	0.48	0	1	0.40	0.49	0	1
2004	0.29	0.45	0	1	0.29	0.46	0	1
	2235				295			

Table 10: Comparing Hospitals in Final Study Sample and in U.S. in 2003

			Sample	*U.S.*
Nonprofit	Percent of beds	0-49	17%	23%
		50-99	16%	19%
		100-199	25%	24%
		200-399	27%	25%
		>=400	15%	9%
	Percent of urban		67%	62%
	N		807	2,794
For-profit	Percent of beds	0-49	13%	22%
		50-99	19%	20%
		100-199	36%	34%
		200-399	31%	20%
		>=400	2%	4%
	Percent of urban		74%	73%
	N		118	667

Table 11.1: Nonprofit Hospital Distribution by Regulatory Intensity

Certificate-of-Need (CON)

CON Intensity Index	*Freq.*	*Percent*
0	646	28.9
3.5	21	0.94
4.8	171	7.65
6.3	151	6.76
8.1	170	7.61
12.1	167	7.47
12.8	91	4.07
14.4	128	5.73
15	212	9.49
15.2	23	1.03
16	185	8.28
18.4	177	7.92
20.7	93	4.16
Total	2,235	100

Table 11.2: Community Benefit Requirement

Community Benefit Requirement Intensity Index	*Freq.*	*Percent*
0	1,665	74.5
1	299	13.38
2	235	10.51
3	36	1.61
Total	2,235	100

Table 11.3: Uncompensated Care Pool

Uncompensated Care Pool Intensity Index	*Freq.*	*Percent*
0	1,280	57.27
1	114	5.1
2	841	37.63
Total	2,235	100

Table 12.1: For-profit Hospital Distribution by Regulatory Intensity

Certificate-of-Need (CON)

CON Intensity Index	*Freq.*	*Percent*
0	61	20.68
3.5	9	3.05
4.8	10	3.39
6.3	136	46.1
12.1	3	1.02
12.8	7	2.37
14.4	3	1.02
15	2	0.68
16	21	7.12
18.4	14	4.75
20.7	29	9.83
Total	295	100

Table 12.2: Community Benefit Requirement

Community Benefit Requirement Intensity Index	*Freq.*	*Percent*
0	260	88.14
1	13	4.41
2	2	0.68
3	20	6.78
Total	295	100

Table 12.3: Uncompensated Care Pool

Uncompensated Care Pool Intensity Index	*Freq.*	*Percent*
0	210	71.19
1	38	12.88
2	47	15.93
Total	295	100

CHAPTER FIVE

ESTIMATION AND RESULTS

Estimation

We use panel data for our analysis because they present several advantages over cross section or time series data. Cross section data measure an observation at a point in time and time series data follows an observation across time, while panel data combine cross section and time series data. As a result, our sample size increases because an observation was repeatedly measured at different points in time. Additionally, since we follow the same cross section unit over time, we are able to obtain consistent estimators in the presence of omitted variables using proper panel data techniques.

There is some concern that omitted variables might be a problem because some hospital characteristics might not be observable or measurable. In other words, there is a hospital specific latent variable α_i as defined in the component error term ε_{it} :

$$UC_{it} = \beta_0 + \beta_1 Hospital_{it} + \beta_2 Market_{it} + \beta_3 Regulation_{it} + \beta_4 Year + \beta_5 State + \varepsilon_{it}$$

where $\varepsilon_{it} = \alpha_i + \eta_{it}$. This latent variable can be, for example, the preferences of hospital administrators/boards of trustees towards uncompensated care provision, or hospital managerial quality or structure that tend to be constant over time. Depending on whether this unobserved α_i is correlated with some right-hand side hospital specific explanatory variables such as size, structure (i.e., whether the hospital maintains an emergency department) or technological sophistication, we test different estimation methods: pooled

Ordinary Least Squares or pooled OLS, random effects Generalized Least Squares (GLS), and a Hausman Taylor instrumental variable (HTIV) approach.

Three Estimation Approaches: Pooled OLS, GLS and HTIV

The general form of our empirical model can be expressed as

$$Y_{it} = X_{it}\beta + \varepsilon_{it} \qquad t=1, 2, 3 \qquad (1)$$

$$\varepsilon_{it} = \alpha_i + \eta_{it}$$

ε_{it} is a composite error term which represents the sum of the unobserved effect and an idiosyncratic error. We first estimate our empirical model using a pooled OLS. The pooled OLS estimator requires no correlation between X_{it} and ε_{it} (i.e., $E(X_{it}' \varepsilon_{it})=0$ and $E(X_{it}'\alpha_i)=0$) to obtain a consistent estimator of β in model (1). This estimator, however, ignores hospital specific unobserved effects.

We then re-estimate the model using an improved estimation --- random effect GLS that controls for random hospital specific effects using variation over both time and cross sectional units to estimate the parameter β vector. In addition, it exploits the serial correlation in the composite error $\varepsilon_{it} = \alpha_i + \eta_{it}$ to produce more efficient estimators than pooled OLS or fixed effects. Similar to pooled OLS, it also requires orthogonality between α_i and X_{it}. In other words, both pooled OLS and random effects GLS rely on the assumption that unobservable hospital characteristics are not correlated with our right-hand side variables.

However, there is concern that such a correlation might exist. Some evidence suggests that the hospital industry, acting as a powerful interest group, is able to influence state policy making such as the adoption of CON regulations so that the hospitals can preserve a profitable patient mix or volume (Wendling and Werner 1980; Lanning, Morrisey et al. 1991). Although such a concern might be legitimate, there is also evidence suggesting that a state's adoption of such regulations is motivated by its concern over inefficiency or market failure in the system rather than pure interest group transfers (Cone and Dranove, 1986; Morrisey and Ohsfeldt, 1991). As previously discussed in the theory of regulation and hospital regulation in particular (Chapter 2), a state's decision to adopt certain policies can be viewed as in the public interest. For example, CON approval by regulators is made contingent, through formal conditions or informal negotiation, upon the willingness of the hospital to provide services (e.g., uncompensated care) that are perceived by the regulators as in the public interest (Salkever, 2000). Therefore, industry capture might not be a concern if adoption of these policies is intended to amend market failure and is meant to protect the public interest. However, if we allow for the possibility of interest group influence and relax the assumption of strict exogeneity, our regulations will be endogenous as they are correlated with the latent hospital characteristics α_i . In other words, if the industry capture theory holds true, unobserved hospital motivations to lobby for regulations might influence the level of uncompensated care they ultimately provide (by the patient mix/volume they choose).

To allow such a correlation, we re-estimate the empirical model with a Hausman-Taylor instrumental variables procedure (HTIV) that relaxes the independence assumption by allowing unobservable hospital characteristics to be correlated with our

right-hand side variables. Some previous studies have used fixed effects to eliminate potential endogeneity resulting from this omitted latent variable problem. However, fixed effects estimation removes time constant variables, such as the regulatory variables in our model. As we only have recent years of hospital discharge data, the lack of variation in the regulatory variables over time will prohibit us from estimating their impact on hospital behaviors with fixed effects estimation. Fortunately, Hausman and Taylor (1981) proposed a model that conveniently solves the potential correlation between omitted variables and the explanatory variables but still allows us to estimate the effects of time constant variables of interest.

In a Hausman-Taylor procedure, the general form of our empirical model can be expressed as:

$$Y_{it} = X_{it}\beta + Z_i\gamma + \varepsilon_{it}, \qquad (1)$$

$$\varepsilon_{it} = \alpha_i + \eta_{it}$$

where i = 1 to N and, t = 1 to T; β and γ are k and g vectors of coefficients associated with time varying (X_{it}) and time-invariant (Z_i) observable variables respectively. In our case, X_{it} will contain variables such as percentage of network/system in the market, percentage of public hospitals in the market, HHI, per capita income, uninsurance rate, teaching status, technology intensity, bed size, ER, HMO penetration, and percentage of population over 65, while matrix Z_i will include regulatory measures and state dummies.

Intuitively the Hausman-Taylor procedure follows an instrumental variable approach. It uses variables in the model as instruments for the endogenous time-invariant variables. This has the advantage over traditional instrumental variables methods in that it

does not rely on excluded exogenous instruments which are usually difficult to obtain. However, the Hausman-Taylor procedure does require *a priori* information: the ability to distinguish columns of X and Z which are asymptotically correlated with α_i from those which are not. In our application, we have reason to believe that hospital characteristics such as technology intensity, size, and whether a hospital has an Emergency Department are influenced by the latent individual hospital effect. CON laws may also be correlated if we further assume that unobserved hospital motivation to lobby for CON also influences the level of uncompensated care they ultimately provide (by the patient mix/volume they choose). However, percent of network/system in the market, percent of public hospitals in the market, HHI, percentage of population that are uninsured, other regulations, state dummies, HMO and percent of population over 65 are not correlated.

Once we distinguish the time-varying/time invariant, exogenous/endogenous variables, X_{it} and Z_i can be further partitioned as $X_{it} = (x_{it1}, x_{it2})$ and $Z_i = (z_{i1}, z_{i2})$, where x_{it1} is a $1 \times k_1$ time-varying exogenous vector, x_{it2} a $1 \times k_2$ time-varying endogenous vector, z_{i1} a $1 \times g_1$ time-invariant exogenous vector, and z_{i2} a $1 \times g_2$ time-invariant endogenous vector. A vector of deviations from means averaged over time Q_v was used as part of the instruments to transform equation (1). Thus by construction, Q_v is orthogonal to any time-invariant vector of observations (i.e., $Q_v Z_i = 0$ and $Q_v \alpha_i = 0$). Unfortunately, since Q_v is also orthogonal to Z_i, which violates the requirement that instruments be correlated with all the endogenous variables, Hausman and Taylor (1981) added the columns of x_{it1} and z_{i1} so that we now have the matrix $[Q_v \vdots X_{it1} \vdots Z_{i1}]$ as

instruments. However, one necessary condition for all the parameters in equation (1) to be identified is $k_1 \geq g_2$, Recall that the vector with $1 \times k_1$ time-varying exogenous variables is x_{it1} which includes eight variables (per capita income, percent of network/system in the market, percent of public hospitals in the market, HHI, percentage of population that are uninsured, HMO, teaching, and percent of population over 65). The vector with $1 \times g_2$ time-invariant endogenous variables is z_{i2} that includes seven regulatory variables and their interactions (see Table Z). Thus our model is over-identified ($k_1 > g_2$). However, some of the time varying exogenous variables have low variation across the study period, which prohibits the HTIV model from constructing strong internal instruments. Percent of public hospital and teaching have zero variation for about half of the study sample. In addition, all of the over time variation for variables HMO penetration, percent of population over 65 and percent uninsured comes from population adjustment, which further weakens the identification. Specifically, these variables are constructed in the following ways. For example, for the HMO penetration variable, we take the year when county level data on this variable are available and multiply it by the county population for each year to obtain the number of people enrolled in HMO plans each year. We then sum the total number of enrollees in the market defined by patient flows and divide it by the total population in that market for each study year. As a result, a small amount of within group or over time variation was introduced in the market level HMO penetration variable, which is used in the analysis. Although this is the best we can achieve with the existing county level data to obtain the market level HMO penetration, percent of population over 65, and uninsurance rate, we need to be cautious about the potential problems this manipulation could create. The amount of the

variation created by our population adjustment is low and does not represent the true underlying changes in variable trends over time. Even though the real HMO penetration, percent of population over 65, and percent of population uninsured in different years would also reflect population changes, our adjustment yields variations that are not the same as having information on the changes in the real underlying variable. As a result, the Hausman Taylor procedure will still use these variables as instruments despite their low over-time variation, but may not perform well: low variation could result in weak identification, and hence large standard errors. In addition, because not all three variables are affected by population growth trend in the same way, a new bias is introduced and creates a measurement error that may bias the Hausman Taylor estimates.

Table 13: List of Time Varying/Invariant and Endogenous/exogenous Variables

	Endogenous	***Exogenous***
Time Varying Variables (*X*)	Emergency Department technology intensity hospital size	Percent network Percent of public hospital Teaching HHI HMO penetration* Percent over 65* Per capita income Percent uninsured*
Time Invariant Variables (*Z*)	CON Pool Requirement CON*Pool CON*Requirement Pool*Requirement All three	Rural

*Within group variation represents population weighted averages.

Cluster Correlated Errors

The model is also examined for cluster correlated errors. Clustering can occur when residuals of hospitals within the same state correlate with each other. This intragroup correlation of the errors may create a clustering effect that could produce inconsistent estimates of the covariance matrix. One assumption for the Hausman-Taylor model to produce consistent and efficient parameter estimates is that the idiosyncratic errors are homoskedastic, with zero mean and constant variance across time and individuals (i.e., $\eta_{it} \sim$ iid $(0, \sigma_{\eta}^{2})$). In the presence of clustered errors, the off-diagonal elements of the covariance matrix might not be zero due to potential correlations of the errors among hospitals within the same state. In addition, the diagonal elements might not be identical since the clustering of hospitals by states might lead to different variances along the diagonals of the covariance matrix. As a result, the parameter estimates will be inefficient although they are still consistent.

The Breusch-Pagan (1980) Lagrangian Multiplier (LM) and Cook-Weisberg tests are performed on the pooled cross-sectional final sample to test for state effects in the form of cluster correlated errors. Under the null hypothesis, both tests follow a Chi-square distribution. We should note that the LM test is not designed specifically to test for cluster-correlated errors. It captures other types of heteroskedasticity as well. Table 14 presents the Breusch-Pagan / Cook-Weisberg test statistics. The critical value for the Chi-squared distribution with 30 degrees of freedom is 43.77. The table therefore shows that with a test statistics of 3674.05, there is almost no probability that the distribution is Chi-squared. The null hypothesis of homoskedasticity is rejected, meaning there is some

evidence that the errors are correlated or heteroskedastic. A robust cluster estimator of the variance covariance matrix should be used to correct for the estimated residuals.

Table 14: Breusch-Pagan / Cook-Weisberg Test for Heteroskedasticity

	Uncompensated Care		
Final Sample	chi2(30)	= 3674.05,	Prob > chi2 = 0.0000

However, the literature reveals no commonly adopted corrections to obtain robust cluster estimators for the Hausman-Taylor procedure. Thus, the HTIV estimator does not correct for cluster correlated errors. Because such a robust estimator exists in the pooled OLS and the random effects GLS model, we report robust variance matrix estimator for these estimation procedures.

A Test for Endogeneity

The Hausman test is devised for a number of model specifications in econometrics including endogeneity as a result of unobserved individual factors (Hausman 1978). To the extent that unobserved hospital heterogeneity remains an omitted influence on our right hand side variables, we conduct the Hausman test using the property of fixed effects (FE) estimation[*****]. FE will produce consistent parameter estimates in the presence of endogeneity as a result of unobserved hospital effects. However, in the absence of such an endogeneity and/or the presence of cluster correlated

[*****] FE will only be used for the purpose of the specification test and not as part of the estimation procedure because FE does not allow us to estimate the coefficients on the regulatory variables.

errors, such estimates will be asymptotically inefficient. Similar to FE, an HTIV estimator is consistent under both the null and alternative hypothesis. On the other hand, under the hypothesis of no misspecification (i.e., no latent hospital effects), random effect GLS models will yield consistent and asymptotically efficient estimators, where efficiency is defined as attaining the asymptotic Cramer-Rao upper/lower bound. We therefore utilize the properties of these three estimators (FE, HTIV and GLS) to construct several tests of misspecification.

Results

The Hausman test based on the difference between FE and GLS estimates yields χ^2 =45.02 with 12 degrees of freedom which is significant (p=0) for the nonprofit hospitals sample (Table 15.1). This rejects the null that there is no correlation between the individual hospital effects and explanatory variables. In other words, there is evidence that latent individual effects exist and GLS will yield inconsistent parameter estimates. The Hausman test based on the difference between FE and HTIV estimator yields χ^2 =1.5 with one degree of freedom which is not significant at the 5% level (p=0.22) (Table 15.2). The same tests yield similar results for the for-profit hospital sample. The Hausman test based on the difference between FE and GLS estimates yields χ^2 =35.9 with 11 degrees of freedom which is significant (Table 15.3) and χ^2 =4.26 with two degrees of freedom which is not significant at the 5% level (p=0.12) when testing for the difference between FE and HTIV estimators (Table 15.4) Results from the Hausman tests justify the use of the HTIV method.

Table 15.1: Hausman Test for Nonprofit Hospitals: FE vs. GLS

Number of Admissions	*(b)*	*(B)*	*(b-B)*	*sqrt(diag(V_b-V_B))*
	a	b	Difference	S.E.
Technology Intensity	-6.25	18.48	-24.72	13.07
ER	26.53	47.49	-20.95	28.39
Teaching hospital status	-64.72	37.62	-102.34	57.10
Proportion with public owner	-22.53	-38.76	16.23	10.76
Hospital size	0.71	1.68	-0.96	0.25
Proportion network/system member	-1.33	-1.56	0.22	1.23
HHI	191.62	-148.73	340.35	318.43
HMO penetration	-27.63	-3.23	-24.40	43.40
Percentage of population 65+	-0.31	-1.04	0.73	165.34
Per capita income	56.46	-0.63	57.09	12.90
Percent uninsured	-283.09	10.37	-293.46	318.98
Rural	62.61	-21.79	84.41	108.46

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(12) = (b-B)'[(V_b-V_B)^(-1)](b-B)

= 45.02

Prob>chi2 = 0.0000

Table 15.2: Hausman Test for Nonprofit Hospitals: FE vs. HTIV

Number of Admissions	*(b)*	*(B)*	*(b-B)*	*sqrt(diag(V_b-V_B))*
	a	b	Difference	S.E.
Technology Intensity	-6.25	-2.50	-3.75	4.80
ER	26.53	26.06	0.47	13.92
Teaching hospital status	-64.72	-56.88	-7.84	14.65
Proportion with public owner	-22.53	-19.33	-3.19	3.73
Hospital size	0.71	0.72	-0.01	0.05
Proportion network/system member	-1.33	-1.57	0.23	0.41
HHI	191.62	172.02	19.60	64.69
HMO penetration	-27.63	-18.65	-8.99	31.93
Percentage of population 65+	-0.31	-108.47	108.15	93.76
Per capita income	56.46	54.48	1.98	2.96
Percent uninsured	-283.09	31.11	-314.20	289.77
Rural	62.61	16.60	46.01	48.55

b = consistent under Ho and Ha; obtained from xtreg

B = inconsistent under Ha, efficient under Ho; obtained from xthtaylor

Test: Ho: difference in coefficients not systematic

chi2(1) = (b-B)'[(V_b-V_B)^(-1)](b-B)

= 1.50

Prob>chi2 = 0.2201

Table 15.3: Hausman Test for For-profit Hospitals: FE vs. GLS

Number of Admissions	*(b)*	*(B)*	*(b-B)*	*sqrt(diag(V_b-V_B))*
	a	b	Difference	S.E.
Technology Intensity	-42.28	22.03	-64.31	16.72
ER	-9.16	87.95	-97.11	43.03
Teaching hospital status	-59.30	-64.21	4.91	99.11
Proportion with public owner	-41.11	-14.24	-26.87	38.20
Hospital size	0.04	1.14	-1.10	0.27
Proportion network/system member	-3.09	-1.59	-1.50	5.97
HHI	-131.55	-59.99	-71.56	763.52
HMO penetration	230.54	-0.78	231.32	122.36
Percentage of population 65+	390.48	-1.51	391.99	476.92
Per capita income	25.91	9.88	16.03	22.69
Percent uninsured	91.35	34.12	57.23	416.74

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(11) = (b-B)'[(V_b-V_B)^(-1)](b-B)

= 35.90

Prob>chi2 = 0.0002

Table 15.4: Hausman Test for For-profit Hospitals: FE vs. HTIV

Number of Admissions	*(b)*	*(B)*	*(b-B)*	*sqrt(diag(V_b-V_B))*
	a	b	Difference	S.E.
Technology Intensity	-42.28	-40.34	-1.94	15.58
ER	-9.16	-10.85	1.69	54.64
Teaching hospital status	-59.30	-53.72	-5.57	74.55
Proportion with public owner	-41.11	-40.04	-1.07	26.43
Hospital size	0.04	0.07	-0.03	0.21
Proportion network/system member	-3.09	-5.17	2.08	4.36
HHI	-131.55	-58.81	-72.74	498.27
HMO penetration	230.54	14.96	215.59	119.85
Percentage of population 65+	390.48	45.95	344.53	471.01
Per capita income	25.91	25.97	-0.06	14.88
Percent uninsured	91.35	98.22	-6.87	393.55

b = consistent under Ho and Ha; obtained from xtreg

B = inconsistent under Ha, efficient under Ho; obtained from xthtaylor

Test: Ho: difference in coefficients not systematic

chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)

= 4.26

Prob>chi2 = 0.1188

However, some important caveats should be noted. First, HTIV estimation has weak identification due to data limitations. Some time-varying exogenous variables which the HTIV procedure uses to construct internal instruments have low variation. In addition, variables such as uninsurance rate, percent of population over 65 and HMO penetration are adjusted by population growth due to lack of data for some study years. Specifically, we computed values for 2003 and 2004 market level variables using the 2002 county level data. As a result, the internal instruments constructed based on these population adjusted variables not reflect the true underlying changes in the HMO penetration, percent over 65, and uninsurance rate. However, these internal instruments are not completely invalid because even real changes in these variables reflect population changes over time to some extent because changes in population could change the

percentage of HMO penetration, population that are over 65 or uninsurance rate. However, this manipulation of multiplying all three variables by the same growth trend likely introduces a new measurement bias to the parameter estimates. Second, there may be potential misclassification of endogenous/exogenous variables. Third, comparing FE and HTIV estimators, a few coefficient estimates such as the uninsurance rate in the nonprofit model and the percent of population over 65 in the for-profit model exhibit large differences. However, most of the estimates are similar in both magnitude and sign.

Table 16 and Table 17 present results from the GLS and HTIV estimation respectively. Pooled OLS results are reported in Appendix G. Even though the Hausman specification tests show evidence of inconsistency, the GLS procedure yields meaningful estimates. First, all the significant regulatory variables in the GLS model are of similar signs to those in the HTIV model, which, despite its problems discussed previously, are not significantly different from the consistent but less efficient FE model as shown by the Hausman test. Second, comparing with the HTIV results, endogeneity due to omitted variables or unobserved heterogeneity seems to bias our GLS estimates for the regulatory variables downward for the nonprofit hospital sample. This may suggest that the magnitude of the true regulatory effects might be even larger than what we have estimated using the GLS procedure. Significant variables therefore in our GLS model could be even more significant if the magnitude of the true effects are greater. For the for-profit hospital sample, the comparison of GLS vs. HTIV again shows that GLS tends to underestimate the magnitude of the true regulatory effects but the HTIV estimates are extremely large. It is not clear to us whether the large HTIV estimates for the regulatory

variables in the for-profit model result from the problem discussed previously or the limited sample size (*N*=295).

Given the caveats of each model, findings are reported based on the GLS estimation and validated by the HTIV estimates. Even though both the GLS and HTIV methods have their limitations, our cross-validation provides a way to overcome some of the drawbacks. A comparison of the fixed effects estimation with the HTIV using the Hausman test shows that most of the HTIV estimates are consistent despite the problems with identification and measurement. A comparison of the GLS and HTIV estimates gives us some information on the direction of the bias for the GLS model. Results from these analyses should however be interpreted with caution.

Table 16: GLS Results for Hospital Provision of Uncompensated Care

	Nonprofit		*For-profit*	
Variables	Number of Admissions	Percent of Admissions	Number of Admissions	Percent of Admissions
CON	10.73**	0.07**	3.95	0.25***
REQUIREMENT	9.71	-0.63***	-42.34***	0.69***
POOL	51.55*	0.51*	-131.97***	1.14*
CON*REQUIREMENT	-1.91	0.02	-	-
CON*POOL	26.82***	0.14***	18.67***	0.004
POOL*REQUIREMENT	46.33	0.35	231.69***	-0.12
CON*REQUIREMENT*POOL	-20.49***	-0.11	-19.57***	0.03
Technology Intensity	35.57	-0.26**	39.37	-0.36**
ER	19.61	0.28	51.08	0.19
Teaching hospital status	56.27	0.22	-28.81	-0.18
Proportion with public owner	-2383.43***	-7.35	-872.67	-1.66
Hospital size	1.60***	-0.001	0.97***	-0.004***
Proportion network/system member	-191.01	-2.79*	-254.34	-6.12
HHI	-62.6	-0.21	-148.07**	0.31
HMO penetration	-214.63***	-1.68	-123.36	2.87
Percentage of population 65+	-11.23***	-0.06	0.25	-0.08
Per capita income	-2.27	-0.004	8.03**	0.06
Percent uninsured	3.42	0.17	36.24***	0.06
Rural	-0.56	0.02	-19.28	0.67
2003	37.17**	0.07	34.40**	0.34
2004	81.56***	0.18	108.85***	1.07
Constant	123.27	3.78***	-578.55***	-2.48
N	2235		295	

*$p \leq .10$; **$p \leq .05$; ***$p \leq .01$

Table 17: HTIV Results for Hospital Provision of Uncompensated Care

	Nonprofit		*For-profit*	
Variables	Number of Admissions	Percent of Admissions	Number of Admissions	Percent of Admissions
CON	38.87	0.07	738.43	6.90
REQUIREMENT	-77.61	-3.36	3342.12	30.07
POOL	382.01	1.42	5030.90	65.76
CON*REQUIREMENT	15.71	0.17	-	-
CON*POOL	66.32	0.25	-484.41	-5.61
POOL*REQUIREMENT	385.07	3.68	-3231.54	-45.64
CON*REQUIREMENT*POOL	-49.15	-0.21	148.01	1.68
Technology Intensity	-2.50	-0.19	-40.34	-0.45
ER	26.06	0.22	-10.85	-0.19
Teaching hospital status	-56.88	-0.58	-53.72	0.92
Proportion with public owner	-19.33	-0.22	-40.04	-0.40
Hospital size	0.72***	0.85	0.07	0.0016
Proportion network/system member	-1.57**	-0.03	-5.17	-0.06
HHI	172.02	-2.04	-58.81	-2.42
HMO penetration	-18.65	-0.03	14.96	0.76
Percentage of population 65+	-108.47	-0.15	45.95	-0.06
Per capita income	54.48	-0.04	25.97	-0.70*
Percent uninsured	31.11	0.24	98.22	5.33
Rural	16.60	0.0022	359.39	4.34
2003	27.78***	-0.19	66.16***	-1.41***
2004	69.26***	-0.11	138.09***	-0.71***
Constant	-264.45	7.58	-9083.74	-30.29
N	2235		295	

*$p \leq .10$; **$p \leq .05$; ***$p \leq .01$

Regulatory Variables

Results obtained from the GLS procedure show that controlling for other covariates, CON laws, acting individually, have increased both the number and percent of nonprofit hospital admissions for the uninsured. Results obtained from the HTIV procedure yield larger estimates for the CON variable in the number of admissions model and the same estimates in the percent of admissions model, but neither of them is statistically significant at the conventional levels. Although there are limitations with both the GLS and HTIV procedure, the cross validation suggests that the true effects of CON on nonprofit hospital admissions for the uninsured is positive and may be larger than what the GLS model predicts, indicating that nonprofit hospitals are more capable of providing such care in states with CON laws. This finding is consistent with what the model predicts.

Compared to nonprofit hospitals, GLS results did not show that CON laws alone have any effect on for-profit hospital's number of uncompensated care admissions. However, CON laws are significantly positively related to the percent of admissions for the uninsured by for-profit hospitals. The HTIV model yields much larger estimates for the regulatory effects and the signs are consistent with the GLS estimates. The cross-validation shows that CON may have a positive impact on for-profit hospital's percent of uninsured admissions, suggesting that for-profit hospitals in CON states tend to devote a larger share of their resources to provide services to the uninsured. Since for-profit hospitals perceive the failure to obtain CON as a profit loss, they might increase their uncompensated care provision in states with such a regulation. However, given the

limited for-profit sample and potential problem of weak identification with the HTIV model, this result deserves further investigation.

Both the GLS and the HTIV estimation report a positive effect of the pool on nonprofit hospitals for the number and percent of admissions for the uninsured, though the HTIV model shows a much greater magnitude. This is consistent with our prediction that uncompensated care pools, acting alone, lead to more nonprofit hospital admissions for the uninsured. It suggests that nonprofit hospitals respond to price subsidies by increasing their uncompensated care provision. For for-profit hospitals, uncompensated care pools are found to be negatively associated with the number of admissions for the uninsured but positively related to the percent of admissions in the GLS model. The HTIV model did not yield consistent results with the GLS estimates. This finding is confounding and needs further investigation given our small for-profit sample size (N=295) and limited number of years (N=3) in the sample.

Community benefit requirement laws are found to have a positive but insignificant impact on the number of uninsured admissions and a significant negative effect on the percent of self-pay/charity admissions for nonprofit hospitals. The HTIV estimation yields a negative yet insignificant impact on both the number and percent of admissions for nonprofit hospitals. The cross-validation suggests that community benefit requirement laws tend to decrease nonprofit hospital's percent of uninsured admissions. There are two possible explanations. First, nonprofit hospitals may decrease their uncompensated care provision as a result of adjusting to the amount required by community benefit requirement laws. If nonprofit hospitals are already providing a higher level of uncompensated care than required by the regulation, community benefit

requirement laws may become a non-binding constraint. Since these laws explicitly communicate the amount of uncompensated care nonprofit hospitals should provide, they might send a signal to those hospitals that are already providing a higher level than expected by the community. Consequently, these hospitals decrease their uncompensated care provision because they realize that they are unnecessarily over-producing such care. Second, these laws may have improved preventive/primary care for the uninsured which led to a decrease in the demand for inpatient care. Since community benefit requirement laws typically require that nonprofit hospitals provide health promotion services, research and education, open access to services, and community orientation in addition to uncompensated care (Ginn & Moseley, 2006), it is possible that community benefit requirement laws have enhanced access to preventive/primary care for the community. As a result, there is a decrease in the overall demand for inpatient care, which might lead to a decrease in admissions for the uninsured. Since we only have inpatient care data, we are limited in establishing a causal link between community benefit requirement laws and the decrease in self-pay/charity admissions. However, this remains a possibility.

These laws have led to a different result for for-profit hospitals. The GLS finding shows that community benefit requirement laws are negatively related to the uninsured admissions and positively associated with the percent of admissions for the uninsured among for-profit hospitals, suggesting that the laws may decrease the total number of the admissions but decrease the uninsured admissions less. The HTIV model shows a larger positive effect on the percent of uninsured admissions by for-profit hospitals. The overall evidence indicates that for-profit hospitals devote a larger share of their resources to uncompensated care. It could be that both the overall admissions and the number of self-

pay/charity admissions decreased as suggested by reasons such as improved overall preventive/primary care, but for-profit hospitals devote a larger share of their resources to uncompensated care in response to community benefit requirement laws despite such a decrease in demand among the general population. Or as the HTIV results suggest, for-profit increase their uncompensated care provision in response to such laws. This can be explained by reasons suggested by previous literature that for-profit hospitals treat failure to meet community expectations as a cost. Since community benefit requirement laws explicitly express community expectations, it is not surprising that for-profit respond to community expectations by increasing their uncompensated care provision, even though these laws are not intended for them. It is a profit maximizing strategy for for-profit hospitals to increase their uncompensated care provision in the presence of community benefit requirement laws. Again we need to be cautious about these findings given the limitations of both the GLS and HTIV models.

Results from the estimations also show evidence of significant policy interaction effects. The GLS model shows that CON laws and uncompensated care pools have jointly increased nonprofit hospital's uncompensated care provision, indicating that CON laws and uncompensated care pools may have reinforced each other's effectiveness for the nonprofit hospitals. Results from the HTIV estimation provide support for this observation. One possible explanation for this result for nonprofit hospitals is that with CON laws creating a marketplace of less competition, price subsidies may be more effective in encouraging hospitals to increase their provision of services to the uninsured.

We also calculated the total effect of the regulations on uninsured admissions based on the GLS estimates. Tables 18.1-2 present results from this calculation. The

green columns provide the parameter estimates for the total effects of the regulations on the number/percent of admissions and the yellow columns present regulatory intensities as discussed previously in the sample construction. For example, in Table 18.1, the first green column represents estimated total effects for CON when states have either both CON and pool or all three regulations and the second column reports estimated total effects of uncompensated care pools when states have either both CON and pool or all three regulations. The different values of CON correspond to the total effects of pool or CON as the intensity of CON increases. Specifically, it shows that as the intensity of CON laws increases on the intensity scale from 8.1 to 15, to 18.4, the total effects of CON on nonprofit hospital uncompensated care provision increase from 521, to 966, to 1184 admissions for states that have both CON laws and mandatory uncompensated care pools (POOL is evaluated at 2 on the intensity scale). For for-profit hospitals, although the GLS estimates yields a positive association between CON laws interacted with uncompensated care pools and number of uninsured admissions, the HTIV estimates give the opposite results. It is possible that this discrepancy is a result of the small for-profit sample since the HTIV procedure is sensitive to sample sizes. The consistent estimates between the GLS and HTIV estimations for the larger nonprofit sample support this possibility. Nevertheless, due to such limitations with our sample and methodology, we do not have sufficient evidence to show that CON laws acting jointly with uncompensated care pools might have a substitution effect on public subsidies.

Results from the GLS suggest that community benefit requirement laws, acting jointly with the uncompensated care pools, have slightly increased the for-profit number of admissions for the uninsured. However, again the HTIV estimates are inconsistent

with the GLS results. Although it is likely that the true effects could be larger than what the GLS model predicts, given the tendency of the GLS model to underestimate the regulatory effect, we do not have enough evidence to substantiate this claim. Further investigation is needed to confirm if for-profit hospitals in states with both a mandatory pool and a moderate community benefit requirement regulation tend to have more self-pay/charity care admissions than those in states with only CON regulations.

All three policies working together were found to decrease the number of admissions for the uninsured among nonprofit hospitals, which are supported by both the GLS and HTIV estimates although the latter are not statistically significant. While CON laws and uncompensated care pools have jointly increased the number of admissions for the uninsured, adopting all three policies tends to reduce that number. As a result, the total effect of implementing CON or uncompensated care pool results is a reduction in uncompensated care provided by nonprofit hospitals if states adopt all three policies (Table 18.1). One possible explanation might be that community benefit requirement laws have reduced inpatient admissions and thus reducing nonprofit hospitals' reliance on public subsidies and cross-subsidization of uncompensated care. Another potential explanation would be that if the community benefit requirement is set below the level at which hospitals actually provide uncompensated care, it could provide a signal to reduce their provision of care by suggesting that their prior levels of such care are above the levels expected by the community. We, however, are not able to distinguish the impact of the joint effects on the number or percent of admissions for the uninsured among for-profit hospitals. In our for-profit hospital sample, the interactions of three policies working together happen to be perfectly collinear with the joint variations of CON laws

and requirement regulations. The binary interaction was dropped out of the model and consequently we are not able to conclude whether the parameter estimate on the three-way interactions is due to the impact of all three policies working jointly.

Table 18.1: Total effects of Regulations on Nonprofit Hospital Provision of Uncompensated Care (GLS)

Number of Admissions				*Percent of Admissions*	
Estimated Total Effects of CON		Estimated Total Effects of Pool		Estimated Total Effects of CON	
	when POOL=2 and		when POOL=2 and		when POOL=2 and
521.397	CON=8.1	528.836	CON=8.1	0.891	CON=8.1
965.55	CON=15	891.5	CON=15	1.65	CON=15
1184.408	CON=18.4	1070.204	CON=18.4	2.024	CON=18.4
	when POOL=2; REQUIREMENT=3 and		when POOL=2; REQUIREMENT=3 and		
-173.421	CON=8.1	-135.04	when CON=8.1		
-321.15	CON=15	-337.9	when CON=15		
-393.944	CON=18.4	-437.86	when CON=18.4		

Table 18.2: Total effects of Regulations on For-profit Hospital Provision of Uncompensated Care (GLS)

Number of Admissions			
Estimated Total Effects of Community Benefit Requirement		Estimated Total Effects of Pool	
			when POOL=2 and
1263.12	when POOL=2 and REQUIREMENT=3	-28.698	CON=6.3
		508.998	CON=20.7
		1126.2	when POOL=2 and REQUIREMENT=3

To compare our results with previous studies that do not typically control for policy interactions, we also test how our estimation results differ from prior findings. Using the same GLS estimation, Tables 19.1-19.2 show that when CON laws alone are

included in the model, there is a positive but insignificant impact on uncompensated care provision by nonprofit hospitals, and a negative but insignificant effect on number of uninsured admissions by for-profit hospitals. Both signs are in the expected direction. In addition, we find a significant positive, yet marginal, effect on the percent of admissions by for-profit hospitals. A one unit increase on the intensity scale is associated with a .19 percent increase in the for-profit hospital admissions for the uninsured. Uncompensated care pools are found to significantly increase both the number and percent of uncompensated care admissions by nonprofit and for-profit hospitals. This finding is consistent with the existing evidence. For community benefit requirement laws, the coefficient on the number of uncompensated care variable for nonprofit hospitals is positive and insignificant and that for for-profit hospital is negative and significant, which is the same with what we find when other policies and their interactions are included. The findings are identical for the percent of uncompensated care admissions variable with or without other policies and their interactions. These results indicate that community benefit requirement laws tend not to be significantly influenced by CON laws or uncompensated care pools regulations. This is reasonable given that hospitals are expected to abide by community benefit requirement laws if they are considered as binding requirements.

Table 19.1: GLS: Comparing Estimates w/ and w/o Other Policy or Interactions (Nonprofit)

	W/O Other Policies or Interactions		***W/ Other Policies or Interactions***	
Variables	Number of Admissions	Percent of Admissions	Number of Admissions	Percent of Admissions
CON	3.26	-0.02	10.73**	0.07**
REQUIREMENT	9.71	-0.63***	9.71	-0.63***
POOL	154.27***	0.88***	51.55*	0.51*
CON*REQUIREMENT	-	-	-1.91	0.02
CON*POOL	-	-	26.82***	0.14***
POOL*REQUIREMENT	-	-	46.33	0.35
CON*REQUIREMENT*POOL	-	-	-20.49***	-0.11

*$p \leq .10$; **$p \leq .05$; ***$p \leq .01$

Table 19.2: GLS: Comparing Estimates w/ and w/o Other Policy or Interactions (For-profit)

	W/O Other Policies or Interactions		***W/ Other Policies or Interactions***	
Variables	Number of Admissions	Percent of Admissions	Number of Admissions	Percent of Admissions
CON	-2.26	0.19*	3.95	0.25***
REQUIREMENT	-42.34***	0.67***	-42.34***	0.69***
POOL	117.82***	2.15**	-131.97***	1.14*
CON*REQUIREMENT	-	-	-	-
CON*POOL	-	-	18.67***	0.004
POOL*REQUIREMENT	-	-	231.69***	-0.12
CON*REQUIREMENT*POOL	-	-	-19.57***	0.03

*$p \leq .10$; **$p \leq .05$; ***$p \leq .01$

Market Characteristics

Our GLS results for the market level characteristics are largely consistent with the previous literature. HMO penetration is found to have a significant negative impact on the number of nonprofit hospital admissions for uninsured patients and a non-significant negative impact on the percent of admissions for uninsured patients. The HTIV results validate this association but the coefficients are statistically insignificant. One reason to explain this negative relationship is that high levels of HMO penetration tend to reduce the price for paying patients, and as a result, nonprofit hospitals have less revenue to cross-subsidize services to the uninsured. At the same time, market penetration by HMOs might also reduce the admissions for the insured patients, which makes the proportion of admissions for the uninsured largely unchanged. Given our relatively small sample size (N=295), we fail to find a significant impact of HMO penetration on the number or percent of admissions for the uninsured among for-profit hospitals in the GLS estimation. The HTIV procedure yields a positive effect of HMO penetration on for-profit hospitals. Although the sign is of the expected direction, the coefficient is not statistically significant.

The GLS results show a negative association between HHI and the for-profit hospital's uncompensated care provision, which is consistent with the HTIV estimate. In other words, in markets with higher HHI, which implies higher industry concentration, for-profit hospitals have fewer uncompensated care admissions. This finding based on the cross-validation of both models is consistent with our prediction that for-profit hospitals respond to higher competition by increasing their uncompensated care provision and react to lower competition by decreasing it. A plausible explanation is higher industry

concentration might have made paid care more expensive and hence the cost of uncompensated care is higher. Although we fail to find a significant association between market concentration and nonprofit hospital uncompensated care provision, this is consistent with findings from previous studies that examine the impact of various other regulations on hospital provision of uncompensated care (Bazzoli, Lindrooth et al. 2006).

A higher percentage of uninsured was found to be significantly associated with more admissions for the uninsured for for-profit hospitals in the GLS estimation and insignificant in the HTIV estimation. The percent of population over 65 was negatively related to uncompensated care provision for nonprofit hospitals in both estimation procedures. These results could suggest that in places where health insurance coverage for the non-elderly is low, hospitals face greater demand for uncompensated care. Per capita income is found to be positively related to the number of admissions for the uninsured for for-profit hospitals in the GLS estimation. This finding is contradictory to our prediction and merits further attention. Even though we did not find a significant impact of the percent of uninsured on nonprofit hospital provision of uncompensated care, this finding is consistent with results from prior studies (Bazzoli, Lindrooth et al. 2006).

Hospital Characteristics

Some hospital characteristics have also significantly influenced a hospital's ability to provide uncompensated care. For both nonprofit and for-profit hospitals, technological intensity is found to be negatively related to their percent of uncompensated care admissions in both the GLS and HTIV estimations although the HTIV estimates are insignificant. This cross-validation could mean that hospitals that are more technologically sophisticated have higher number of admissions for paying patients.

One explanation for this result might be that such hospitals may provide better quality of care than hospitals with lower technology intensity and hence attracting more paying patients.

Not surprisingly, for both types of hospitals increasing bed size is associated with an increasing number of admissions that are self-pay or charity. However, among for-profit hospitals, size is negatively related to the percent of admissions for the uninsured in the GLS estimation, while we are unable to detect any effect of bed size on the share of uncompensated admissions among non-profit hospitals. This finding was not validated by the HTIV model and requires further investigation.

The percent of public hospitals in the market is significantly negatively related to the number of admissions for the uninsured among nonprofit hospitals in both GLS and HTIV estimations. This means that public hospitals may have crowded out nonprofit hospitals in terms of their uncompensated care provision. Similarly, we find that the higher the percent of hospitals that belong to a network/system, the lower the percent of uncompensated care admissions by nonprofit hospitals as validated by both the GLS and HTIV procedures. Since research indicates that hospitals within a network/system provide more uncompensated care than those that are not in a network/system (Bazzoli, Lindrooth et al. 2006), it is not surprising that their presence will lead to a crowd-out effect on nonprofit hospital provision of such services. We did not, however, find any significant impact of public hospitals or network/systems hospitals on for-profit hospitals although both GLS and HTIV estimation yield a negative but insignificant association. We might not have enough data to identify the effect given our sample size.

Wrapping up, our findings from the cross-validation of the GLS and HTIV are summarized in Table 20. The strength of the evidence was indicated by three stars (meaning the GLS and HTIV procedures yield consistent results) or no star (meaning the GLS and HTIV model produces inconsistent results). The table also shows whether our results conformed to the hypotheses. Even though both the GLS and HTIV methods have their limitations, our cross-validation provides a way to overcome some of the drawbacks. As can be seen from the table, most of our GLS and HTIV findings are consistent and conform to our predictions. Some of our results however need further investigation because we do not have strong evidence to reach a conclusion.

Table 20: Summary of Effects on Uncompensated Care Provision

	Uncompensated Care					
Variables	**Nonprofit**			**For-profit**		
	Predicted	Found		Predicted	Found	
		Number of Admissions	Percent of Admissions		Number of Admissions	Percent of Admissions
Regulatory Measures						
CON	+	+***	+***	+/-		+***
POOL	+	+***	+***	+	-	+***
REQUIREMENT	+		-***	+/-	-	+***
CON*POOL	+	+***	+***	+/-	+	
CON* REQUIREMENT	+/-			+/-		
POOL*REQUIREMENT	+/-			+/-	+	
CON*POOL* REQUIREMENT	+/-	- ***		+/-	-	
Hospital Characteristics						
Teaching hospital status	+			+		
Percent of public hospital	-	-***		+		
Technology intensity	+		-***	+		
Hospital size	+	+***		+	+***	-
ER	+			+		
Percent of network/system member	-		-***	+		
Market Characteristics						
HHI	+			-	-***	
HMO penetration	-	-***		+		
Percentage of population aged 65 or above	-	-***		-		
Per capita income	-			-	+***	
Percentage of population that are uninsured	+			+	+***	
Rural	-			-		

CHAPTER SIX

CONCLUSION

This chapter presents a summary of the dissertation research. The first section summarizes the results while the second section discusses policy implications. Study limitations and extensions for future research are provided in the last section.

Summary

This dissertation examines the effects of various state regulations on hospital provision of uncompensated care and analyzes both for-profit and nonprofit hospitals' responsiveness to the regulatory environment.

Despite the limitations with our data and methodology, our findings from the cross-validation of the GLS and HTIV models suggest that nonprofit and for-profit hospitals respond to some policy instruments similarly and others differently. For example, our evidence suggests that both nonprofit and for-profit hospitals respond to CON laws by increasing their uncompensated care provision. This may be partially attributed to the fact that nonprofit hospitals behave differently in markets with different levels of industry concentration. As suggested by the literature, nonprofit hospitals increase their uncompensated care provision when industry concentration grows. For-profit hospitals, although responding to CON regulations in similar ways, may view failure to obtain CON regulations as a cost. Their increase in uncompensated care provision is a strategy to maximize profits. Nonprofit and for-profit hospitals also respond to policy incentives such as community benefit requirement laws differently. These laws were found to decrease the uncompensated care provision by nonprofit

hospitals, while increasing the provision of such care by for-profit hospitals. This is an interesting finding suggesting that community benefit requirement laws may have sent a signal of overproducing uncompensated care to the nonprofit hospitals that are already providing a higher level of uncompensated care than mandated. They may have also improved preventive/primary care for the uninsured which consequently led to a decrease in demand for inpatient care. However, we lack primary/preventive care data to validate such a connection. The findings also suggest that again for-profit hospitals might consider providing uncompensated care as a profit maximizing strategy and hence respond to community benefit requirement laws by increasing their supply of uncompensated care. It is also plausible that in markets where nonprofit hospitals reduce their uncompensated care provision, for-profit hospitals increase their provision of such care. This is because a decrease in uncompensated care provision increases unmet demand for such care, which in turn increases community expectations regard hospital provision of uncompensated care. Since for-profit hospitals respond to an increase in community expectations by increasing their uncompensated care provision, they might increase such provision when nonprofit hospitals decrease it. However, it is not clear to us if the total market level of uncompensated care has changed as a result of such a shift.

In addition to the above differences between nonprofit and for-profit hospitals, regulations working together can in some cases enhance the effectiveness of one another. For example, uncompensated care pools, when interacted with CON laws, have greatly increased uncompensated care provision by nonprofit hospitals. When the three policies are implemented together, community benefit requirement laws seem to have limited the need for nonprofit hospitals to seek support from the uncompensated care pools or cross-

subsidization of services. Specifically, these laws might have improved preventive/primary care for the uninsured so that the demand for the more costly inpatient care is reduced. As a result, nonprofit hospitals could reduce their reliance on uncompensated care pools to reimburse for their free care. Another potential explanation is these laws might have send a signal to nonprofit hospitals already providing a higher level of uncompensated care than required by such a regulation to reduce their care.

Some hospital characteristics also influence uncompensated care provision by nonprofit and for-profit hospitals. Larger hospitals tend to provide more uncompensated care than smaller hospitals, both nonprofit and for-profit. Nonprofit hospitals that are more technologically sophisticated tend to have a lower percentage of uncompensated care. The presence of public hospitals and hospitals that belong to a network/system in a local market lead to lower uncompensated care provision by nonprofit hospitals in that same market.

Both nonprofit and for-profit hospitals respond to the market environment by adjusting their uncompensated care provision. For-profit hospitals decrease their uncompensated care provision when market concentration is high and increase such provisions when uninsured populations increase. Nonprofit hospitals decrease their uncompensated care provision when HMO penetration increases market competition.

Policy Implications

The study results have significant implications for state health policies that aim at improving access to care for the underinsured and uninsured. Reductions in the provision of uncompensated care by hospitals have limited access to care for those who need it most. Further the disproportionate distribution of the uncompensated care burden has started to jeopardize the financial stability of some hospitals, particularly those that are considered as safety-net hospitals for the economically disadvantaged. Understanding the influence of the regulatory environment, especially policy interactions will help policymakers design more complex strategies to address these important issues.

Our study has significant implications for states that do not have CON laws or are reexamining the impact of their existing CON laws on uncompensated care provision. Our findings indicate that both nonprofit and for-profit hospitals respond to CON laws by increasing their uncompensated care provision. As suggested by previous literature, with CON laws creating a marketplace of less competition, nonprofit hospitals have more resources to cross subsidize uncompensated care. For-profit hospitals might perceive the failure to obtain CON as a profit loss and increase their uncompensated care provision in states with such a CON regulation. Therefore, implementing such a policy in either a mixed ownership market or in markets dominated by nonprofit hospitals may be able to increase access to care for the uninsured.

State policies aimed at assisting safety-net hospitals may consider providing public subsidies in combination with regulations that explicitly communicate community expectations. Our evidence suggests that explicit expression of community expectations reduces the provision of uncompensated care by non-profit hospitals and results in greater

provision of such care by for-profit hospitals. This result indicates that the new IRS rulings on nonprofit hospital reporting of community benefits may have unintended indirect effects on for-profit hospitals because in mixed ownership markets where community benefit requirement laws are implemented, for-profit hospitals may provide more uncompensated care. In markets dominated by nonprofit hospitals, implementing community benefit requirement regulations may not increase uncompensated care provision by nonprofit hospitals. Such regulations may send a signal to those hospitals that are already providing a higher level of uncompensated care than expected by the community. Consequently, these nonprofit hospitals decrease their uncompensated care provision because they realize that they are unnecessarily over-producing such care. We do not have enough evidence to show, however, if the total market level of uncompensated care has changed as a result of such a shift of uncompensated care provision from nonprofit to for-profit hospitals. The net changes in the amount of uncompensated care at the market level will depend on the magnitude of the decrease by nonprofit hospitals and increase by for-profit hospitals.

Implementing policies that suppress competition (e.g., CON laws) and public subsidies (e.g., uncompensated care pools) together may increase the effectiveness of both types of regulations for nonprofit hospitals. Because nonprofit hospitals largely rely on cross-subsidization of services to provide uncompensated care, a less competitive market will enhance their financial ability to do so. Further incentives from public subsidies will increase their willingness to provide uncompensated care.

Other findings of the study indicate that there is a significant crowd-out effect by public hospitals. Nonprofit hospitals are particularly sensitive to the amount of

uncompensated care provided by public hospitals in the same market. They reduce their uncompensated care when there is a large presence of public hospitals in the market. Although public hospitals are not the focus of this study, they play a central role in promoting health in the community. Policy makers need to understand the extent and magnitude of the crowd-out effect in order to write appropriate policy prescriptions to support safety-net hospitals.

Study Limitations and Future Research

The current study benefited from our ability to examine various regulations using comprehensive information on admissions for the uninsured, an improved alternative measure of uncompensated care. However, important limitations must be noted.

First, despite being a powerful technique to correct endogeneity as a result of latent individual effects, the HTIV procedure suffers from weak identification due to our data limitations. Although we cross-validate results using a random effects GLS, future studies will benefit from obtaining data that have more variations for some time-varying variables so as to improve the HTIV estimation.

Second, our measures of the regulatory variables do not capture all the variations of the policies under investigation, so we are unable to completely eliminate the potential confounding factor ---- state effects. In other words, the lack of such a precise measure limits our ability to completely separate the effects of being in a particular state and the effects of the regulations. Future efforts should focus on conducting surveys with the states to collect data on all dimensions of each regulation (e.g., scope, length, restrictiveness and uncertainty). Methods to operationalize these dimensions also deserve further attention.

Another limitation of the study is the lack of hospital discharge data on other non-study states. Although our study represents a comprehensive analysis of these regulations using uncompensated care admission as a measure, we only have data on 17 states. Selection bias remains a potential problem even though we have good reasons to believe that HCUP participating and non-participating states are not systematically different in terms of their uncompensated care provision. In addition, because we worked with only

17 states, the lack of variation on the regulatory measures limits our ability to examine a broader scope of policies such as conversion and AWP-FOC laws. Future studies should identify datasets with information on more states to obtain greater variation on the entire spectrum of policies.

It is also important to note that neither the Hausman-Taylor nor the random effects GLS procedure corrects for the bias as a result of reverse causality if we suspect that such bias indeed exists. In other words, hospitals might have endogenously selected themselves into different programs based on their level of uncompensated care. In such cases, a propensity score matching technique might prove useful. Intuitively, the propensity score matching constructs a control group from the group of untreated individuals and ensures that the control group is as similar as possible as the treatment group with respect to observable characteristics that affect both the outcome and the treatments. Matching has some important advantages over the Hausman-Tayor procedure. As a non-parametric method, matching does not impose any specific linearity assumptions on the evaluated effects that are inherent in regression-based modeling. Furthermore, matching explicitly tries to find for each untreated unit a similar treated unit to evaluate the counterfactual, i.e. what would happen to the treatment group without the treatment. If sample selection remains a concern, additional information on policy adoption needs to be collected. Unfortunately, these data were not available at the time of the study. However, since our unit of analysis is the individual hospital and the adoption of various regulations by the states might be influenced by the magnitude of the uncompensated care at the state level, such endogeneity problems might be mitigated. Another reason to believe that reverse causality will not significantly bias our results is

that policy adoptions are unlikely to be correlated with recent level of hospital uncompensated care provision. Most our states adopted these regulations several decades ago. Even if a state's decision to adopt these policies was based on its level of uncompensated care, it is more likely to be determined by the aggregated level of uncompensated care then. In other words, regulations do not correlate with the level of uncompensated care during the same time periods. Nevertheless, future research needs to control for the first stage selection using data containing information that predicts adoption.

Additional concern about endogeneity lies in the potential spillover effects. In other words, states with policies that encourage uncompensated care provision might attract the uninsured from adjacent states with less friendly polices to seek care from their hospitals. As information on patient origin for the self-pay/charity care patients is missing from our data, we are unable to examine the proportion of patients that are from a contiguous state with less generous uncompensated care policies. However, we do not expect that such a spillover, if it indeed exists, will significantly bias our results. The uninsured tend to seek care locally for three main reasons. First and foremost, they typically delay care until symptoms worsen to the point when they end up being admitted into an ER in a local hospital. Second, they lack the information about which hospitals provide charity care, not to mention which states have more uninsured-patients-friendly policies. Third, the uninsured might not be able to afford travelling to another state to seek care, given that they typically have very low income.

Finally, we had access only to inpatient data, which limited our ability to analyze the regulatory effects on primary/preventive care. For example, if a particular bundle of

regulations (e.g., community benefit requirements and uncompensated care pools) encourages hospitals to provide primary/preventive care to the underserved population, we were not able to empirically test if the decrease in uncompensated care admissions is due to the effect of that incentive. Future research should focus on incorporating data on primary/preventive care to capture the intermediate effect of these regulations so that we are able to not only assess the full spectrum of the regulatory effects but also improve our understanding of the mechanisms by which each regulation or a bundle of regulations influences uncompensated care provision for the underinsured and uninsured populations.

Future work should focus on obtaining more data on HMO penetration, percent of population over 65, and uninsurance rate so that there will be real changes over time for the HTIV method to yield robust instruments. Furthermore, model identification could also be improved by adopting the county based market measure. Using patient flows to define market has the potential for endogeneity bias when we investigate the effects of competition on hospital cost and outputs (Wong, Zhan et al. 2005). Since our market groups were constructed based on hospital admissions and the dependent variable is also admissions, it is likely that our market level variables are correlated with the random error term. Given that the HTIV procedure is sensitive to endogeniety, we should be able to obtain improved estimates with an exogenous county based market measure. Finally, we should further adjust admissions by case-mix to account for the intensity of resource use so that our measure could better reflect the actual hospital effort for uncompensated care. As suggested by some studies comparing adjusted and unadjusted utilization measures, case mix has significantly affected the level of hospital resource use (Weiner, Starfield et al. 1991; Berlowitz, Ash et al. 1998; Liu, Sales et al. 2003; Lee and Roh

2007). Future work should include in the empirical model a case mix severity measure from the discharge data using the ICD codes.

In conclusion, despite the limitations, our study represents a comprehensive examination of competition (CON), subsidy (uncompensated care pool) and requirement (community benefit requirement) regulations that have the most influence on hospital uncompensated care provision. It overcomes the limits of previous research that focused primarily on the effect of a single regulation in a given state. The current study not only improves generalizability by examining hospitals in 17 U.S. states, it also investigates multiple policy interventions and their interactions, which are argued to be crucial in understanding the impact of the regulatory environment on hospitals provision of uncompensated care. In addition, the current study improves upon measures of uncompensated care using a more direct measure of the actual care delivered to the uninsured --- admissions for self-pay/charity patients. Findings from this study suggest that nonprofit and for-profit hospitals view and respond to policy incentives differently. In addition, regulatory interactions are found to significantly influence the uncompensated care provision by both nonprofit and for-profit hospitals. The study helps improve policy maker's understanding of the impact of the regulatory environment on nonprofit and for-profit hospital behaviors and their uncompensated care provision. It contributes to the current debate over the new IRS ruling on community benefit reporting for tax exempt nonprofit hospitals.

APPENDIX A

REGULATORY VARIATIONS

The following table presents study regulations for all 48 U.S. states.

Table B.1: Hospital Regulations in 48 U.S. States (by 2007)

States	*CON*	*Duration*	*REQUIREMENT*	*Duration*	*POOL*	*Duration*	*CONVERSION*	*Duration*	*AWP/FOC*	*FOC Duration*	*AWP Duration*
Alabama	X	1979-									
Arizona*		1971-1985			X	1992-	X				
Arkansas†	X	1975-			X				X	1995-	1995-
California		1969-1987	X	1997- effective, passed in 1994	X	1988-	X				
Colorado*		1973-1987			X	1983-The Reform Act for Provision of Care to the Medically Indigent	X				
Connecticut	X	1973-	X	2001-		1991-1994	X				
Delaware	X	1978-									
Florida*	X	1973-				1984-1996					
Georgia	X	1974-			X		X		X		1976-
Idaho		1980-1983	X						X		1994-
Illinois	X	1974-	X						X		1994-
Indiana		1980-1996, 1997-1999	X	1994- reporting	X	HCI			X		1994-
Iowa*	X	1977-									
Kansas		1972-1985									
Kentucky*	X	1972-							X		1994-
Louisiana†	X	1991-					X		X		1995-
Maine*	X	1978-									
Maryland*	X	1968-	X	2001-	X	1974-	X				
Massachusetts*	X	1972-	X	1994-voluntary	X	1985-1988, 1989-1991, 1992-1997, 1998-					
Michigan	X	1972-									
Minnesota		1971-1985	X								
Mississippi	X	1979-							X		1984-
Missouri	X	1979-	X	1994- Access							
Montana	X	1975-									1991-1993
Nebraska†	X	1979-			X		X	1996-			
Nevada*	X	1971-	X	2005-	X	Property tax funded					
New Hampshire	X	1979-	X	2000- effective, passed in 1999			X				
New Jersey*	X	1971-			X	1980-1993, 1993-					
New Mexico		1978-1983			X				X	1979-	
New York*	X	1966-	X	1991- general	X	1974-1997, 1997-					

* Study state

† Long-term care facility only

Appendix B: Continued

States	*CON*	*Duration*	*REQUIREMENT*	*Duration*	*POOL*	*Duration*	*CONVERSION*	*Duration*	*AWP/FOC*	*FOC Duration*	*AWP Duration*
North Carolina*	X	1978-	X	2005-							
North Dakota		1971-1995							X	1985-	
Ohio†	X	1975-			X						
Oklahoma	X	1971-			X				X	1996-	
Oregon†*	X	1971-					X				
Pennsylvania		1979-1996	X	1997-mini	X						
Rhode Island*	X	1968-	X	1999- effective, passed in 1997			X				
South Carolina	X	1971-									
South Dakota		1972-1988									
Tennessee	X	1973-									
Texas		1975-1985	X	1993- mini					X	1975-	1992-
Utah*		1979-1984	X								
Vermont	X	1979-	X								
Virginia	X	1973-			X	SLH 1946-1989, 1989-			X		1983-
Washington*	X	1971-					X				
West Virginia*	X	1977-			X	Property tax funded					
Wisconsin†*	X	1977-1987, 1993-							X	1975-	
Wyoming		1977-1989							X		1990-
Total	34		18		18		12		15		

* Study state

† Long-term care facility only

APPENDIX B

MARKET DEFINITION

To define markets by patient flow, we use the HCUP SID data to implement the following algorism[18]. We first determined patients' origin by their zip code and the county/counties that correspond to that zip code. We then found the hospitals they attended and the county/counties that correspond to those hospitals. We defined markets as county/counties that sent at least 50 percent of its patients to another county. As a result, all counties that share the initial market were grouped.

Counties that do not belong to any markets after the initial grouping were then added to the market groups if a county sent at least 21 percent of its patients to a county that is already in a market. Counties that belong to multiple markets were then placed into the market to which it sent its largest number of patients greater than 21 percent. After all markets were defined, smaller markets were absorbed into larger markets if the combination of the markets was logical in terms of spatial proximity and patient flow.

For example, Maryland has 24 counties with 22 counties that have hospitals in our sample[19]. In the first step, Allegany and Garrett were grouped in the same market since 98 percent of Allegany patients were from Garrett. Baltimore county and Baltimore city were put in the same market as 70 percent of Baltimore county patients were from Baltimore city. After the initial grouping, we have 12 market groups and three counties

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[18] We use counties as markets for Nevada, New York, and Rhode Island since either zip code or patient unique identifier/medical records are missing for these three states. For Massachusetts, Maryland, Maine, West Virginia and Utah, we use the first three digits of patients' zip codes to determine the county-to-county patient flow table.

[19] Queen Anne's and Caroline counties do not have hospitals in our sample, so we did not include those counties in our market groups.

(Talbot, Kent and Dochester) that were not assigned to any markets (as shown by the Figure 2). As Kent and Dochester sent most their patients (40 and 55 percent) to Talbot respectively, we grouped them in the same market. Baltimore county belongs to both Baltimore city market and Howard county market, and it sent its largest number of patients greater than 21 percent to its own Baltimore county market. Baltimore city sent 95 percent and Howard County sent 52 percent of their patients to Baltimore county. We therefore group Baltimore county and Baltimore city in the same market. Smaller markets such as Somerset were absorbed into the larger Wicomico/ Worcester market because geographically Somerset borders both counties and it sent a significant number of patients (86 percent) to Wicmico and the remaining 14 percent to Worcester. Calvert was absorbed into the Prince George's market and Howard/Carrol market was absorbed into Baltimore county/Baltimore city market for similar reasons. As a result of all the groupings, we ended up with 10 hospital market groups for Maryland.

APPENDIX C

SENSITIVITY ANALYSIS: MARKET DEFINED BY PATIENT FLOW VS. COUNTY

We performed a sensitivity analysis to test if our results are sensitive to different market measures. Table C.1 defines each market measure. Table C.2 shows that mean market concentration is higher for the county based definition than the patient flow based market definition. Tables C.3-4 represents results from including different HHI measures in otherwise identical hospital uncompensated care admission regressions. The parameter estimates for the regulatory variables are remarkably similar in sign although the level of significance differs slightly. The estimated effects were much lower in absolute value for variables such as CON, CON*POOL and all three variables interacted in the county model than that in the patient flow model, and the magnitude of uncompensated care pool variable is much higher in the county model. In addition, the parameter estimates on the HHI variables were largely similar in sign and magnitude, which is consistent with what Wong et al. (2005) find in their analysis. Their study shows that competition measures based on the geographic boundary definitions and the widely used patient flow definitions yielded the highest correlations with other measures and that empirical studies examining the impact of market competition on hospital costs or outputs are insensitive to the choice of hospital competition measure employed. Lastly, most control variables in both models have the similar signs and effect sizes.

Table C.1: Definition: Herfindahl-Hirschman Index

Variable	*Definition*
HHI_market	Herfindahl-Hirschman Index based on patient flow
HHI_county	Herfindahl-Hirschman Index based on county

Table C.2: Summary Statistics for HHI by Sample and Definition

		Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
Sample w/ Technology Intensity and ER	For-profit	HHI_county	295	4375.01	3154.32	534.05	10000
		HHI_market	295	2571.69	2430.33	316.95	10000
	Nonprofit	HHI_county	2235	5233.36	3425.55	513.36	10000
		HHI_market	2235	3176.62	2953.97	316.95	10000
Sample w/o Technology Intensity and ER	For-profit	HHI_county	500	4099.15	3304.05	513.36	10000
		HHI_market	500	2460.18	2433.56	316.95	10000
	Nonprofit	HHI_county	2625	5091.12	3421.31	513.36	10000
		HHI_market	2625	3165.10	2930.38	316.95	10000

Table C.3: GLS Results for Hospital Provision of Uncompensated Care (Patient Flows)

	Nonprofit		*For-profit*	
Variables	Number of Admissions	Percent of Admissions	Number of Admissions	Percent of Admissions
CON	10.73**	0.07**	3.95	0.25***
REQUIREMENT	9.71	-0.63***	-42.34***	0.69***
POOL	51.55*	0.51*	-131.97***	1.14*
CON*REQUIREMENT	-1.91	0.02	-	-
CON*POOL	26.82***	0.14***	18.67***	0.004
POOL*REQUIREMENT	46.33	0.35	231.69***	-0.12
CON*REQUIREMENT* POOL	-20.49***	-0.11	-19.57***	0.03
Technology Intensity	35.57	-0.26**	39.37	-0.36**
ER	19.61	0.28	51.08	0.19
Teaching hospital status	56.27	0.22	-28.81	-0.18
Proportion with public owner	-2383.43***	-7.35	-872.67	-1.66
Hospital size	1.60***	-0.001	0.97***	-0.004***
Proportion network/system member	-191.01	-2.79*	-254.34	-6.12
HHI	-0.01	-0.00002	-0.01**	0.00003
HMO penetration	-214.63***	-1.68	-123.36	2.87
Percentage of population 65+	-11.23***	-0.06	0.25	-0.08
Per capita income	-2.27	-0.004	8.03**	0.06
Percent uninsured	3.42	0.17	36.24***	0.06
Rural	-0.56	0.02	-19.28	0.67
2003	37.17**	0.07	34.40**	0.34
2004	81.56***	0.18	108.85***	1.07
Constant	123.27	3.78***	-578.55***	-2.48
N	2235		295	

Table C.4: GLS Results for Hospital Provision of Uncompensated Care Controlling for Technology Intensity and ER (County)

	Nonprofit		*For-profit*	
Variables	Number of Admissions	Percent of Admissions	Number of Admissions	Percent of Admissions
CON	7.97	0.06**	1.77	0.22***
REQUIREMENT	-14.96	-0.86***	-24.49*	0.77***
POOL	85.60**	0.40	34.93	1.80***
CON*REQUIREMENT	0.07	0.03	-	-
CON*POOL	23.91***	0.14***	-1.99	-0.05
POOL*REQUIREMENT	-35.59	0.16	49.93	-1.09
CON*REQUIREMENT*POOL	-15.46***	-0.10**	-3.30	0.10*
Technology Intensity	37.00	-0.27**	39.05	-0.38**
ER	18.36	0.28	52.02	0.21
Teaching hospital status	40.47	0.09	-33.88	-0.13
Proportion with public owner	-1447.31**	-7.85	-370.30	-6.91
Hospital size	1.56***	-0.001*	1.00***	-0.004***
Proportion network/system member	-13.26	-1.21	-168.69***	-2.64
HHI	-0.01	-0.0001	0.01	0.0002***
HMO penetration	-163.94*	-1.96	-89.19	-0.50
Percentage of population 65+	-1393.22***	-10.50	-445.78**	-10.33***
Per capita income	-3.26	-0.01	10.41***	0.08
Percent uninsured	6.58	0.18	26.35	0.02
Rural	0.77	-0.004	-26.03	0.52
2003	38.86*	0.06	32.57**	0.33
2004	82.59***	0.17	109.14**	1.07
Constant	165.35	4.97	-548.45**	-1.55
N	2235		295	

APPENDIX D

THE RURAL/URBAN CONTINUUM CODES

The Rural/Urban Continuum Codes are defined as follows:

CODE	METROPOLITAN COUNTIES (1-3)
01	Counties of metro areas of 1 million population or more
02	Counties in metro areas of 250,000 - 1,000,000 population
03	Counties in metro areas of fewer than 250,000 population

NONMETROPOLITAN COUNTIES (4-9)

04	Urban population of 20,000 or more, adjacent to a metro area
05	Urban population of 20,000 or more, not adjacent to a metro area
06	Urban population of 2,500-19,999, adjacent to a metro area
07	Urban population of 2,500-19,999, not adjacent to a metro area
08	Completely rural or less than 2,500 urban population, adjacent to a metro area
09	Completely rural or less than 2,500 urban population, not adjacent to a metro area

99	Missing Value

APPENDIX E

DISTRIBUTION OF HOSPITALS BY OWERSHIP TYPES

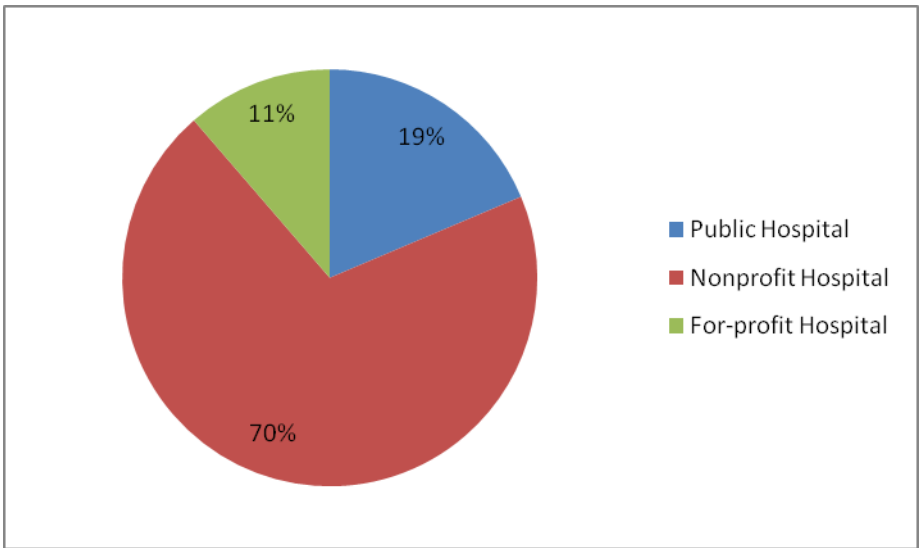

Figure E.1: Percent of Hospitals by Ownership Types 2002

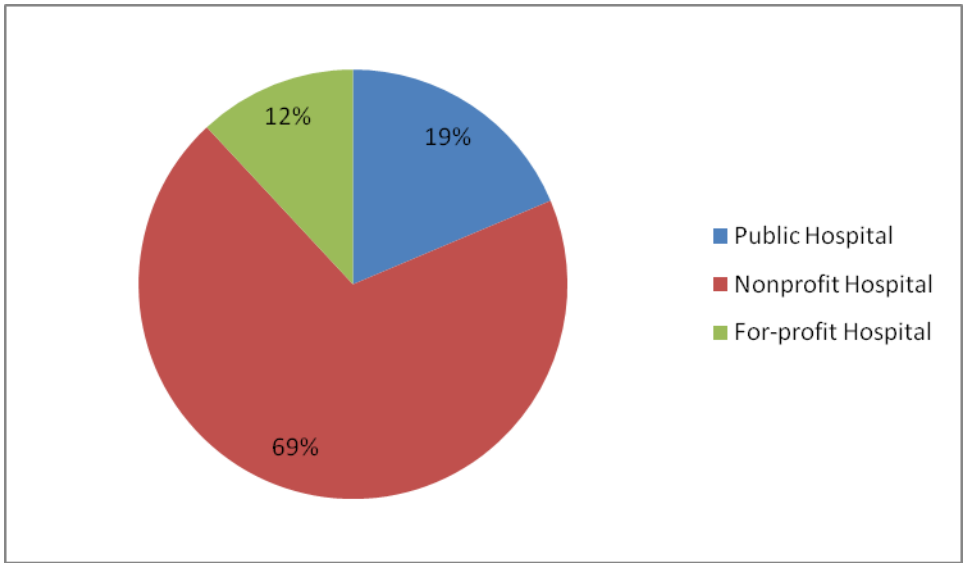

Figure E.2: Percent of Hospitals by Ownership Types 2003

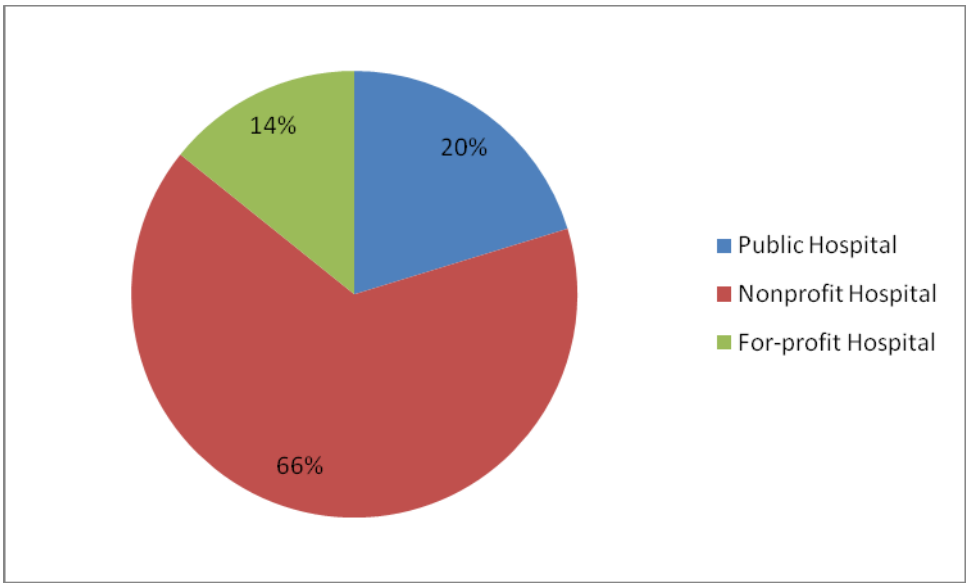

Figure E.3: Percent of Hospitals by Ownership Types 2004

APPENDIX F

COMPARING SAMPLE WITH U.S. STATISTICS

Table F.1: Two Sample *t* Test --- Nonprofit Hospitals

Variable	*Obs*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Conf.*	*Interval]*
Sample	5	0.2	0.0249	0.055678	0.130867	0.269133
U.S.	5	0.2	0.029326	0.065574	0.118579	0.281421
diff	5	2.98E-09	0.020736	0.046368	-0.05757	0.057574

mean(diff) = mean(var1 - var2) t = 0.0000
Ho: mean(diff) = 0 degrees of freedom = 4
Ha: mean(diff) < 0 Ha: mean(diff) != 0 Ha: mean(diff) > 0
Pr(T < t) = 0.5000 Pr(|T| > |t|) = 1.0000 Pr(T > t) = 0.5000

Table F.2: Two Sample *t* Test --- For-profit Hospitals

Variable	*Obs*	*Mean*	*Std. Err.*	*Std. Dev.*	*[95% Conf.*	*Interval]*
var1	5	0.202	0.06127	0.137004	0.031888	0.372113
var2	5	0.2	0.047749	0.106771	0.067427	0.332573
diff	5	0.002	0.032465	0.072595	-0.08814	0.092138

mean(diff) = mean(var1 - var2) t = 0.0616
Ho: mean(diff) = 0 degrees of freedom = 4

Ha: mean(diff) < 0 Ha: mean(diff) != 0 Ha: mean(diff) > 0
Pr(T < t) = 0.5231 Pr(|T| > |t|) = 0.9538 Pr(T > t) = 0.4769

APPENDIX G

Table I.1: Hospital Provision of Uncompensated Care by Type of Ownership (Pooled OLS)

	Nonprofit		*For-profit*	
Variables	Number of Admissions	Percent of Admissions	Number of Admissions	Percent of Admissions
CON	4.939*	0.047*	6.58	0.33***
REQUIREMENT	2.295	-0.627**	-29.71	0.44
POOL	102.322***	0.426	-162.14**	1.50*
CON*REQUIREMENT	-0.598	0.030	-	-
CON*POOL	27.864***	0.212***	23.59***	-0.06
POOL*REQUIREMENT	-4.547	0.655	246.09	-1.46
CON*REQUIREMENT*POOL	-18.596***	-0.153***	-27.84**	0.09
Teaching hospital status	114.729***	0.102	-187.14***	-1.27**
Proportion with public owner	-1421.311***	4.517	-2128.67***	-6.68
Hospital size	1.904***	-0.002***	1.83***	-0.005***
Proportion network/system member	-316.237**	-4.582***	-48.57	-0.42
HHI	-0.007	-0.0001	-0.03***	-0.0000003
HMO penetration	-293.959***	-2.148***	-105.19	5.97***
Percentage of population 65+	-7.761**	-0.038	-0.32	-0.14***
Per capita income	-4.156***	-0.021	7.79**	0.06
Percent uninsured	9.870**	0.169***	38.51***	-0.07
Rural	-3.997	0.058	-18.41	0.82***
2003	40.473*	-0.042	41.01	0.38
2004	84.793***	0.205	106.42***	1.08**
Constant	144.676	4.127***	-566.86***	-2.00
N	2322		295	

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