ANALYSIS OF RURAL HOSPITAL ACQUISITIONS AND UTILIZATIONS IN TEXAS

A Dissertation

by

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ABSTRACT

The main goal of this dissertation research is to explore the impacts of rural hospital acquisition on patients' access to tertiary care and treatment patterns, as well as to predict the medical care utilization provided by rural hospitals by applying a Bayesian hierarchical modeling approach.

In the first two studies, I target cross-market rural hospital acquisition between a tertiary hospital (i.e., acquiring hospital) and a local community hospital (i.e., acquired hospital) and investigate impacts of hospital acquisition on local patients' access to tertiary care and treatment patterns using Difference-in-Difference approach with Texas Inpatient Public Use Data Files (PUDF). Patients' access to tertiary care is measured on two levels: (1) on ZIP code (i.e., hospital market) level, the acquiring hospital's market share of patients before and after the acquisition; (2) on discharge (i.e., patient) level, whether a patient would be admitted by an acquiring hospital. Patients' treatment patterns are measured as: (1) on ZIP code level, the proportion of patients receiving an interventional treatment and the acquiring hospital's market share of the interventional treatment; (2) on discharge level, whether a patient would receive an interventional treatment and whether an interventional treatment would be performed at an acquiring hospital. I find that the impacts of rural hospital acquisition are different by the market competition status, various types of care, and patients' characteristics. When there is no competing hospital in the same market as the acquired hospital, the impacts on access to tertiary care are positive for inpatient newborn and cardiovascular care. The impacts are different by patients' expected payer source and severity of illness. A similar pattern is observed in the investigation of impacts on treatment patterns.

In the third study, I apply a Bayesian hierarchical modeling approach to predict the newborn delivery utilization at small hospitals in rural areas using the PUDF data. The results show that the Bayesian approach can provide a more accurate predication on the medical service utilization than a maximum likelihood approach, indicating that the Bayesian approach application might support a rational allocation of limited health care resources for rural hospitals.

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All other work conducted for the dissertation is completed by the student independently.

NOMENCLATURE

ACA	Patient Protection and Affordable Care Act
ACF	Autocorrelation function
ACS	American Community Survey
AHA	American Hospital Association
APR-DRGs	All Patient Refined Diagnosis Related Groups
BIC	Bayesian Information Criteria
CABG	Coronary Artery Bypass Grafting
CAD	Coronary Artery Disease
CI	Confidence Interval
CMS	Centers for Medicare & Medicaid Services
COPSS	Committee of Presidents of Statistical Societies
DiD	Difference-in-Difference
DMCA	Danbury Medical Center at Angleton
DSHS	Department of State Health Services
HHI	Herfindahl-Hirschman Index
HMO	Health Maintenance Organization
HRRs	Hospital Referral Regions
HSAs	Hospital Service Areas
ICD-9-CM	International Classification of Diseases, Ninth Revision, Clinical Modification
ICD-10-CM	International Classification of Diseases, Tenth Revision,

	Clinical Modification
ICD-10-PCS	International Classification of Diseases, Tenth Revision, Procedure Coding System
M&A	Mergers and Acquisitions
MCMC	Monte Carlo Markov Chain
MSE	Mean Squared prediction Error
NBER	National Bureau of Economic Research
THCIC_ID	Texas Health Care Information Collection_Identifier
OR	Odds Ratio
PCI	Percutaneous Coronary Intervention
PS	Propensity Score
PUDF	Public Use Data Files
REML	Restricted Maximum Likelihood Estimation
SMR	Standardized Mortality Rate
UTMB	University of Texas Medical Branch

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1. INTRODUCTION

1.1 History of hospital consolidation in the U.S.

Before the 1990s, an initial wave of hospital consolidation occurred among national or regional-level hospital systems in the United States (Dor and Friedman, 1994; Dranove and Lindrooth, 2003). There was also some consolidation between local hospitals especially when it came to markets with less intense certificate-of-need regulation (Dor and Friedman, 1994). Overall, the number of general short-term hospitals decreased by 5%, from 5,904 in 1980 to 5,579 in 1988, according to statistics released by American Hospital Association (AHA) in 1990 (American Hospital Association, 1990).

The 1990s witnessed a second wave of hospital consolidation, mainly involving intra-market consolidation. From 1986 to 1994, there were 112 intra-market consolidation transactions announced, with potentially mixed impacts on cost savings for consumers (Connor et al., 1997). Researchers found that a locally concentrated hospital system had been formed as a result of this wave (Cuellar and Gertler, 2005). They also investigated influences of hospital consolidation on the local markets and found that the reorganized system gained greater market power but did not improve quality of care.

After relatively little consolidation in the early 2000s, the most recent consolidation wave began around 2010, which coincides with the timeframe in which hospitals were anticipating implementation of the Patient Protection and Affordable Care Act (ACA). Before investigating the current trend, it is important to take a closer look at hospital consolidation from different perspectives.

1.2 Hospital consolidation under various lenses

In the evolving hospital market, hospital consolidation is one common strategy of restructuring individual hospitals. Each consolidation wave may have distinct features, but the nature of consolidation has not substantially changed.

To increase profitability, hospitals may game market rules and government regulations. On the one hand, hospitals attempt to increase their operating efficiencies and strengthen market power by consolidation (Connor et al., 1997; Dranove and Shanley, 1995). For example, a small local hospital might join a large tertiary hospital to reduce costs by sharing capital investments, physicians, specialties and spreading fixed costs. In particular, when facing the current reimbursement pressure, smaller hospitals are merging or aligning with larger hospitals in order to operate effectively (Fulton, 2017). Meanwhile, large hospitals or even mega-hospital systems pursue a consolidation to expand their health care delivery network and gain greater bargaining power (Cuellar and Gertler, 2005). On the other hand, regulation may accelerate hospital consolidation intentionally or unintentionally. For instance, Dor and Friedman reviewed the consolidation in 1980s (the initial wave) and concluded that consolidation of health care facilities were encouraged by the Health Planning Act of 1974 (Dor and Friedman, 1994). Some researchers also pointed out that the hospital consolidation wave in the 1990s (the second wave) might have been exacerbated by the health care reform proposed by the Clinton administration (Reardon and Reardon, 1995). Currently, scholars are raising their concerns about potential side effects of the Affordable Care Act (ACA) on hospital consolidation (Dafny, 2014).

Hospital consolidation can be horizontal or vertical, just like consolidation in many other industries (Hernandez, 2000). Horizontal integration refers to combinations of entities from the same level of a supply chain (Miller, 1996). Horizontal hospital consolidation generally indicates combinations among competitors, such as two or more hospitals providing similar types of health care services in the same neighborhood markets (Starkweather, 1971). Vertical integration means combinations of entities from various levels of the supply chain. Vertical consolidation in health care services involves a combination of hospitals, primary care facilities, clinical practitioners, and specialists (Conrad and Dowling, 1990). One classic example of vertical consolidation is hospitals acquiring physician groups. However, it may be difficult to distinguish between the two types of consolidation. For instance, a local hospital that provides medical care services joins a tertiary hospital. In this scenario, the combination of the two hospitals may not be a purely horizontal or vertical integration and it should be carefully specified.

Hospital consolidation sometimes can be categorized as same-market or cross-market consolidation depending on the geographic location of the involved hospitals (Dafny et al., 2019). In addition, hospital mergers and acquisitions (M&A) are also used to represent different types of hospital consolidation. A hospital merger is a mutual decision between independent hospitals, which are usually located within the same market (Ho and Hamilton, 2000). An acquisition (or takeover) is the consolidation where one hospital entity (acquiring hospital) takes over the other hospital (acquired hospital). Acquisitions tend to occur when the two hospitals are located in different markets, and therefore may not lead to a higher concentration for a local market (Ho and Hamilton, 2000). Due to the complexity of hospital consolidation, researchers usually focus on only one type and specify its definition and features in each particular study.

1.3 The current wave of hospital consolidation

Regulation can play an important role in incentivizing consolidation among hospitals. On average, there were 210 hospitals/health systems in the U.S. involved in consolidation transaction deals since 2010 (Kaufman Hall & Associates, 2017). As the ACA was launched in 2010, it seemed to trigger this wave of hospital consolidation, and then hospital markets became even more concentrated throughout the decade (Fulton, 2017). Hospital leaders promptly responded to the reform and declared that hospital mergers would facilitate health care coordination, quality improvement, and cost saving (Noether and May, 2017).

Under this current wave, hospital consolidation between a local and a tertiary hospital is often promised to enhance care coordination. This type of consolidation shares some common features with traditional horizontal or vertical consolidations, but it also has its own features. For example, there are more specialties and advanced equipment for diagnosis and treatment in a tertiary hospital than a local hospital, and therefore the consolidation is vertical with regard to some specific care services. Yet, the local hospital usually has a moderate number of beds and can provide general inpatient medical services. From a general medical care perspective, this consolidation is not exactly a classical vertical consolidation between physicians and hospitals. Moreover, the geographic distance between the local community and the tertiary hospital may make the consolidation be cross-market, especially for people who have transportation barriers or need social support. On the contrary, the consolidation may not be cross-market when transportation and support are not priority concerns. Thus, this type of consolidation could have various influences on local residents' access to tertiary care depending on the type of medical services and characteristics of local patients.

1.4 Impacts of hospital consolidation on various aspects of health care services

Hospital consolidation can affect many aspects of health care services, including cost, price, access to care, treatment patterns, and outcomes. Researchers have extensively studied the impacts of hospital consolidation on cost and price, while few studies have explored the impacts on patients' access to tertiary care and treatment patterns (Gaynor and Town, 2011; Vogt and Town, 2006).

1.4.1 Cost and price

Overall, researchers found that consolidation might improve operating efficiency or reduce cost when there were pressures from payers/insurers or when the consolidation was among independent hospitals. For instance, Alexander and colleagues found a positive impact of consolidation on operating efficiency when hospitals were under prospective payment system pressures (Alexander et al., 1996). Connor et al. described that merger-related price reductions were more likely to occur in the areas with higher Health Maintenance Organization (HMO) penetration (Connor, et al., 1997). Spang et al. observed an effect on cost saving when comparing mergers with non-merging rival hospitals in the same market with high HMO penetration (Spang et al., 2001). Dranove and Lindrooth noticed that consolidation between independent hospitals might generate cost savings while the effect was not observed in hospital system consolidation (Dranove and Lindrooth, 2003).

Despite the impact of hospital consolidation on cost savings, consolidation may facilitate price increases. Researchers have previously attempted to evaluate the association between hospital market concentration and price using cross-sectional study design. Most previous studies reported a positive correlation between highly concentrated hospital markets and prices/profits, while one paper presented an inconsistent result for private non-profit hospitals (Dauda, 2018; Dranove et al., 2008; Dranove et al., 1993; Keeler et al., 1999; Krishnan, 2001; Lynk, 1995; Melnick et al., 1989; Melnick et al., 2011; Moriya et al., 2010; Noether, 1988, Simpson and Shin, 1998 and Robinson, 2011). Meanwhile, Capps and Dranove used 'willingness to pay' as the measurement of market and found a positive relationship between market power and profit (Capps et al., 2003).

If panel data are available, researchers prefer to perform longitudinal study design to investigate impact of hospital consolidation across various contexts. Capps and Dranove found increased prices paid by preferred provider organizations after hospital consolidation comparing with other nearby hospitals (Capps and Dranove, 2004). Town and his colleagues aimed to estimate consolidation impact on consumer surplus, and their results indicated a considerable amount of consumer surplus loss due to mergers (Town et al., 2006). The results from these observational studies were challenged by unobserved factors that might bias the results. Dafny combined instrumental variables and rival analysis to tackle this issue, and identified a positive impact of hospital mergers on price using data from non-merging hospitals (Dafny, 2009). Other studies targeting merger and control hospitals also reported price increases after mergers (Gowrisankaran et al., 2015, Gowrisankaran, 2011, Haas-Wilson and Garmon, 2011, Lewis and Pflum, 2017). Overall, these results have consistently shown increased prices for consumers (e.g., negative effects on consumer welfare) associated with hospital mergers relative to control hospitals from the most recent decade of published studies.

1.4.2 Treatments and outcomes

Previous studies showed that hospital consolidation influenced not only price but also treatment patterns and outcomes. Bogue et al. conducted a survey study and reported that hospital consolidation might eliminate acquired hospitals' acute services or expand acquiring hospitals' acute care networks after reorganization (Bogue et al., 1995). Meanwhile, empirical evidence indicated the treatment intensity would depend on managed care penetration, hospital competition status, and patients' severity of illness. Bundorf et al. explored the impacts of managed care on treatment patterns and found patients were more likely to receive invasive treatment when they were admitted in highly-competitive hospital markets (Bundorf et al., 2004). Kesslar and Geppert found heterogeneity in the association between hospital market competition status and treatment pattern. In particular, low-risk patients were more likely to receive intensive treatments in uncompetitive hospital markets than in competitive markets while high-risk patients were more likely to receive intensive treatments in more competitive markets (Kessler and Geppert, 2005). One study directly examined the impact of hospital mergers on treatment intensity and identified a positive association using inpatient discharge data (i.e., acute myocardial infarction and ischemic heart disease) from 1990 to 2006 in California (Hayford, 2012). In particular, a hospital merger was associated with a 4% increase in the interventional treatment (i.e., angioplasty and bypass surgery). Therefore, the impact of hospital consolidation on patient level may vary by multi-level factors, including hospital market, insurance market, and patients' characteristics.

The impact of hospital consolidation on patients' outcomes is found to be mixed. Ho and Hamilton (2000) focused on heart attack and stroke patients and reported a negative impact of hospital consolidation on readmission rates, but they did not observe any significant impact on inpatient mortality rates. Hayford (2012) investigated the impact of hospital consolidation on patients with coronary artery diseases, and found a negative impact on inpatient mortality rates. One recent study did not found that the negative impact of hospital consolidation on mortality rates and readmission, though they reported that consolidation was associated with worse patient experiences (Beaulieu et al., 2020). To date, these results are inconsistent with no definite conclusion.

1.4.3 Access to care

Previously, few studies inspected the impact of hospital consolidation on patients' access to care. Two previous studies explored the effect of hospital acquisition on patients' access to tertiary care. Using data from 1992-1999 for the State of New York, Huckman investigated the influence of hospital acquisition on referral patterns, and found that referrals were increased for cardiac surgery (Huckman, 2006). Nakamura et al. conducted a similar investigation using discharge data from 1995-2000 for both Florida and New York, and reported that patients with more generous health insurance were more likely to receive referrals (Nakamura et al., 2007).

1.5 Shortage of inpatient care at rural hospitals

Across the country, rural hospitals have been experiencing increasing risk of closure. According to a report from the North Carolina Rural Health Research and Policy Analysis Center, 121 rural hospitals out of 2,250 have closed, and 40% of the rest have been struggling to stay open since 2010 (North Carolina Rural Health Research Program, 2014). Meanwhile, 46 million people (about 15% of the population) live in rural areas and need access to fundamental medical care.

Many rural hospitals now are planning to end inpatient care services or explore alternative healthcare facilities, including emergency departments and primary care clinics (Spade and Strickland, 2015). Previous studies have found that there were a substantial decrease in medical admissions and potential barriers to receive medical care in time after hospital closures or conversions to other types of facilities (Miller et al., 2020; Rosenbach and Dayhoff, 1995). Numerous concerns about the limited access to care in rural areas are raised from the public, hospital stakeholders, and policy makers, such as a shortage of inpatient care services (National Advisory Committee on Rural Health & Human Services, 2015).

The main challenge faced by rural hospitals and communities is a rational allocation of limited health care resources. Due to low reimbursement rates and low case volumes, rural hospitals neither can support as many fixed costs nor can recruit full-time physicians as a full-size hospital (United States Government Accountability Office, 2018). Moreover, residents living in rural areas have higher rates of chronic diseases, even though patient volumes of rural hospitals are low (Downey, 2013). To meet the need for medical care services and facilitate rural hospitals' transition, it is imperative to have reliable predictions of inpatient care utilizations (National Advisory Committee on Rural Health & Human Services, 2015).

1.6 An overview of the three studies in this dissertation research

As we learn from the history of hospital consolidation, when hospital markets experience a consolidation wave, each consolidation would affect health care services in a variety of ways and the resulting impacts may continue for years. Aligning with the ACA debate and reform, most hospital consolidations promise their local communities' better access to tertiary care since 2008.

However, better access to tertiary care would not come into reality by itself. As Dr. Dafny pointed out in an interview from *New England Journal of Medicine*, researchers could hardly find evidence supporting hospital M&A successfully did what they proposed to do (Dafny and Lee, 2015). Thus, it is imperative to investigate the impact of this current consolidation wave on access to care, treatment pattern, quality, and cost for further policy implementation and reform. The main goal of this dissertation research is to explore the impact of rural hospital acquisition between a local hospital and a tertiary hospital on local patients' access to tertiary care and treatment patterns provided by the acquiring hospital.

In the first study (i.e., Section 2), I examine the impact of rural hospital acquisition on patients' access to inpatient care at a tertiary hospital (i.e., acquiring hospital) using a Difference-in-Difference approach. A conceptual framework in Figure 1.1 illustrates the relationship between rural hospital acquisition and patients' access to tertiary care. The main data source used in this analysis is Texas Inpatient Public Use Data Files (PUDF), and the unit of analysis includes discharge (i.e., patient) level and ZIP code (i.e., market) level. I focus on three types of health care services: newborn, cardiovascular, and respiratory care, and identify acquisition exposed and control areas based upon income, geographic distance to the acquiring hospital, and market share of patients. Results of this study indicate that the acquiring hospital's market share of patients would increase after the acquisition when there is no competing hospital in the same market as the acquired hospital. A similar pattern is observed from patient-level analysis. These findings suggest that the overall impact of hospital acquisition on access to tertiary care at acquiring hospitals is positive.

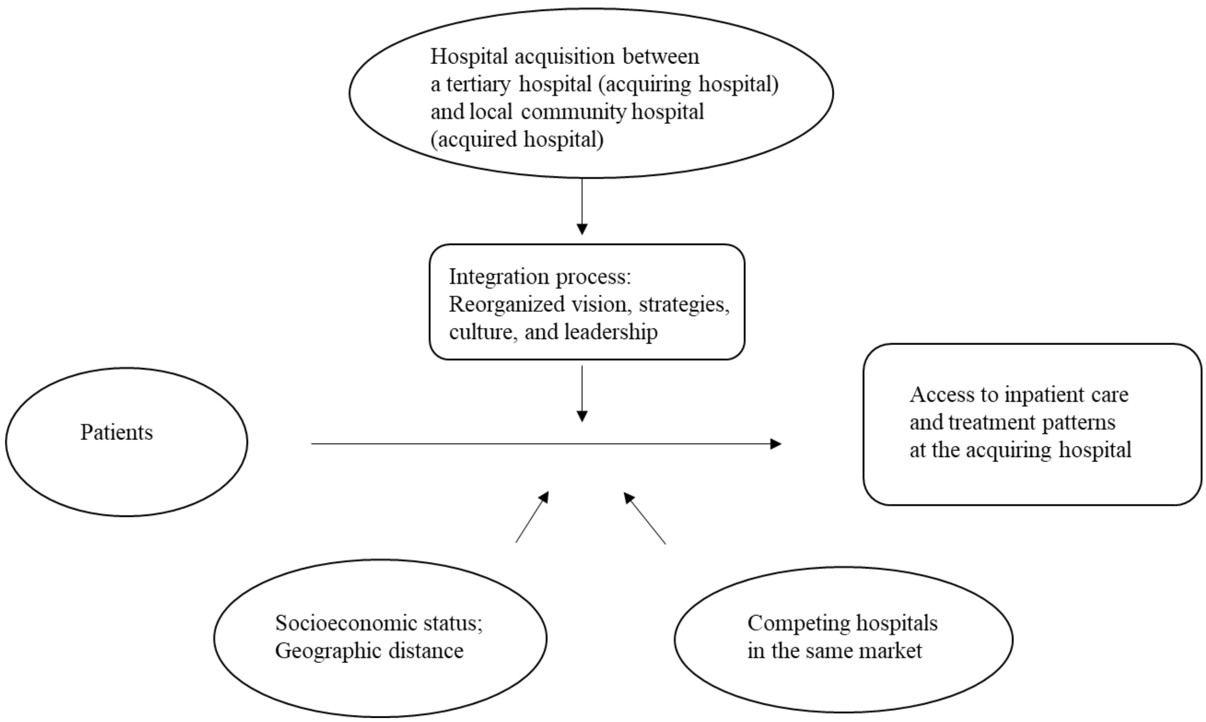
In the second study (i.e., Section 3), I focus on patients with coronary artery diseases, and evaluate the impact of rural hospital acquisition on interventional treatment patterns using a Difference-in-Difference approach. The acquisition exposed and control areas identified in the first study (i.e., Section 2) are also used in this study. On ZIP code level, two response variables used to measure the treatment patterns are: the proportion of patients receiving the interventional treatment and the acquiring hospital's market share of the interventional treatment received by patients. On discharge level, two response variables are: whether the patient receive an interventional treatment or not and whether the interventional treatment is performed at the acquiring hospital or other hospitals. Results from this study indicate that the acquiring hospital's market share of the interventional treatment would increase after the acquisition, while the overall proportion of patients receiving the interventional treatment would not significantly change. Furthermore, I observe that some acquiring hospitals might employ a "cherry-picking" strategy to select patients with private health insurance plans for higher reimbursement rates.

In the third study of this dissertation research (i.e., Section 4), I apply a Bayesian hierarchical modeling approach to predict newborn delivery service utilization at rural hospitals using data from Texas inpatient PUDF. The results show that the predicted utilization of newborn delivery service using the Bayesian hierarchical modeling approach is more accurate than a conventional maximum likelihood estimation approach. This Bayesian approach may support rational allocation of limited medical resources for rural hospitals.

Detailed data sources and unit of analysis used in the three studies of this dissertation research are summarized in Table 1.1.

1.7 Figures

Figure 1.1 The Conceptual Framework of Hospital Consolidation Impact on Access to Inpatient Care and Treatment Patterns at a Tertiary Hospital



1.8 Tables

Table 1.1 A Summary of Data Sources, Unit of Analysis, and Targeted Medical Care Used in This Dissertation Research

	Study 1 (**Section 2)**	**Study 2** (**Section 3)**	**Study 3** (**Section 4)**
Data sources	AHA, PUDF, ACS, NBER	AHA, PUDF, ACS, NBER	AHA, PUDF, ACS
Unit of analysis	ZIP code level; Patient level	ZIP code level; Patient level	Hospital level
Type of services	Newborn, cardiovascular, and respiratory care	Cardiovascular care	Newborn delivery care

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2. THE IMPACT OF RURAL HOSPITAL ACQUISITIONS ON PATIENTS' ACCESS TO TERTIARY CARE

2.1 Background

Healthcare reform efforts resulting from the 2008 U.S. presidential election have brought a new wave of hospital mergers and acquisitions, leading to more concentrated hospital markets (Dafny, 2014). The Patient Protection and Affordable Care Act of 2010 (henceforth "ACA") encourages health care providers to cooperate and improve patients' access to care (Robinson, 2010). Aligning with the reform, regional hospital networks have become more common, such as hospital acquisition between a tertiary hospital system and a free-standing local community hospital (Ibrahim et al., 2019). Executives of both the tertiary hospital system and the local community hospital often promise better access to tertiary care for local residents, while studies found that local communities' access to tertiary care is still lacking due to inadequate oversight (Khaikin and Uttley, 2016).

Theoretically, hospital acquisition can improve patients' access to tertiary care by streamlining administrative processes (Hernandez, 2000). After the acquisition, the patient referral process to the tertiary hospital system could be simplified through various strategies, such as sharing medical records and real-time appointment scheduling. As a result, patients can more easily access physicians at the tertiary hospital system or be referred/transferred into the system with fewer bureaucratic barriers (Burns and Pauly, 2002). Therefore, the tertiary hospital's market share would increase after acquisition. However, as Dr. Dafny, a researcher who has extensively studied the relationship between ACA reform and hospital mergers and acquisitions in the U.S., pointed out in an interview published in the *New England Journal of Medicine,* there was a lack of evidence for the streamlining and patient access goals from the proposed "good mergers" (Dafny and Lee, 2015).

In reality, the acquisition process can be influenced by several key factors, including acquisition vision, culture, strategy, and leadership from the reorganized hospital system (Hall and Ginsburg, 2017, Holmgren and Ford, 2018). For example, during a reorganization period, clinicians may be challenged by the shortage of necessary infrastructures, unfamiliar patient populations, and new clinical settings due to a lack of hospital acquisition strategies in practice (Haas et al., 2018). Another critical question is whether there would be any disparities in the better access to tertiary care, and published research and expert opinion have both pointed out that hospitals are incentivized to "cherry-pick" and "lemon-drop" after the acquisition (Pollack and Armstrong, 2011). There were two previous studies examining the impact of vertical integration on patients' access to tertiary care, and the results showed that hospital acquisition might mainly target lucrative patients and increase the volume of more profitable treatments (Huckman, 2006; Nakamura et al., 2007). Using 1992-1999 State of New York data, Huckman explored the impact of vertical acquisition on referral patterns and found that referrals were increased for cardiac surgery (Huckman, 2006). Nakamura et al. conducted a similar investigation using discharge data from 1995-2000 for both Florida and New York, and reported that patients with more generous health insurance were more likely to receive the referral (Nakamura, et al., 2007). Meanwhile, it is found that competing hospitals in the same market area might respond to hospital mergers and acquisitions. Competing hospitals may compete for patients through all kinds of efforts, such as attracting physicians or developing contracts with more insurers

(Zwanziger et al., 1996). Therefore, more patients could be admitted by other competing hospitals in the same market area, and the tertiary hospital's market share of patients may not increase even after the acquisition.

Texas has more hospitals than any other state, with 626 registered hospitals according to the 2016 American Hospital Association (AHA) report (American Hospital Association, 2016). At least one hospital merger or acquisition has occurred in Texas every year from 2008 to 2016, and there were eight announced hospital merger and acquisition transaction deals during 2017, making Texas one of the top three states in terms of the number of merger and acquisition deals (Irving Levin Associates, 2018). For example, a local community hospital, Danbury Medical Center at Angleton (DMCA), located in Brazoria County, Texas, merged with the University of Texas Medical Branch (UTMB) Health Systems in 2014. Leadership of DMCA said that a major motive was that their local patients would gain greater access to UTMB resources after the acquisition (Rice, 2014).

Despite the promising announcement from the hospital perspective, it is not clear whether the intended outcome actually has been achieved without any empirical evidence to support the promise. To the best of my knowledge, there has been no study examining the impact of rural hospital acquisition between a tertiary hospital system and a free-standing local community hospital on access to inpatient care provided by the tertiary hospital system.

In the first study of this dissertation, I examine the impact of hospital acquisition on access to tertiary care using inpatient discharge data and hospital acquisition data in Texas from 2006 to 2016. I focus on hospital acquisition between a tertiary hospital system (i.e., acquiring hospital) and a local community hospital (i.e., acquired hospital), whose market areas were not overlapping before the acquisition. The main aim of this study is to evaluate the impact of the cross-market hospital acquisition on access to tertiary care within one state, rather than an investigation on hospital efficiency or performance after the acquisition. The conceptual framework outlines in Figure 2.1. Figure 2.2 and Figure 2.3 illustrate key concepts used in this study. Below are research questions and the hypotheses.

Research question 1: How would the acquiring hospital's market share of patients change after a hospital acquisition?

***<u>Hypothesis 1.1</u>*: An increase is expected in the acquiring hospital's market share of patients living in the acquisition exposed area relative to the control areas, when there is no competing hospital in the same market area.**

I assume that a total number of patients living in the exposed area would not change in a relatively short time period (i.e., five years for this study), and no other competing hospitals in the same market could influence access to inpatient care at the acquiring hospital. This hypothesis stems from the assumption that patients living in the exposed area where the acquired hospital mainly served before the acquisition would be more likely to be admitted by the acquiring hospital system after their acquisition if the acquisition has been completed as expected. I select hospital acquisition exposed and control areas based upon geographic distance and income matching criteria. I verify that there are no competing hospitals located in the same market as the acquired hospital, and all other competing hospitals in the exposed area have stable market shares of patients through the acquisition periods. I hypothesize that the increased market share of patients living in the exposed area results from the acquisition between the acquired hospital and the acquiring hospital.

***Hypothesis 1.2*: When there is a competing hospital(s) in the same market area, the acquiring hospital's market share of patients living in the exposed area relative to the control areas would not increase after acquisition.**

Competing hospitals can influence the acquiring hospital's market share of patients living in the same exposed area. When a competing hospital in the same market responds to the acquisition by strategically attracting patients, I would observe an increase in the competing hospital's market share of patients. Thus, I hypothesize that the acquiring hospital's market share of patients would not increase after the acquisition in this case. I search and identify all competing hospitals located in the same area as the acquired hospital. I verify that there are no hospital openings or closures in the acquisition exposed and control areas to avoid their potential impacts on access to inpatient care provided by the acquiring hospital system.

Research question 2: Would there be any disparities in the access to inpatient care by type of health insurance or illness severity from the acquisition exposed area?

<u>Hypothesis 2.1</u>*: In the acquisition exposed area, patients with private insurance plans would be more likely to be admitted into the acquiring hospital compared to those covered by Medicaid or lacking insurance.

The reorganized hospital system may have a vision to improve their financial position after the acquisition through the expanded network (i.e., the hospital acquisition exposed area). I hypothesize that the reorganized hospital system has strategies to prioritize lucrative patients with private insurance, which would lead to patients with private insurance plans being more likely to be admitted by the reorganized acquiring hospital system.

<u>Hypothesis 2.2</u>*: In the acquisition exposed area, patients with higher severity of illness would be more likely to be admitted into the acquiring hospital compared to those with lower severity of illness.

By definition, tertiary hospitals provide tertiary care to patients who need it. Patients with higher severity of illness are usually more likely to need tertiary care. After the acquisition, I assume that the administrative processes between the acquired and the acquiring hospitals have been streamlined. Therefore, patients with higher severity of illness would be more likely to be admitted by the acquiring hospital after acquisition.

2.2 Methods

2.2.1 Study design

In this retrospective observational study, the “intervention” is hospital acquisition, and three time periods are considered: pre-, concurrent, and post- acquisition periods. I focus on hospital acquisitions between an acquiring hospital and an acquired hospital occurring in Texas from 2008 through 2014, and use data from 2006-2007 and 2015-2016 (two years before 2008 and two years after 2014) as the pre- and post- acquisition periods for the earliest and latest hospital acquisition. The acquiring hospital’s market share is measured at the ZIP code level, and the disparities in access to inpatient care are evaluated using hospital discharges on individual level as the unit of analysis.

Difference-in-Difference (DiD) methodology is applied to investigate the impact of hospital acquisition on access to inpatient care at the acquiring hospital for people living in the acquisition exposed area, where the acquired hospital mainly served before the acquisition. DiD is a quasi-experimental approach that can be used to evaluate an impact of hospital acquisition (Alexander et al., 1996; Dranove and Lindrooth, 2003; Gowrisankaran, 2011; Ho and Hamilton, 2000). In most previous studies, the DiD approach was used to compare costs between acquisition hospitals and control hospitals. The impact of hospital acquisition is estimated based upon the expected difference if the acquisition had not occurred and the observed difference between the two groups of hospitals. Yet, this approach is not the perfect design for every study because it requires that researchers can find proper control hospitals, which should be similar with the exposed hospitals in terms of type of services, ownership, geographic location, and size.

In this analysis, the research question focuses on the access to inpatient care at the acquiring hospital for patients rather than costs for hospitals. Given the acquiring hospital's geographic location, size, and ownership, it is very hard to find a proper control hospital. Also, the subject of interest for this study is patients, not hospitals. Thus, I employ a combination of the DiD approach with ZIP code-level market area, which has been developed previously (Hayford, 2012; Nakamura et al., 2007). Since the residency of local populations is unlikely to change due to hospital acquisition in the short term, this technique allows researchers to obtain market-level estimation.

As the analysis is based upon ZIP code -level hospital market area, I combine both fixed and variable radius approaches to identify appropriate hospital markets in this study. Fixed radius and variable radius are two typical methods used for hospital market definition. Fixed radius is mainly defined by arbitrary geographic distance, and the most common fixed radiuses used in hospital market research are 10 or 15 miles (Ghiasi et al., 2017). The shortcoming of this fixed radius is that it does not account for potential differences in population density, which may lead to underestimated or overestimated market competition. The variable radius method defines hospital market according to the potential demand of patients. For example, the most common market definitions used to measure hospital competition are Hospital Service Areas (HSAs) and Hospital Referral Regions (HRRs), which are measured using Medicare patients' flow. The HSAs and HRRs information is publicly available online. Though HSAs and HRRs are convenient for researchers to use, these market definitions may not be appropriate for all studies. In fact, researchers found that HSAs could be too wide to capture patient flows. One study identified that for 45% of HSAs, more than a half of patients were admitted to hospitals out of the HSA of their residence (Kilaru et al., 2015). For this study, I first use a fixed geographic distance to identify a set of ZIP code areas as potential market areas for each hospital acquisition. Then, patient flow is calculated to select final hospital market areas for further analyses. A detailed definition of hospital market and its identification process are described in the next section (2.2.2). This ZIP code level- analysis may not allow me to gauge the impact of hospital acquisition on hospital level, but it does assess the impact on the geographic market level of patients.

2.2.2 Data

Data used in this study are derived from multiple sources. Discharge-level data represent individual patients' information and hospital-level data reflect hospitals' features. ZIP code-level data are used to adjust potential confounders among various geographic areas. The final dataset used for analysis in this study has been linked through hospital names, addresses, and five-digit ZIP codes.

2.2.2.1 Hospital Acquisition

All hospital acquisition information is derived from the Landscape Changes in U.S. Hospitals files released by AHA every year. AHA collects hospital information through an annual hospital survey, also identifies hospital acquisitions, closures, and additions annually (https://www.aha.org/data-insights/aha-data-products). AHA annual survey database contains hospital features, and Landscape Changes in U.S. Hospital files summarize these hospital changes. The Landscape files capture most of hospital acquisitions and mergers in the U.S. Another commercial source to identify hospital acquisitions and mergers is Irving Levin

Associates, where all information has been verified. Researchers previously compared the two sources of hospital acquisitions and mergers, and concluded that 90% of hospital acquisitions and mergers from the two sources could be matched (Schmitt, 2017). From 2008 through 2014, there were 35 hospital acquisitions and mergers that occurred in Texas according to the records listed in the Landscape Changes files (Table S.1). Mental health/psychiatric hospitals are eliminated from this study since their inpatient discharges and treatments are quite different from most of the general or surgical hospitals. For the purpose of this study, I only focus on cross-market hospital acquisition between an acquired hospital and an acquiring hospital within one state (i.e., Texas).

To be specific, the hospital acquisition for this research is defined to meet all four conditions: (1) an acquired hospital could provide basic newborn, cardiovascular, and respiratory inpatient care for local residents before the acquisition; (2) the number of beds of an acquiring hospital should be at least double the number of beds of an acquired hospital; (3) cross-market acquisition is defined as the geographic distance between the acquiring hospital and the acquired hospital is greater than 10 miles, which means that before acquisition the hospital markets (i.e., patient ZIP codes) of the acquiring and the acquired hospitals were not entirely overlapping; (4) after acquisition two facilities of the reorganized hospital system (i.e., acquiring hospital and acquired hospital) still separately submit the discharge-level inpatient information to Texas Department of State Health Services (DSHS). If the two facilities submit their inpatient information together, I could not distinguish those patients who are admitted into the acquired or the acquiring hospital based on their discharge-level data collected by Texas DSHS. In all, four cross-market hospital acquisitions between an acquiring hospital and an acquired hospital are included in this study

(Acquisition 1, 2, 3, and 4). Hospital ownership and the number of beds of the four acquiring and acquired hospitals are summarized in Table 2.1 and Table 2.2.

Using the AHA files and geographic distance information from National Bureau of Economic Research (NBER), I also identify nearby potential competing hospitals in the same hospital market, where the acquired hospital is located (see Figure 2.3). If the distance between the acquired hospital and a potential competing hospital is less than 10 miles, then the two hospitals are considered to be within the same hospital market. There is no competing hospital in the same market area for Acquisition 1 and 4. Each acquired hospital of Acquisition 2 and 3 has one competing hospital, and the competing hospitals' distances to the acquired hospitals are 4 and 5 miles, respectively.

2.2.2.2 Discharge level

Texas Inpatient Public Use Data Files (PUDF), 2006-2016, are used as an inpatient encounter-level data source. The inpatient data files contain patients' information, including demographics, admission status, health insurance type, clinical diagnosis, and treatment procedure (https://www.dshs.texas.gov/thcic/hospitals/Inpatientpudf.shtm). The impact of hospital acquisition might vary depending on various types of care such as newborn care and cardiovascular care. Thus, it may not be appropriate to treat all discharges as identical individuals and include all of them in the analysis. I choose three collections of diagnoses out of the top ten common causes for inpatient stays: newborn, Coronary Artery Disease (CAD), and respiratory diseases. Newborn is the most common reason for hospitalization, and it accounts for more than 10% of all hospital stays. CAD represents patients transferred from emergency or urgent care units, and in this study CAD includes both Acute Myocardial Infarction and Ischemic Heart Disease. Respiratory diseases rank first among all admissions that transferred from other health care facilities/units, and in this study this collection of diagnoses includes both pneumonia and chronic obstructive pulmonary diseases. Detailed International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) and ICD-10-CM International Classification of Diseases, Tenth Revision, Clinical Modification (ICD-10-CM) are listed in Table S.2. In sum, the total number of these three types of hospitalization causes amounts to approximately 20% inpatient discharges out of all various inpatient discharges, and represents the urgent as well as the elective as two sources of hospital admissions (McDermott et al., 2017).

2.2.2.3 ZIP code level

To identify appropriate hospital acquisition exposed and control ZIP code areas for each hospital acquisition (Figure 2.2), five factors are considered: (1) geographic distance; (2) median income; (3) the acquired hospital's market share of the acquisition exposed and control areas; (4) the acquiring hospital's market share of the acquisition exposed and control areas; and (5) other hospitals' market share of the acquisition exposed and control areas. The geographic distances between two ZIP codes are obtained from NBER, https://www.nber.org/data/zip-code-distance-database.html, and socioeconomic estimates are downloaded from American Community Survey (ACS) (https://www.census.gov/programs-surveys/acs/). Hospital's market share of each ZIP code area is calculated based on discharge-level ZIP code information.

I first identify proper acquisition exposed ZIP code areas and then select optimal control areas using propensity score (PS) matching based upon geographic distance and median income. In particular, the criteria for exposed areas are (1) the ZIP code area is located within 50 miles of the acquired hospital; (2) the acquired hospital's market share of patients living in the exposed ZIP code area, $MS\ (Exposed)_{Acquired}$ is greater than 10% , representing a market area where the acquired hospital mainly served before the acquisition:

$$MS\ (Exposed)_{Acquired}$$

$$= \frac{\text{the number of discharges within the ZIP code area discharged from the acquired hospital}}{\text{the total number of discharges within one exposed ZIP code area}}.$$

"Control market" is considered as a counterfactual, which should have four fundamental features: (1) similar median incomes with the acquisition exposed area; (2) similar geographic distances to the acquiring hospital; (3) people living in control market areas rarely choose the acquired hospital, which means the acquired hospital's market share of the ZIP code area, $MS\ (Control)_{Acquired}$, is smaller than 1%:

$$MS\ (Control)_{Acquired}$$

$$= \frac{\text{the number of discharges within the ZIP code area discharged from the acquired hospital}}{\text{the total number of discharge within one control ZIP code area}}.$$

After PS matching on geographic distance and median income on ZIP code level, the empirical distributions of the two covariates are relatively balanced between acquisition exposed areas and control areas. Table 2.3 compares the characteristics before and after the PS matching. In addition, I construct market shares of patients living in the exposed and control areas for the acquiring hospital on ZIP code level, $MS\ (Exposed)_{Acquiring}$ and $MS\ (Control)_{Acquiring}$. These two market shares are used to verify parallel trends between the exposed and control areas before acquisition and identify any changes after the acquisition:

$$MS\ (Exposed)_{Acquiring}$$

$$= \frac{\text{the number of discharges within the ZIP code area discharged from the acquiring hospital}}{\text{the total number of discharges within one exposed ZIP code area}}.$$

$$MS\ (Control)_{Acquiring}$$

$$= \frac{\text{the number of discharge within the ZIP code area discharged from the acquiring hospital}}{\text{the total number of discharges within one control ZIP code area}}.$$

I also construct all other hospitals' market shares of patients living in the exposed area on ZIP code level. In particular, the competing hospital's market share of patients living in an exposed ZIP code area is:

$$MS\ (Exposed)_{Competing}$$

$$= \frac{\text{the number of discharges within the ZIP code area discharged from the competing hospital}}{\text{the total number of discharge within one exposed ZIP code area}}.$$

2.2.3 Variables and measures

For the unit of analysis on ZIP code level, the response variable is the acquiring hospital's market share of inpatients living in acquisition exposed areas or control areas. As described above, they are $MS\ (Exposed)_{Acquiring}$ and $MS\ (Control)_{Acquiring}$, respectively. Explanatory variables contain acquisition indicator (*acquisition*), time-fixed effects ($\boldsymbol{time_t}$), and their interaction terms. The time-fixed effects are represented by two indicators: concurrent period of acquisition ($time_1$) as well as post-period of acquisition ($time_2$), and the pre-period of acquisition is the reference group.

The AHA hospital files only indicate the year of hospital acquisition, and so it is hard to accurately capture time frame for each hospital acquisition. If a hospital acquisition occurs in the last quarter of the year and the year of acquisition is used to denote the concurrent period, then the concurrent period in fact may partially reflect the pre-period. To deal with this transition period issue, I expand one quarter to before and after the year of hospital acquisition (see Figure 2.4). For instance, if one hospital acquisition occurred in 2013, the pre-, concurrent, post- periods would be 2011Q1-2012Q3, 2012Q4-2014Q1, and 2014Q2-2015Q4, respectively. In this way, the pre-, concurrent, post- periods consist of 7, 6, 7 quarters, a total of five years for each hospital acquisition.

For the analysis on discharge level, the response variable is a dummy variable indicating whether the patient (i.e., discharge) is admitted by the acquiring hospital and this indicator is constructed based on the hospital identifier/Texas Health Care Information Collection_Identifier (THCIC_ID) from Texas inpatient PUDF. The main variables of interest are acquisition indicator (*acquisition*), time-fixed effect ($\boldsymbol{time_t}$), and interaction terms between them. Other explanatory variables at the patient level are: age, gender, race, ethnicity, types of health insurance, types of admission, source of admission, geographic distance from the ZIP code of the patient to the acquiring hospital, and their definitions, values, and data sources of which are summarized in Table S.4.

To measure the hospital competition status of the acquisition exposed area, Herfindahl-Hirschman Index (HHI) and an indicator of the number of competing hospitals are constructed. HHI is the standard measurement for hospital market concentration status used by the Department of Justice, and a market having a HHI between 1,500 and 2,500 is considered to be moderately concentrated. In this study, each hospital's market share of patients living in the hospital acquisition exposed area is calculated first, and then *HHI* is obtained as below:

$$HHI = market\ share_1^2 + market\ share_2^2 + \cdots + market\ share_n^2,$$

where *n* represents the number of hospitals providing inpatient care from exposed or control areas.

The changes of HHI before and after the four acquisitions are found to be from 441 to 392, 720 to 944, 828 to 951, and 639 to 583, respectively. In this case, HHI is not an appropriate measurement for hospital competition status, since there is little variation in HHI for the exposed area.

Then, I identify all hospitals in which patients living in the exposed area are admitted, and calculate their geographic distances to each of the four acquired hospitals. I count the number of competing hospitals whose geographic distances are less than 50 miles to the acquired hospital (i.e., acquisition exposed area), and the total number of competing hospitals ranges from 7 to 9. Therefore, there is still little variation in the number of competing hospitals.

Meanwhile, I find that for Acquisition 2 and 3 there is one competing hospital in the same market where the acquired hospital is located, which means the geographic distance between the two hospitals is less than 10 miles. Thus, indicator of the competing hospital (*rival*) is used to indicate hospital competition status of the acquired hospital market. The exposed areas of Acquisition 2 and 3 are classified into a rival (*rival=1*). For the other two acquisitions, their exposed areas are classified into no rival (*rival=0*).

2.2.4 Statistical analysis

As shown in Table S.3, to detect a 5% difference in market share with an alpha of 0.05 and a power of 0.85, there should be at least 73 ZIP code areas from each exposed and control area. In Table 2.3, there are 18 exposed and 18 control ZIP code areas identified in this study, and each of them has 20 observations over the 20 quarters. When comparing the pre- and post-period, there are 126 ZIP code areas in each exposed or control group. When only using Acquisition 1 and 4, there are 84 ZIP code areas in each exposed or control group. Thus, I have enough power to detect at least 5% change in market share on ZIP code level in this study.

On the discharge-level analysis, I examine the likelihood of being admitted by the acquiring hospital between the acquisition exposed and control areas for the pre- and post-periods. To examine an odds ratio (OR) of 1.25 or higher in the two proportions at a significance level of 0.05 with a power of 0.85, one would need at least 1,251 observations in each group. As shown in Table 2.4, 2.5, and 2.6, the number of discharges by each type of care has enough power to test an odds ratio of 1.25 or higher (equivalent to an OR of 0.8 or lower).

To answer the first research question, I draw overall trends in the acquiring hospitals' market share of patient by exposed and control areas over time to determine whether the parallel trend assumption of DiD is met. As Figure 2.5 shows, the trends before acquisition are approximately parallel and I use the DiD approach:

$$\textit{Acquiring hospital's market share}_{it} =$$

$$\alpha_0 + \boldsymbol{\alpha_1} \times \boldsymbol{time_t} + \alpha_2 \times acquisition + \boldsymbol{\alpha_3} \times acquisition \times \boldsymbol{time_t} + \gamma_i + \epsilon_{it} \qquad (2.1)$$

Acquiring hospital's market share$_{it}$ denotes the acquiring hospital's market share of patients living in the ZIP code area *i* during time period *t*, which is constructed based on *MS (Exposed)*$_{Acquiring}$ and *MS (Control)*$_{Acquiring}$ in 2.2.2. $\boldsymbol{Time_t}$ consists of two indicators: $time_1$ and $time_2$ for concurrent and post- acquisition periods. *Acquisition* is a variable for acquisition exposed area (=1) and control area (=0) otherwise; the interaction between the indicator of *acquisition* and $\boldsymbol{time_t}$ represents the acquisition impact on the acquiring hospital's market share of patients living in exposed areas. The coefficients of interest are $\boldsymbol{\alpha_3}$, indicating increases in the acquiring hospital's market share when they are estimated to be statistically significant and positive. Additionally, $\boldsymbol{\alpha_1}$ indicate fixed time effects in the control area, α_2 refers to a difference of market shares between the acquisition exposed and control areas before the acquisition occurrence. γ_i represents a random effect from ZIP code areas. I also check the potential heteroscedasticity of residuals using a Breusch Pagan test, and use Huber-White standard errors for robust estimations.

It is worth noting that I do not add a three-way and other related two-way interaction terms for *rival* in the regression, and this is because (1) this is not a Difference in Difference in Difference study design and (2) there are relatively small sizes for including additional terms in the model. Thus, I stratify the four acquisitions by their *rival* status and then estimate the parameters separately.

For the analysis on discharge level, the differences in patients' demographic between acquisition exposed and control areas are examined using Chi-square tests by each type of care services. Then, mixed effects logistic regression models on discharge level are used to answer the second research question proposed previously (2.1), and the model is specified as below:

$$log\left(\frac{Pr\left(Y_{ijt}\right)}{1\text{-}\ Pr\left(Y_{ijt}\right)}\right)=$$

$$\beta_0+\boldsymbol{\beta_1}\boldsymbol{\times time_t}+\beta_2\times acquisition+\boldsymbol{\beta_3}\times acquisition\times \boldsymbol{time_t}+\boldsymbol{\beta_4}\boldsymbol{\times payers_{ijt}}+\boldsymbol{\beta_5}\boldsymbol{\times payers_{ijt}}\boldsymbol{\times time_t}$$

$$+\boldsymbol{\beta_6}\boldsymbol{\times payers_{ijt}}\times acquisition\ +\boldsymbol{\beta_7}\boldsymbol{\times time_t}\boldsymbol{\times payers_{ijt}}\times acquisition\ +\boldsymbol{\beta_8}\boldsymbol{\cdot X_j}+\beta_9\cdot D_j+\gamma_i+\epsilon_{ijt} \qquad (2.2)$$

Y_{ijt} indicates whether the patient j living in a ZIP code area i is admitted by the acquiring hospital (=1) or not (=0) during the pre-, concurrent, or the post- acquisition period. $\boldsymbol{Time_t}$ consists of two terms: $time_1$and $time_2$, and indicates concurrent and post- acquisition period, respectively. *Acquisition* is an indicator denoting whether the patient live in an acquisition exposed area (=1) or control area (= 0). $\boldsymbol{Payers_{ijt}}$ is a categorical variable and represents the type of health insurance of patient j living in a ZIP code area i during t period. Three-way interaction would be equal to 1 when the patient comes from acquisition exposed areas, has private insurance, and the discharge time is in the post- acquisition period; equal to zero otherwise. If this three-way interaction is not statistically significant, then it would be dropped, which means there is no significant difference in acquisition impact among various types of health insurance. Next, the acquisition impact would be captured by the two-way interaction between $acquisition\times \boldsymbol{time_t}$, and the interaction term would be equal to one when patient j lived in an exposed area and his/her discharge time is not in the pre- acquisition period. $\boldsymbol{X_j}$ represents a vector of demographic and clinical characteristics of patient j, such as age group and gender (Table S.4). D_j indicates geographic distance from patient j's ZIP code to the acquiring hospital, and γ_i represents a random effect from ZIP code areas.

$\boldsymbol{\beta_7}$ is a set of coefficients of interest, and they represent different impacts of acquisition on patients with various types of insurance. For example, when β_7 (Private versus Medicaid) is positive and statistically-significant, it suggests that the impact of acquisition on patients having private insurance is greater than the impact on Medicaid patients. When the three-way interaction terms are not significant different, $\boldsymbol{\beta_3}$ would capture the overall impact, indicating a person living in an acquisition exposed is more likely to be admitted by the acquiring hospital after acquisition relative to control market if it is positive and statistically significant. $\boldsymbol{\beta_1}$ denotes time fixed effects in control areas; β_2 represents the difference between acquisition exposed and control areas before acquisition; $\boldsymbol{\beta_4}$ reflects fixed effects of various types of health insurance.

In addition to types of health insurance, severity of illness may also affect patients' access to the acquiring hospital, and therefore is considered in the analyses. The regression model and variables are similar to (2.2):

$$log\left(\frac{Pr\left(Y_{ijt}\right)}{1\text{-}\ Pr\left(Y_{ijt}\right)}\right)=$$

$$\beta_0+\boldsymbol{\beta_1}\times\boldsymbol{time_t}+\beta_2\times acquisition+\boldsymbol{\beta_3}\times acquisition\times\boldsymbol{time_t}+\boldsymbol{\beta_4}\times\boldsymbol{level\ of\ severity_{ijt}}$$

$$+\boldsymbol{\beta_5}\times\boldsymbol{level\ of\ severity_{ijt}}\times\boldsymbol{time_t}+\boldsymbol{\beta_6}\times\boldsymbol{level\ of\ severity_{ijt}}\times acquisition$$

$$+\boldsymbol{\beta_7}\times\boldsymbol{time_t}\times\boldsymbol{level\ of\ severity_{ijt}}\times acquisition+\boldsymbol{\beta_8}\cdot\boldsymbol{X_j}+\beta_9\cdot D_j+\gamma_i+\epsilon_{ijt} \qquad (2.3)$$

All analyses are conducted using SAS Version 9.4. (Cary, NC) and figures are plotted using R (Vienna, Austria). Statistical significance level is considered to be 0.05 and 95% Confidence Intervals (CIs) are constructed for all parameters unless otherwise specified.

2.3 Results

2.3.1 Descriptive results of study samples on discharge level

Tables 2.4, 2.5, and 2.6 summarize the characteristics of patients by each acquisition for newborn, cardiovascular, and respiratory care, respectively. Overall, there are few significant differences in the total number of patients for pre-, concurrent-, and post- periods between the acquisition exposed and control areas, which suggests stable patient populations between the two groups of areas over time. There are significant differences observed in race, ethnicity, and types of health insurance between the exposed and control areas, but this might be due to the large sample sizes (See section 2.2.4).

For newborn care, the proportion of White babies is the highest for all four acquisitions, while the proportion of African American babies ranges from 5% to 21%. Overall, more than 60% have Medicaid as their first source of payment, and Medicaid is the major insurance payer for all four acquisitions. The main source for three acquisitions (Acquisition 2, 3, 4) is “transformed from other facilities”. There are no statistically significant differences through all pre-, concurrent, and post- periods for Acquisition 2 and 4, which indicates stable populations over time (Table 2.4). The changes through the three periods are similar for Acquisition 1 and 3, though the p-values suggest statistical differences.

For cardiovascular care, there generally are fewer patients in the 18-39 age group than the over 65 age group for all four acquisitions (Table 2.5). There are more White patients in the control areas than in the exposed areas for all four acquisitions. The empirical distributions of African Americans and other races are different in the exposed and control areas for each acquisition.

Medicare or private insurance are the two main payers for inpatient cardiovascular care, and all four acquisitions tend to have more Medicare patients in acquisition exposed areas. Most inpatients are admitted into hospitals through referrals from other facilities except for Acquisition 1.

Among respiratory care patients, approximately half are older than 65, and Medicare is the main payer (see Table 2.6). There are significant differences in age, race, and types of health insurance between the exposed and control areas for all acquisitions. There are also statistically significant variations in sources and types of admission, but the differences might not be practically significant. For instance, differences in the type of admission are 5% or less for all acquisitions.

2.3.2 Descriptive results of acquired and competing hospitals' market shares on ZIP code level

All the acquired hospitals have decreasing trends in their market shares of inpatients, from 32.3% to 28.6% for Acquisition 1, 39.6% to 35.2% for Acquisition 2, 22.8% to 20.2% for Acquisition 3, and 27.3% to 25.3% for Acquisition 4 (Figure 2.4 b).

Acquisition 2 and 3 have a competing hospital located in the same market as the acquired hospital. In particular, the two competing hospitals are four and five miles away from the acquired hospital for the two acquisitions, respectively. On average, the competing hospital's market share increases from 7.5 % at pre-period to 8.6% at post-period for Acquisition 2, and from 49.7% to 52.8% for Acquisition 3, respectively (Figure 2.4 a).

2.3.3 Impacts of hospital acquisition on acquiring hospitals' market shares

Figure 2.5 displays the trends in acquiring hospital's market shares by each acquisition. Overall, the impact of hospital acquisition on the acquiring hospitals' market share of inpatients is positive, but it is not statistically significant without stratifying for competing hospitals. When there is no competing hospital in the same market as the acquired hospital, the acquiring hospital's market share increases by 4.7% ($p = 0.005$). In particular, the increase in the market share of cardiovascular inpatients is 11% ($p = 0.005$), which is notably larger than the increases in newborn and respiratory care (see Table 2.7). No statistically significant impacts on the market share are observed when there is a competing hospital in the same market (i.e., Acquisition 2 and 3).

2.3.4 Impacts of hospital acquisition on newborn care

The associations of hospital acquisition and patient-level newborn care are different depending on both patients' health insurance types and severity of illness. For Acquisition 1 and 2, the impact of acquisition on newborns with Medicaid are greater than the impact on newborns with private insurance, and their ORs (95% CI) were 2.03 (1.00, 4.09) and 1.86 (1.24, 2.78), respectively (see Table 2.8). No statistically differences are observed in other acquisitions in terms of health insurance status.

For Acquisition 1 and 4, newborns with more severe illness and living in the exposed areas are more likely to get into acquiring hospitals in the post- acquisition period, and their ORs (95% CI) are 3.37 (1.58, 7.18) and 4.54 (1.21, 10.04), respectively. On the contrary, after Acquisition 2 the impact of acquisition on newborns with more severe illness is less than the impact on newborns with less severe illness [OR (95% CI) = 0.36 (0.16, 0.80) for major severity versus OR (95% CI) = 1.39 (1.12, 1.72) for minor severity]. No statistically significant acquisition impact on the access to newborn care is found for Acquisition 3.

2.3.5 Impacts of hospital acquisition on cardiovascular care

Overall, I find positive associations between acquisition and access to cardiovascular care at the acquiring hospitals for Acquisition 1 and 4. Regardless of patient insurance type, Acquisition 1 and 4 have positive impacts on individual-level access to acquiring hospitals for the post-acquisition period, with OR (95% CI) = 4.18 (2.08, 8.39) and OR (95% CI) = 2.88 (1.38, 6.03), respectively (Table 2.9). Furthermore, patients with more severe illness are more likely to be admitted at acquiring hospitals for Acquisition 4 [OR (95% CI) =7.83 (1.40, 43.73)]. No statistically significant acquisition impact on the access to cardiovascular care at the acquiring hospital is found for Acquisition 2 and 3.

2.3.6 Impacts of hospital acquisition on respiratory care

Patients living in the exposed area of Acquisition 4 are more likely to access respiratory care at the acquiring hospital regardless of type of health insurance [OR (95% CI) = 6.85 (2.96, 15.88)] (see Table 2.10). There is a positive impact of Acquisition 1 on access to inpatient respiratory care at the acquiring hospital for concurrent period, but it is not statistically significant [OR (95% CI) = 1.70 (0.95, 3.06)] (see Table 2.10). For Acquisition 2 and 3, patients with private insurance or with less severe conditions are more likely to be admitted by the acquiring hospitals.

2.4 Discussion

In this study, I focus on the cross-market hospital acquisition between an acquiring and an acquired hospital that occurred in Texas from 2008 to 2014, and find that the impact of acquisition is different depending on the hospital competition status. When there is no competing hospital in the same market, the overall acquiring hospital's market share of patients living in the exposed area increases about 5%. If a competing hospital is located in the same market as the acquired hospital, the impact of acquisition on the acquiring hospital's market share is not statistically significant. Furthermore, the impact of acquisition on patients' access to care at the acquiring hospitals vary depending upon patients' health insurance status and severity of illness. Taken together, these findings suggest that the impact of the hospital acquisition investigated in this study may vary based on hospital competition status and patients' characteristics.

Over the recent two decades, the U.S. hospital market has undergone restructuring, and the overall concentration of the market has increased rapidly. Local community hospitals face financial challenges, and so have to either close or be acquired by tertiary hospital systems (Glied and Altman, 2017). After acquisition, it is usually assumed that tertiary hospitals would expand their networks, and more patients would be taken care of at the tertiary hospitals. Yet, this assumption is typically taken for granted, and no published study has been conducted to assess its validity (Dafny and Lee, 2015).

In this study, I focus on cross-market hospital acquisition involving a local community hospital (i.e., acquired hospital) and a tertiary hospital system (i.e., acquiring hospital) in Texas. All acquired hospitals have at least 50 beds, and acquiring hospitals have at least 300 beds. Though the four acquisitions share these common features, the acquisition impact on the tertiary hospitals' market share is different depending on the acquired hospital's market competition status. The impact of Acquisition 4 is positive on patients' access to care at the acquiring hospital for all three types of care, which I investigate in this study. This is consistent with aims of hospital acquisition summarized by Charles River Associates (Noether and May, 2017). Moreover, the increase in the acquiring hospital's market share of cardiovascular care is the largest one among the three types of care. This could be attributed to (1) cardiovascular patients may need tertiary care or (2) tertiary care for cardiovascular patients is more profitable for acquiring hospital (Hayford, 2012; Nakamura, 2010).

Some acquiring hospitals may "cherry-pick" those lucrative patients after their acquisitions. In this study, I find that the impact of Acquisition 2 and 3 on patients' access to care at tertiary hospitals is only positive for patients with private insurance or lower severities of illness (i.e., classified by 3M APR-DRGs) for respiratory care. Previous studies also reported this "cherry-picking" strategy in their investigations on hospital acquisitions (Huckman, 2006; Nakamura et al., 2007). Nevertheless, I also find that the impact of Acquisition 1 and 2 on access to newborn care at the acquiring hospital is positive for babies with Medicaid. In addition, the impact of Acquisition 1 and 4 on the access to newborn care at acquiring hospitals is positive for babies with more severe illness. Various acquisitions may have different visions and strategies to serve patients living in the acquisition exposed areas, and so they prioritize a certain referral process using differential strategies.

There are limitations in this study. First, I only focus on acquisitions between a local community hospital and tertiary hospital in Texas. The results do not represent other types of hospital acquisitions or acquisitions that occurred in other states. Moreover, there is limited information on how these hospital acquisitions were launched, conducted, and completed. For instance, I assume that the tertiary hospital system would "takeover" the local community hospital after each acquisition, though details of each acquisition deal are not included in the AHA files. Nevertheless, I leverage all available hospital information from multiple years of the AHA annual survey data to select the hospital acquisitions for my intended research. The identification of acquisition is based upon hospital features, and the key features considered in this study are: ownership, services types, and the number of beds. The lack of hospital acquisition information should be addressed in future. The time window of acquisition (i.e., "intervention") is another issue in this investigation of hospital acquisition. It has been pointed out that the fruits of mergers might need approximately seven years to be found while most empirical studies set up their frame relying on available data (Burns and Pauly, 2002). In this study, I employ five years of Texas inpatient PUDF discharge-level data, and some influences might not be observed due to the relatively short time frame. Nevertheless, two of the acquisitions explored in this study have permanently closed in 2017 due to Hurricane Harvey, and therefore the impact of the hospital acquisition could not be identified even if the frame had been expanded. In addition, the sample size for ZIP code level-analysis in this study is relatively small, and I am only able to detect a difference of 5% or higher for acquiring hospitals' market share. However, the two sets of ZIP code areas for acquisition exposed and control are selected using PS matching and are relatively balanced on median income and geographic distance to the acquiring hospital. If more ZIP code areas had been included, there might have been additional sources of variation. Last, no mechanisms of hospital acquisition impact on patients' access to tertiary care are explored in this study. According to previous theories and empirical evidence, hospital consolidation may influence patients' access through coordination of care, physician referral process, or insurance expansion. This study is not designed to identify any specific mechanism, and future studies should be conducted to find out how hospital acquisitions would influence patients' access to tertiary care.

In this study, I find that the impact of hospital acquisition on patients' access to care at the acquiring hospitals is different by hospital competition status and patients' characteristics. These findings suggest that when there is one nearby substitute hospital, patients living in the acquisition exposed area might go to the nearby hospital rather than the relatively far acquiring hospital. When there is no such substitute hospital, local patients are more likely to be admitted by the acquiring hospital. However, I could not tell whether patients would prefer to be admitted by the acquiring hospital or have no other choice to go, as no alternative hospital is available in their neighborhood. Thus, it is important to explore and investigate patients' experiences before and after acquisitions in future studies.

2.5 Figures

Figure 2.1 Conceptual Framework of This Study

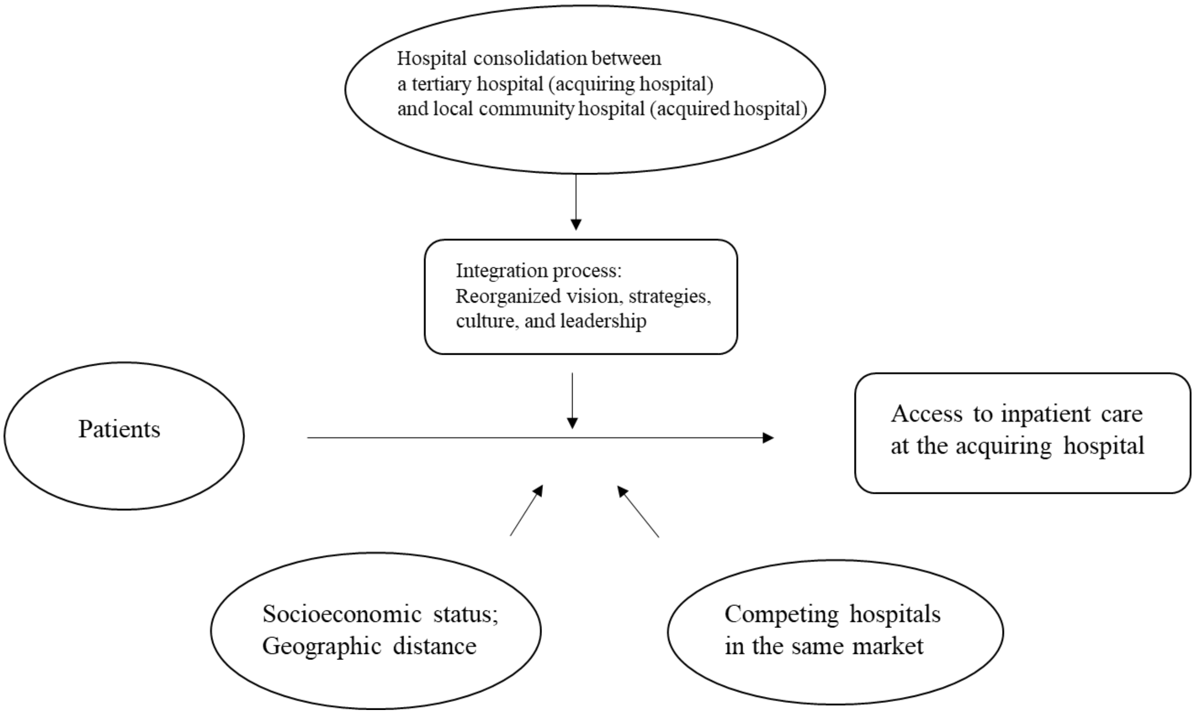


Figure 2.2 An Illustration of Hospital Acquisition Exposed and Control Areas on ZIP Code Level

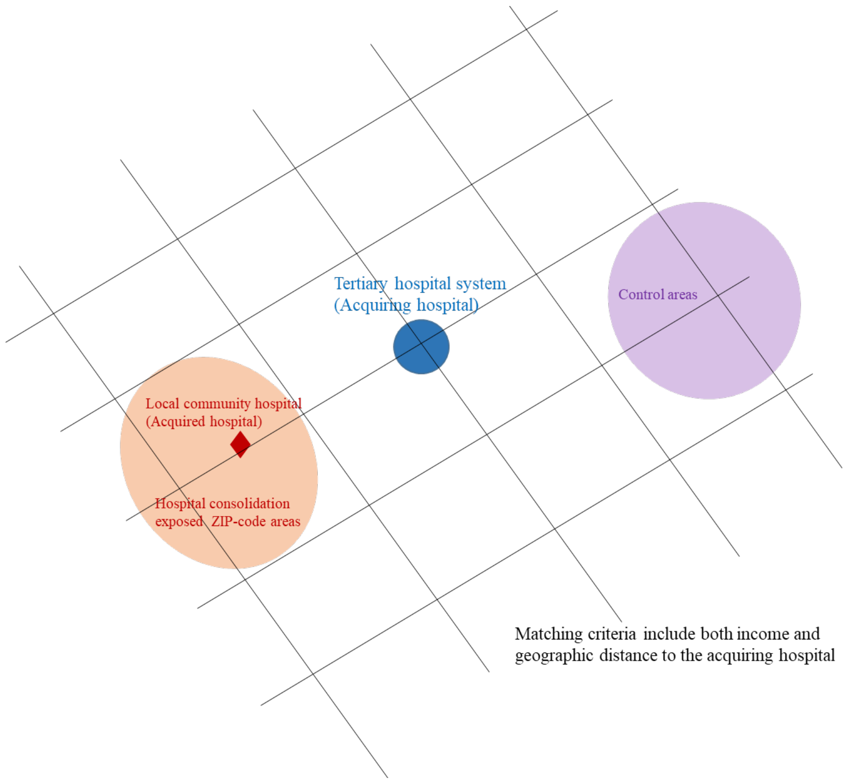


Figure 2.3 An Illustration of Competing Hospital and Acquired Hospital in the Same Market

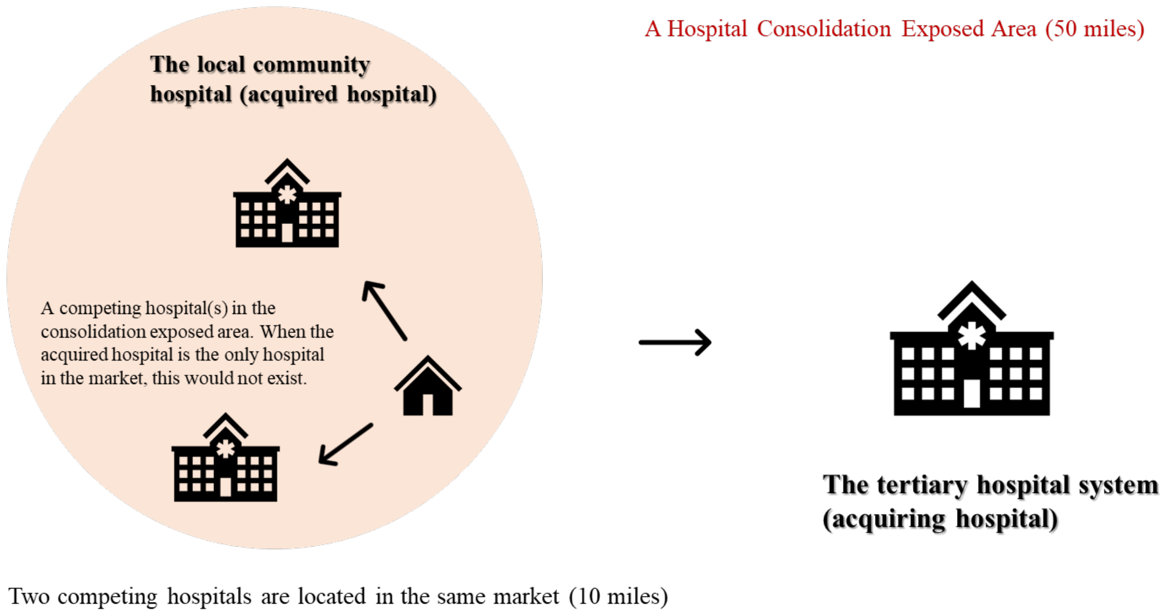


Figure 2.4 An Illustration of Pre-, Concurrent, and Post- Acquisition Periods Used in This Study

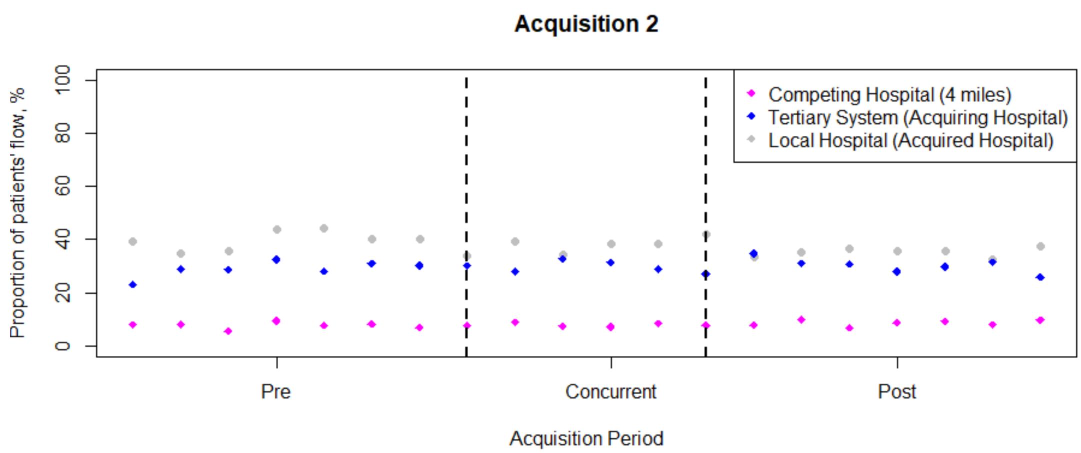
The year of hospital consolidation indicated in AHA files

Year 1				Year 2				***Year 3***				Year 4				Year 5			
Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Pre-	Pre-	Pre-	Pre-	Pre-	Pre-	Pre-	Concu	Concu	Concu	Concu	Concu	Concu	Post-	Post-	Post-	Post-	Post-	Post-	Post-

Six quarters of PUDF discharge-level data were used for a concurrent consolidation period

Figure 2.5 Acquired, Acquiring, and Competing Hospitals' Market Shares of Patients Living in the Acquisition Exposed Areas

(a) Figure 2.5A There is a competing hospital located in the same market as the acquired hospital



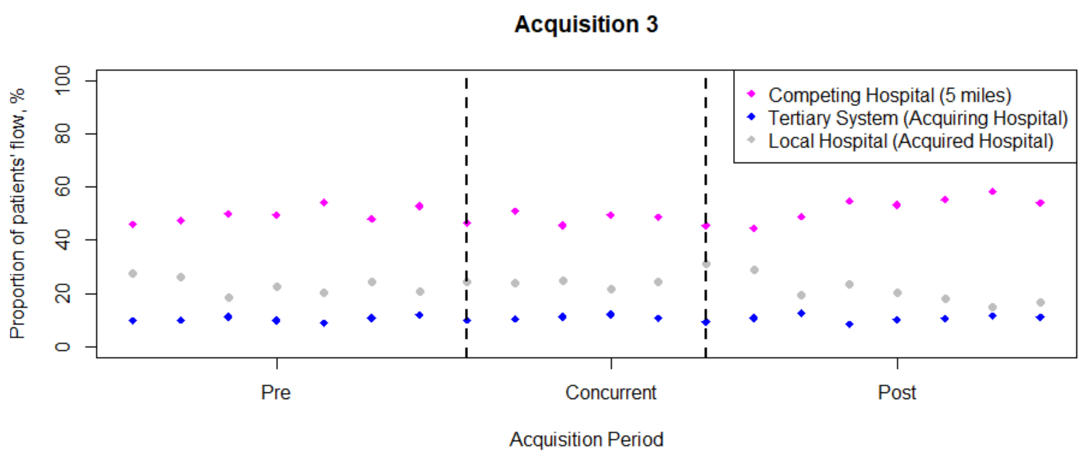
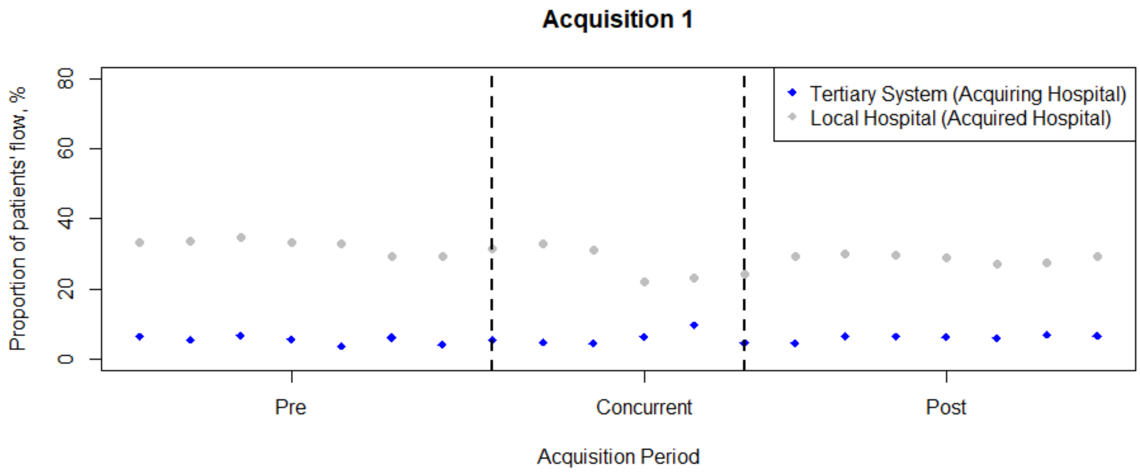


Figure 2.5 Continued

(b) Figure 2.5B. There is no competing hospital located in the same market as the acquired hospital



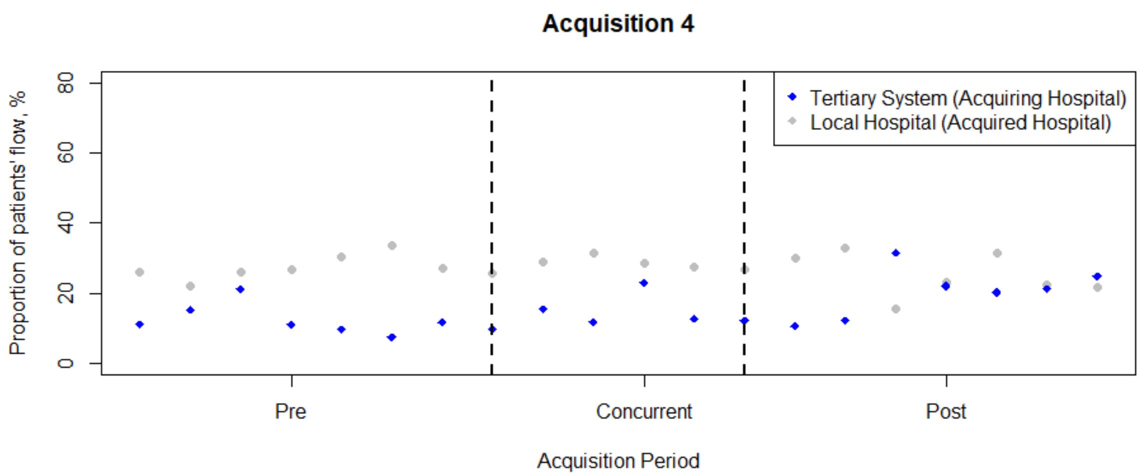


Figure 2.6 Acquiring Hospitals' Market Share of Patients Living in the Acquisition Exposed and Control Areas over Years by Each Hospital Acquisition in This Study

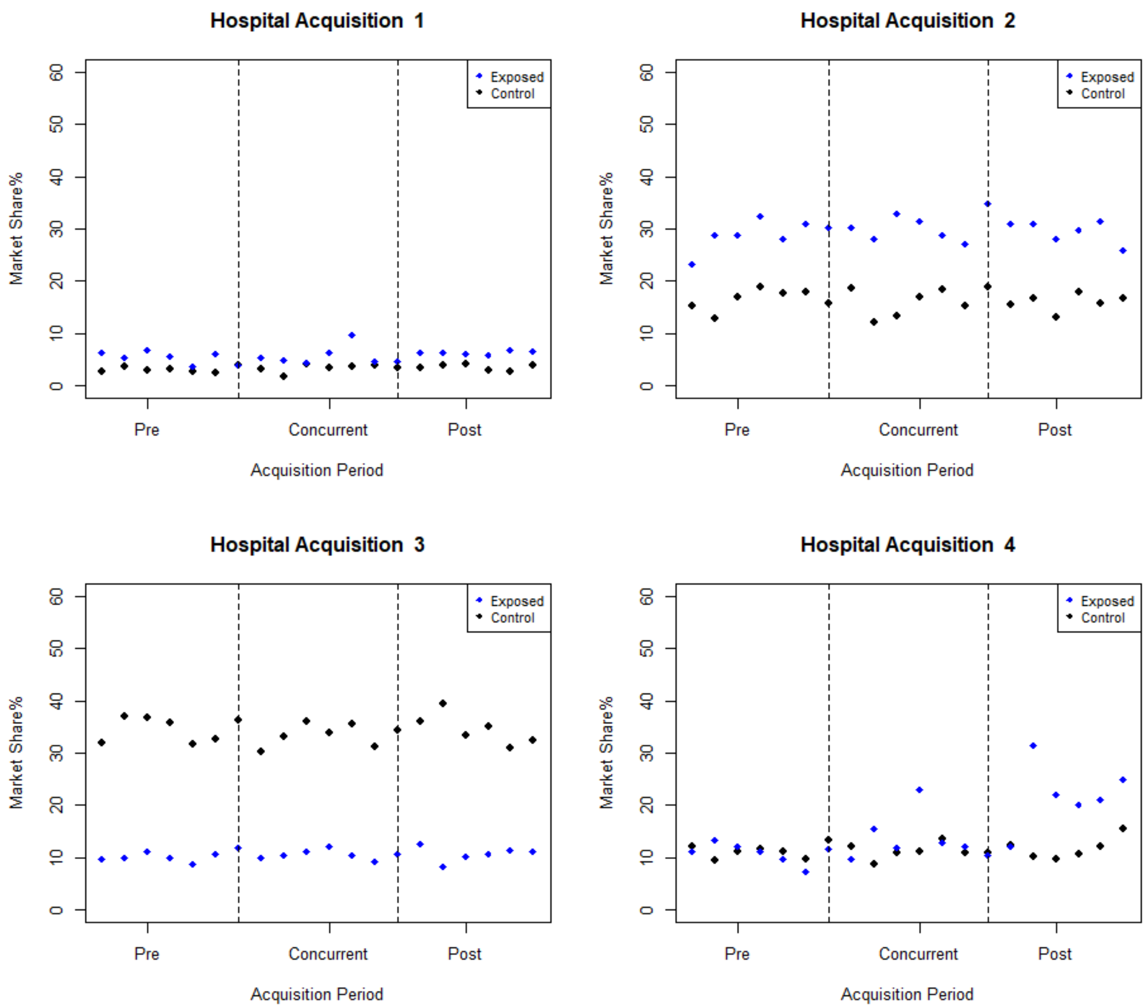


Figure 2.7 Acquiring Hospitals' Market Shares of Newborn Hospitalizations over Years by Each Hospital Acquisitions in This Study

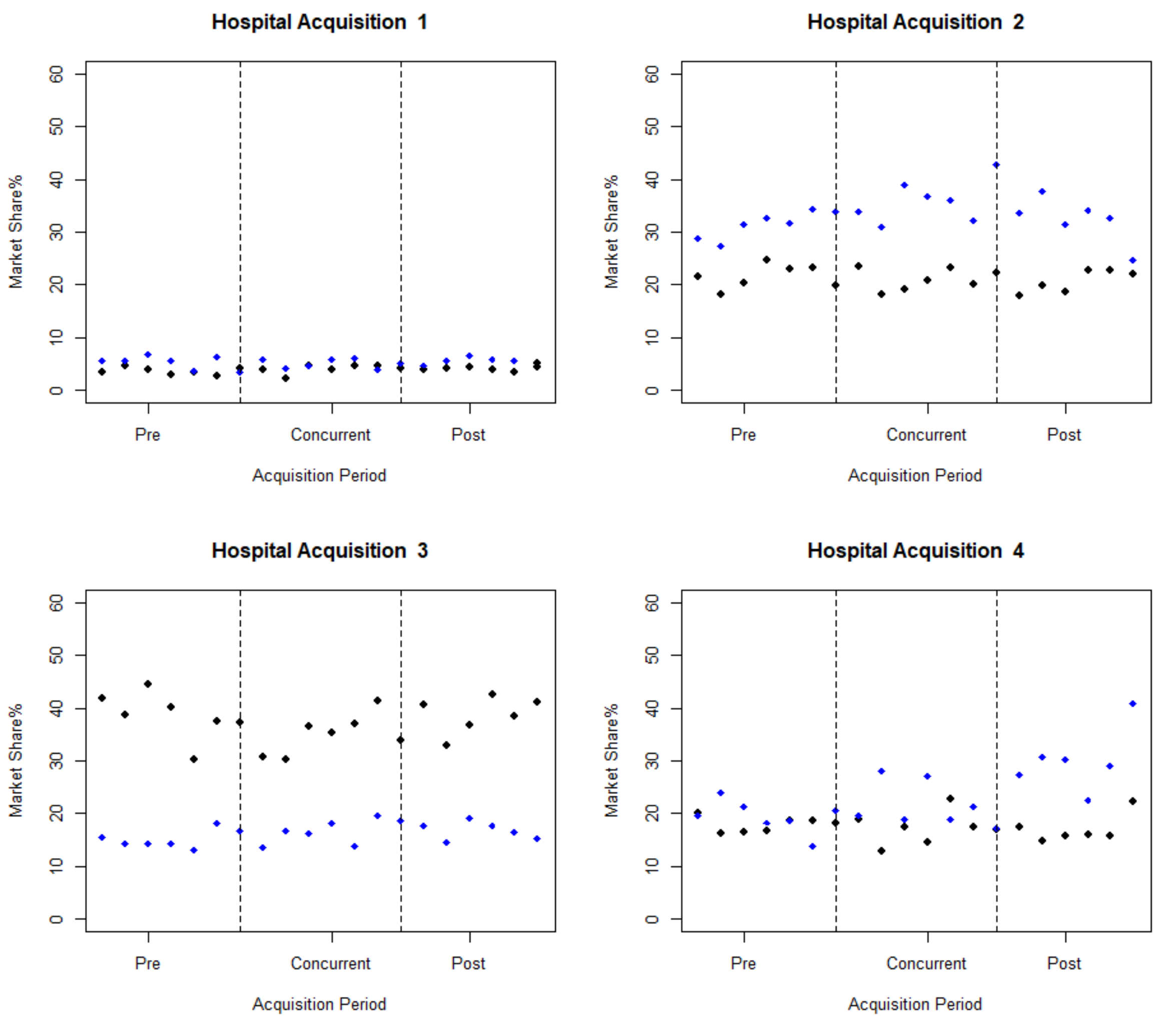


Figure 2.8 Acquiring Hospitals' Market Shares of Hospitalizations due to Coronary Artery Diseases over Years by Each Hospital Acquisition in This Study

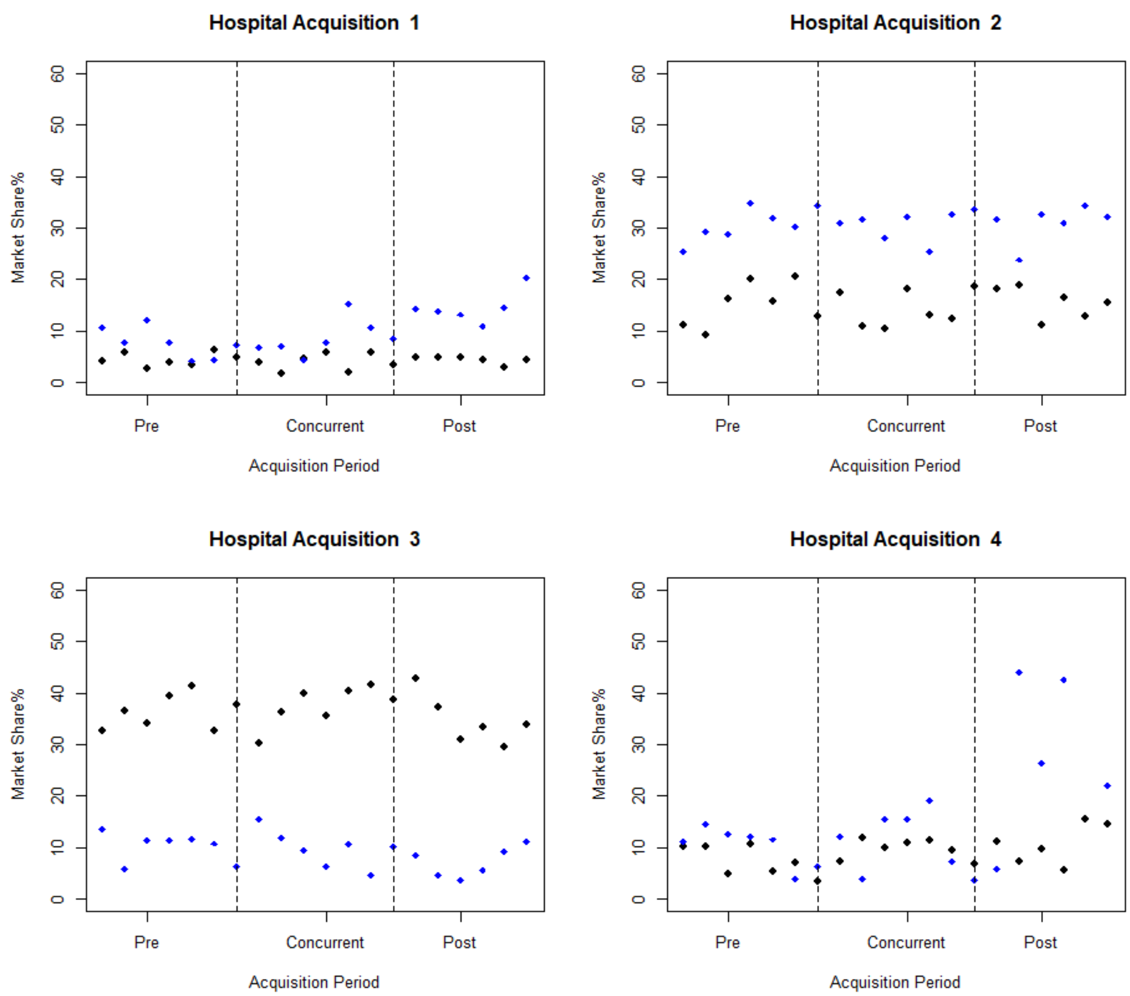
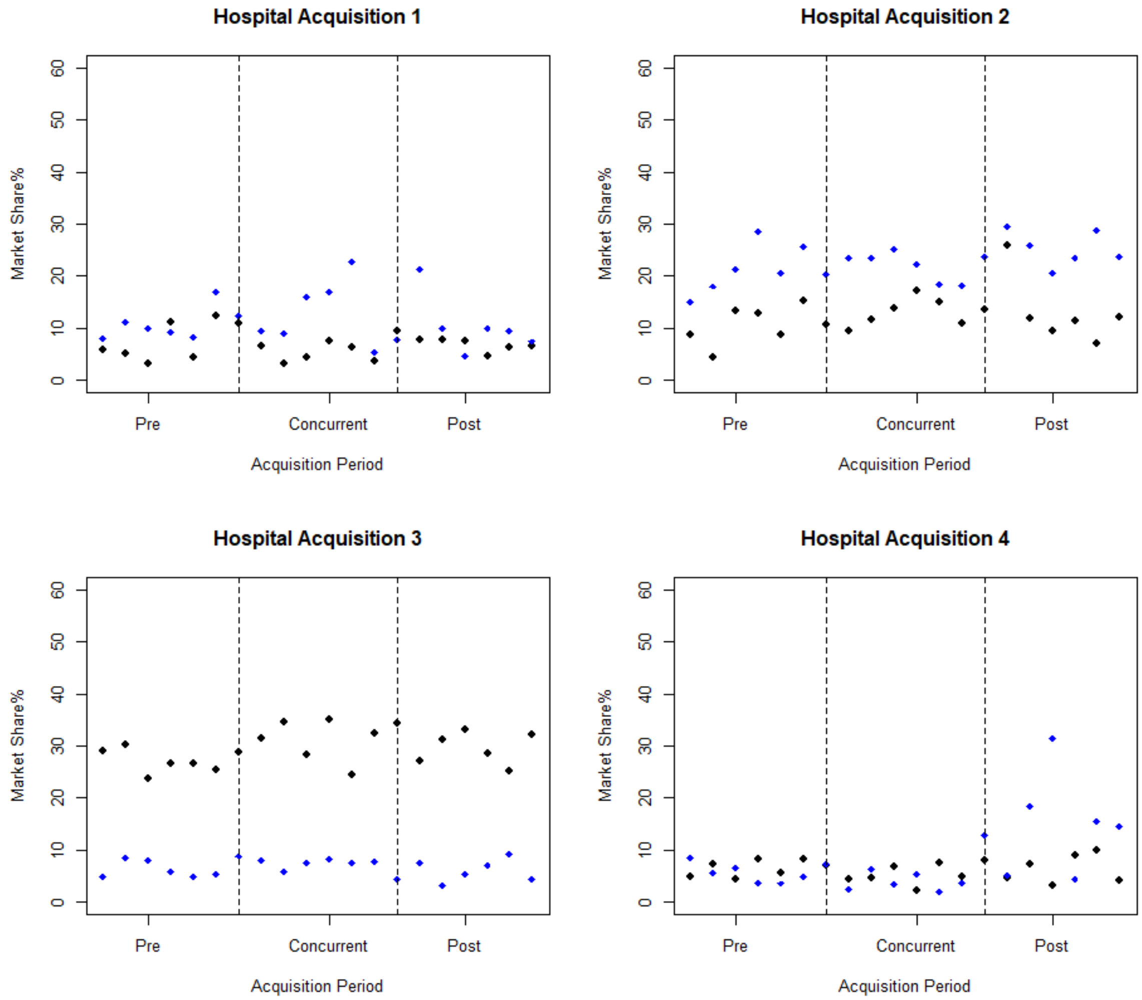


Figure 2.9 Acquiring Hospitals' Market Shares of Hospitalizations due to Respiratory Diseases over Years by Each Hospital Acquisition in This Study



2.6 Tables

Table 2.1 The List of Hospital Acquisition Included in This Study

Acquisition	**Hospital Name**	**Acquisition Status**	**Year of Acquisition**
1	East Houston Regional Medical Center	Acquired	2008
1	Bayshore Medical Center	Acquiring	2008
2	Mainland Medical Center	Acquired	2010
2	Clear Lake Regional Med Center	Acquiring	2010
3	CHRISTUS Hospital-St. Mary	Acquired	2011
3	CHRISTUS Hospital-St. Elizabeth	Acquiring	2011
4	Angleton Danbury Medical Center	Acquired	2014
4	University of Texas Medical Branch Hospitals	Acquiring	2014

Table 2.2 A Summary of Hospital Features before Their Acquisition

Basic Features	Tertiary Hospital (Acquiring Hospital)	Local Community Hospital (Acquired Hospital)
Ownership		
Non-profit	1 (25%)	1 (25%)
Profit	2 (50%)	2 (50%)
Government	1 (25%)	1 (25%)
Bed size		
50-99 beds	-	1 (25 %)
100-199 beds	-	1 (25 %)
200-299 beds	-	2 (50 %)
300-399 beds	2 (50 %)	-
400-499 beds	2 (50%)	-
500 or more beds	-	

Table 2.3 A Comparison of Income and Geographic Distance to the Acquiring Hospitals of Exposed and Control ZIP Code Areas Before and After Propensity Score Matching

Acquisition		**Before Matching**		**After Matching**
1	n	7	202	7
	Median income, $	Acquisition exposed	Control	Control
	Mean (SD)	45,540 (11,032)	60,594 (27,190)	43,494 (8,469)
	Median (Q1, Q3)	45,572 (35,912, 53,695)	54,239 (40,581, 75,396)	42906 (35,673, 52114)
	Distance, mile			
	Mean (SD)	10.73 (3.74)	25.01 (12.61)	10.18 (3.55)
	Median (Q1, Q3)	10.22 (8.08, 13.01)	23.90 (15.16, 33.93)	9.32 (8.06, 13.14)
2	n	7	191	7
	Median income, $			
	Mean (SD)	52,668 (13,719)	60,512 (27,179)	53,547 (8,369)
	Median (Q1, Q3)	49,017 (44,589, 58,292)	53,940 (40,581, 75,322)	49,861 (45,104, 59,159)
	Distance, mile			
	Mean (SD)	13.70 (2.86)	27.80 (11.97)	13.32 (3.69)
	Median (Q1, Q3)	12.75 (12.04, 16.50)	26.81 (19.75, 37.10))	12.75 (10.43, 15.90)
3	n	6	52	6
	Median income, $			
	Mean (SD)	49,110 (13,690)	48,150 (19,536)	50,714 (6,336)
	Median (Q1, Q3)	55,069 (32,841, 59,729)	46,009 (36,979, 54,909)	49570 (47,394, 54,538)
	Distance, mile			
	Mean (SD)	15.24 (3.41)	28.78 (14.11)	20.23 (8.21)
	Median (Q1, Q3)	16.24 (12.43, 18.05)	29.11 (18.12, 39.82)	23.95 (10.62)
4	n	5	102	5
	Median income, $			
	Mean (SD)	54,514 (10,681)	58,264 (27,467)	53,487 (11,478)
	Median (Q1, Q3)	53,342 (52,444, 56,250)	50,988 (39,559, 70,243)	52,760 (49,746, 57,228)
	Distance, mile			
	Mean (SD)	42.87 (9.98)	36.92 (11.55)	41.21 (10.59)
	Median (Q1, Q3)	40.72 (35.19, 52.55)	40.21 (39.57, 46.50)	43.34 (32.76, 49.66)

Table 2.4 Patients' Characteristics between the Hospital Acquisition Exposed and Control Areas for Newborn Care *

	Acquisition 1			Acquisition 2		
	Exposed	Control	p-value	Exposed	Control	p-value
Age <1 year old	14,635	16,149		6,499	10,361	
Female	7193 (49.14)	8117 (50.24)	0.133	3221 (49.56)	5058 (48.82)	0.347
Race			< .001			<.001
African	2011 (13.74)	2192 (13.57)		1386 (21.33)	1073 (10.36)	
White	5021 (34.31)	6478 (40.11)		3927 (60.42)	4500 (43.43)	
Other	7603 (51.95)	7479 (46.31)		1186 (18.25)	4788 (46.21)	
Ethnicity			<.001			<.001
Hispanic Origin	9887 (67.61)	9205 (57.05)		1868 (28.80)	4972 (48.02)	
Non Hispanic Origin	4735 (32.38)	6931 (42.95)		4618 (71.20)	5384 (51.96)	
Health Insurance			<.001			<.001
Self-pay	1540 (10.52)	1939 (12.01)		221 (3.40)	568 (5.48)	
Private	3077 (21.02)	3973 (24.60)		1956 (30.10)	3302 (31.87)	
Medicare	47 (0.32)	32 (0.20)		-	-	
Medicaid	9615 (65.70)	9904 (61.33)		4081 (62.79)	6216 (59.99)	
other	356 (2.43)	301 (1.86)		241 (3.71)	275 (2.65)	
Source of Admission			<.001			0.002
Referral	-	-		-	-	
Transformed	5323 (36.37)	5465 (33.84)		5125 (78.86)	7959 (76.82)	
other	9312 (63.63)	10684 (66.16)		1374 (21.14)	2402 (23.18)	
Periods			<.001			0.448
Pre	5025 (34.34)	5977 (37.01)		2457 (37.81)	4006 (38.66)	
Concurrent	4862 (33.22)	5214 (32.29)		1942 (29.10)	3015 (29.10)	
Post	4748 (32.44)	4958 (30.70)		3340 (32.24)	3340 (32.24)	

* If the number in a cell is less than 10, then it will be denoted using '-'.

Table 2.4 Continued *

	Acquisition 3			Acquisition 4		
	Exposed	Control	p-value	Exposed	Control	p-value
Age <1 year old	7170	4810		3569	9668	
Female	3491 (48.69)	2339 (48.63)	0.948	1767 (49.57)	4747 (49.10)	0.635
Race			<.001			<0.001
African	1458 (20.33)	226 (4.70)		337 (9.44)	704 (7.28)	
White	3316 (46.25)	4120 (85.65)		2408 (67.47)	5346 (55.30)	
Other	2396 (33.42)	464 (9.65)		824 (23.09)	3618 (37.42)	
Ethnicity			<.001			0.27
Hispanic	1723 (24.08)	275 (5.72)		1538 (43.19)	4274 (44.24)	
Non Hispanic	5433 (75.92)	4532 (94.24)		2023 (56.81)	5386 (55.76)	
Insurance			<.001			<0.001
Self-pay	100 (1.39)	79 (1.64)		-	-	
Private	2288 (31.91)	2030 (42.20)		1253 (35.12)	2734 (28.31)	
Medicare	-	-		-	-	
Medicaid	4568 (63.71)	2579 (53.62)		2213 (62.02)	6421 (66.48)	
other	214 (2.98)	122 (2.54)		102 (2.86)	503 (5.21)	
Source of Admission			0.320			
Referral	-	-		-	-	
Transformed	7028 (98.02)	4702 (97.75)		3569	9668	
other	142 (1.98)	108 (2.25)		-	-	
Periods			0.001			0.913
Pre	2437 (33.99)	1780 (37.01)		1257 (35.22)	3387 (35.03)	
Concurrent	2081 (29.02)	1401 (29.13)		1116 (31.27)	3003 (31.06)	
Post	2652 (36.99)	1629 (33.87)		1196 (33.51)	3278 (33.91)	

* If the number in a cell is less than 10, then it will be denoted using '-'.

Table 2.5 Patients' Characteristics between the Hospital Acquisitions Exposed and Control Areas for Cardiovascular Care *

	Acquisition 1			Acquisition 2		
	Exposed	Control	p-value	Exposed	Control	p-value
Age			0.002			<.001
18-39	69 (2.17)	89 (1.91)		62 (1.86)	61 (1.79)	
40-64	1667 (52.42)	2270 (48.69)		1381 (41.48)	1595 (46.82)	
>65	1444 (45.41)	2303 (49.40)		1886 (56.65)	1751 (51.39)	
Female	1385 (43.55)	1978 (42.43)	0.589	1362 (40.91)	1419 (41.65)	0.5394
Race			<.001			<.001
African	778 (24.47)	756 (16.22)		715 (21.48)	294 (8.63)	
White	1622 (51.01)	2614 (56.07)		2231 (67.02)	2341 (68.71)	
Other	780 (24.53)	1292 (27.71)		383 (11.50)	772 (22.66)	
Ethnicity			0.079			<.001
Hispanic	694 (21.85)	942 (20.21)		287 (11.64)	591 (17.35)	
Non Hispanic	2482 (78.15)	3719 (79.79)		2939 (88.36)	2816 (82.65)	
Insurance			<.001			<.001
Self-pay	333 (10.47)	420 (9.01)		162 (4.87)	235 (6.90)	
Private	1374 (43.21)	1800 (38.61)		1138 (34.18)	1482 (43.50)	
Medicare	1173 (36.89)	2063 (44.25)		1750 (52.57)	1392 (40.86)	
Medicaid	154 (4.84)	197 (4.23)		133 (4.00)	151 (4.43)	
other	146 (4.59)	182 (3.90)		146 (4.39)	147 (4.31)	
Source of Admission			0.008			<.001
Referral	953 (29.97)	1551 (33.27)		1695 (51.38)	1887 (55.42)	
Transformed	336 (10.57)	455 (9.76)		472 (14.31)	343 (10.07)	
other	1891 (59.47)	2656 (56.97)		1134 (34.06)	1175 (34.49)	
Type of Admission			0.034			0.02
Emergency	2646 (83.21)	3792 (81.34)		2661 (80.66)	2821 (82.85)	
Elective	534 (16.79)	870 (18.56)		638 (19.34)	584 (17.15)	
Periods			0.304			0.493
Pre	1284 (40.38)	1951 (41.85)		1250 (37.89)	1327 (38.97)	
Concurrent	985 (30.97)	1442 (30.93)		967 (29.31)	956 (28.08)	
Post	911 (28.65)	1269 (27.22)		1082 (332.80)	1122 (32.95)	

* If the number in a cell is less than 10, then it will be denoted using '-'.

Table 2.5 Continued *

	Acquisition 3			Acquisition 4		
	Exposed	Control	p-value	Exposed	Control	p-value
Age			<.0001			0.893
18-39	38 (1.23)	34 (1.39)		26 (1.77)	51 (1.57)	
40-64	1119 (36.16)	1135 (46.27)		661 (45.06)	1467 (45.03)	
>65	1938 (62.62)	1284 (52.34)		779 (53.10)	1739 (53.38)	
Female	1246 (40.27)	976 (39.79)	0.715	605 (41.24)	1335 (40.98)	0.61
Race			<.001			0.005
African	587 (18.97)	90 (3.67)		144 (9.82)	260 (7.98)	
White	1502 (48.53)	2223 (90.62)		1037 (70.69)	2242 (68.82)	
Other	1006 (32.50)	140 (5.71)		286 (19.50)	756 (23.20)	
Ethnicity			<.001			0.005
Hispanic	131 (4.24)	38 (1.55)		208 (14.20)	567 (17.45)	
Non Hispanic	2959 (95.76)	2415 (98.45)				
Insurance			<.001			0.001
Self-pay	69 (2.23)	147 (5.99)		-	-	
Private	1280 (41.36)	956 (38.97)		533 (36.33)	1332 (40.88)	
Medicare	1530 (49.43)	1132 (46.15)		748 (50.99)	1420 (43.59)	
Medicaid	83 (2.68)	85 (3.47)		51 (3.48)	140 (4.30)	
other	133 (4.30)	133 (5.42)		135 (9.20)	366 (11.23)	
Source of Admission			<.001			<0.001
Referral	2586 (83.55)	1826 (74.44)		1018 (69.63)	2827 (87.04)	
Transformed	113 (3.65)	77 (3.14)		444 (30.37)	421 (12.96)	
other	396 (12.79)	550 (22.42)		-	-	
Type of Admission			<.001			0.099
Emergency	1905 (61.55)	1779 (72.52)		1247 (85.29)	2828 (87.07)	
Elective	1190 (38.45)	674 (27.48)		215 (14.71)	420 (12.93)	
Periods			<.001			0.499
Pre	1055 (34.09)	984 (40.11)		479 (32.76)	1120 (34.48)	
Concurrent	970 (31.34)	686 (27.97)		413 (28.25)	904 (27.83)	
Post	1070 (34.57)	783 (31.92)		570 (38.99)	1224 (37.68)	

* If the number in a cell is less than 10, then it will be denoted using ‘-’.

Table 2.6 Patients' Characteristics between the Hospital Acquisitions Exposed and Control Areas for Respiratory Care *

	Acquisition 1			Acquisition 2		
	Exposed	Control	p-value	Exposed	Control	p-value
Age			<.001			<.001
<1 year old	122 (4.43)	212 (4.99)		65 (1.74)	108 (3.37)	
1-17	315 (11.43)	538 (12.65)		186 (4.98)	331 (10.32)	
18-39	162 (5.88)	261 (6.14)		125 (3.34)	169 (5.27)	
40-64	946 (34.34)	1185 (27.87)		1218 (32.58)	923 (28.79)	
>65	1210 (43.92)	2056 (48.35)		2144 (57.36)	1675 (52.25)	
Female	1591 (57.75)	2430 (57.15)	0.62	2198 (58.80)	1871 (58.36)	0.709
Race			<.001			<.001
African	538 (19.53)	734 (17.26)		817 (21.86)	296 (9.23)	
White	1562 (56.70)	2213 (52.05)		2614 (69.93)	2318 (72.30)	
Other	655 (23.77)	1305 (30.69)		307 (8.21)	592 (18.47)	
Ethnicity			0.003			<.001
Hispanic Origin	696 (25.28)	943 (22.20)		300 (8.03)	521 (16.25)	
Non Hispanic	2057 (74.72)	33.05 (77.80)		3435 (91.94)	2685 (83.75)	
Insurance			<.001			<.001
Self-pay	262 (9.51)	376 (8.84)		188 (5.03)	179 (5.58)	
Private	892 (32.38)	1141 (26.83)		901 (24.10)	1047 (32.66)	
Medicare	1012 (36.73)	1962 (46.14)		2102 (56.23)	1430 (44.60)	
Medicaid	503 (18.26)	684 (16.09)		415 (11.10)	434 (13.54)	
other	86 (3.12)	89 (2.09)		132 (3.53)	116 (3.62)	
Source of Admission			0.012			0.007
Referral	569 (20.65)	839 (19.73)		1837 (49.14)	1661 (51.81)	
Transformed	95 (3.45)	208 (4.89)		273 (7.30)	182 (5.68)	
other	2091 (75.90)	3205 (75.38)		1628 (43.55)	1363 (42.51)	
Type of Admission			<.001			0.007
Emergency	2573 (93.39)	3860 (90.78)		3551 (95.00)	2926 (91.27)	
Elective	182 (6.61)	392 (9.22)		187 (5.00)	280 (8.73)	
Periods			<.001			0.001
Pre	952 (34.56)	1697 (39.91)		1326 (35.50)	1164 (36.31)	
Concurrent	921 (33.43)	1371 (32.34)		1111 (29.75)	1058 (33.00)	
Post	882 (32.01)	1184 (27.85)		1298 (34.75)	984 (30.69)	

* If the number in a cell is less than 10, then it will be denoted using '-'.

Table 2.6 Continued *

	Acquisition 3			Acquisition 4		
	Exposed	Control	p	Exposed	Control	p
Age			<.001			<.001
<1 year old	370 (9.66)	86 (2.95)		23 (1.20)	46 (1.39)	
1-17	680 (17.75)	285 (9.79)		77 (4.01)	202 (6.12)	
18-39	147 (3.84)	105 (3.61)		81 (4.22)	131 (3.97)	
40-64	895 (23.36)	820 (28.17)		584 (30.40)	1195 (36.18)	
>65	1740 (45.41)	1615 (55.48)		1156 (60.18)	1729 (52.35)	
Female	1562 (56.15)	1484 (58.43)	0.093	1169 (60.85)	1819 (55.07)	<.001
Race			<.001			0.028
African	925 (24.14)	85 (2.92)		145 (7.55)	283 (8.57)	
White	1596 (41.65)	2707 (92.99)		1506 (78.40)	2482 (75.14)	
Other	1311 (34.21)	119 (4.09)		270 (14.06)	538 (16.29)	
Ethnicity			<.001			0.773
Hispanic Origin	400 (10.44)	36 (1.24)		268 (14.00)	451 (13.72)	
Non Hispanic Origin	3431 (89.56)	2872 (98.76)		1646 (86.00)	2837 (86.28)	
Insurance			<.001			<.001
Self-pay	80 (2.09)	104 (3.57)		-	-	
Private	1273 (33.22)	852 (29.27)		366 (19.02)	1062 (32.21)	
Medicare	1590 (41.49)	1541 (52.94)		1214 (63.10)	1483 (44.98)	
Medicaid	724 (18.89)	322 (11.06)		213 (11.07)	403 (12.22)	
other	165 (4.31)	92 (3.16)		131 (6.81)	349 (10.59)	
Source of Admission			<.001			0.007
Referral	3041 (79.36)	2044 (70.22)		1756 (91.51)	3081 (93.51)	
Transformed	80 (2.09)	62 (2.13)		163 (8.49)	214 (6.49)	
other	711 (18.55)	805 (27.65)		-	-	
Type of Admission			<.001			0.002
Emergency	2918 (76.15)	2371 (81.45)		1856 (97.24)	3149 (95.57)	
Elective	913 (23.83)	540 (18.55)		53 (2.76)	146 (4.43)	
Periods			<.001			0.901
Pre	1349 (35.20)	1217 (41.81)		703 (36.63)	1223 (37.12)	
Concurrent	1306 (34.08)	890 (30.57)		598 (31.16)	1008 (30.59)	
Post	1177 (30.72)	804 (27.62)		618 (32.20)	1064 .29)	

* If the number in a cell is less than 10, then it would be denoted using ‘-’.

Table 2.7 Estimates of the Hospital Acquisition Impact on Acquiring Hospital's Market Shares without Competing Hospitals Located in the Same Market as the Acquired Hospital (Acquisition 1 and 4)

		Estimate	**SE**	**p-value**
Overall	Control	ref	ref	ref
	Exposed	0.95	1.15	0.411
	Pre	ref	ref	ref
	Concurrent	0.12	1.19	0.919
	Post	0.39	1.15	0.737
	Exposed * Pre	ref	ref	ref
	Exposed * Concurrent	1.73	1.69	0.309
	Exposed * Post	**4.70**	**1.63**	**0.005 *****
Newborn Care				
	Control	ref	ref	ref
	Exposed	1.58	1.27	0.218
	Pre	ref	ref	ref
	Concurrent	-0.12	1.33	0.930
	Post	-0.07	1.25	0.955
	Exposed * Pre	ref	ref	ref
	Exposed * Concurrent	1.46	1.88	0.441
	Exposed * Post	**4.94**	**1.81**	**0.008 *****
Cardiovascular Care				
	Control	ref	ref	ref
	Exposed	3.12	2.79	0.267
	Pre	ref	ref	ref
	Concurrent	1.18	2.91	0.687
	Post	1.26	2.79	0.654
	Exposed * Pre	ref	ref	ref
	Exposed * Concurrent	0.23	4.12	
	Exposed * Post	**11.44**	**3.95**	**0.005 *****
Respiratory Care				
	Control	ref	ref	ref
	Exposed	1.26	1.73	0.469
	Pre	ref	ref	ref
	Concurrent	-1.86	0.79	0.304
	Post	-0.19	1.72	0.91
	Exposed * Pre	ref	ref	ref
	Exposed * Concurrent	2.11	2.54	0.408
	Exposed * Post	**4.23**	**2.443**	**0.087 ***

Significance level: <0.1 "*", <0.05 "**", <0.01 "***"

Table 2.8 Associations of Hospital Acquisition with Access to Newborn Care at the Acquiring Hospital by Types of Health Insurance

	Acquisition 1 OR (95%CI)		Acquisition 2 OR (95%CI)	
Exposed	1.33	(0.90, 1.96)	2.91	(2.34, 3.62)
Period (Pre-)	Ref	Ref	Ref	Ref
Period (Concurrent)	1.21	(0.80, 1.82)	0.90	(0.74, 1.10)
Period (Post)	1.04	(0.66, 1.63)	0.94	(0.77, 1.15)
Exposed*Period (Concurrent)	1.00	(0.57, 1.76)	1.19	(0.88, 1.59)
Exposed*Period (Post), private as ref	**0.46 ****	**(0.25, 0.86)**	0.89	(0.67, 1.19)
Exposed *Period (Concurrent)*Self-pay	2.89	(0.75, 11.20)	0.64	(0.25, 1.64)
Exposed *Period (Concurrent)* Medicaid	0.87	(0.45, 1.68)	1.35	(0.89, 2.04)
Exposed *Period (Concurrent)*Other payers	0.59	(0.09, 3.90)	1.20	(0.35, 4.05)
Exposed *Period (Post)*Self-pay	2.52	(0.55, 11.60)	0.82	(0.24, 2.79)
Exposed *Period (Post)* Medicaid	**2.03 ****	**(1.00, 4.09)**	**1.86*****	**(1.24, 2.78)**
Exposed *Period (Post)*Other payers	2.46	(0.40, 15.24)	2.67*	(0.96, 7.38)
Period (Concurrent)* Self-pay	0.80	(0.32, 2.01)	2.39	(1.29, 4.43)
Period (Concurrent)* Medicaid	0.78	(0.49, 1.26)	0.88	(0.66, 1.17)
Period (Concurrent)*Other payers	0.63	(0.17, 2.31)	0.70	(0.29, 1.72)
Period (Post) *Self-pay	1.08	(0.42, 2.78)	2.47	(1.13, 5.40)
Period (Post)* Medicaid	0.59	(0.37, 0.95)	0.86	(0.65, 1.13)
Period (Post)*other payer	0.64	(0.16, 2.52)	0.65	(0.31, 1.36)
Exposed *Self-pay	0.54	(0.19, 1.56)	1.25	(0.67, 2.33)
Exposed * Medicaid	0.74	(0.47, 1.16)	0.69	(0.53, 0.92)
Exposed *other payer	0.72	(0.21, 2.48)	0.46	(0.21, 1.02)
White	Ref	Ref	Ref	Ref
African American	0.33	(0.23, 0.47)	0.47	(0.41, 0.53)
Other race	3.37	(2.88, 3.94)	1.57	(1.39, 1.78)
Hispanic	0.83	(0.70, 0.97)	0.29	(0.26, 0.33)
Medicaid	Ref	Ref	0.36	(0.24, 0.56)
Self-pay	0.59	(0.31, 1.11)	0.37	(0.30, 0.44)
Private	1.61	(1.17, 2.22)	0.98	(0.54, 1.77)
Other payers	1.99	(0.83, 4.78)	0.86	(0.76, 0.99)
Referral	Ref	Ref	Ref	Ref
Other source of admission	0.68	(0.56, 0.84)	0.99	(0.91, 1.07)
female	0.93	(0.83, 1.04)	1.20	(0.96, 1.49)
geographic distance	0.93	(0.91, 0.94)	0.83	(0.81, 0.85)

Significance level: <0.1 "*", <0.05 "**", <0.01 "***"

Table 2.9 Associations of Hospital Acquisition with Access to Cardiovascular Care at the Acquiring Hospital for Acquisition 1 and 4

	Acquisition 1 OR (95%CI)		Acquisition 4 OR (95%CI)	
Control	Ref	Ref	Ref	Ref
Exposed	1.93	(1.24, 3.00)	3.28	(1.58, 6.80)
Pre-	Ref	Ref	Ref	Ref
Concurrent-	0.90	(0.54, 1.52)	1.96	(1.22, 3.14)
Post-	0.69	(0.38, 1.27)	2.42	(1.57, 3.72)
Exposed*Concurrent	1.72	(0.90, 3.29)	1.36	(0.60, 3.07)
Exposed*Post	**4.18*****	**(2.08, 8.39)**	**2.88*****	**(1.38, 6.03)**
Age >=65 years old	Ref	Ref	Ref	Ref
40-64 years old	0.63	(0.47, 0.83)	1.86	(1.35, 2.56)
White	Ref	Ref	Ref	Ref
African American	0.44	(0.29, 2.11)	1.36	(0.92, 2.01)
Other races	1.20	(0.80, 1.79)	0.10	(0.05, 0.18)
Hispanic	1.39	(0.92, 2.11)	3.85	(2.50, 5, 91)
Medicare	Ref	Ref	Ref	Ref
Self-pay	1.84	(1.11, 3.03)	NA	NA
Private	1.96	(1.44, 2.68)	0.32	(0.22, 0.45)
Medicaid	1.66	(0.86, 3.20)	1.86	(1.08, 3.22)
Other payers	2.20	(1.14, 4.23)	0.96	(0.62, 1.49)
Referral	Ref	Ref	Ref	Ref
Transferred	0.03	(0.00, 0.24)	1.38	(0.99, 1.92)
Other sources	1.05	(0.73, 1.50)	NA	NA
Urgent/Emergent	Ref	Ref	Ref	Ref
Elective	2.02	(1.35, 3.02)	1.58	(1.12, 2.21)
Female	1.03	(0.80, 1.33)	0.96	(0.74, 1.23)
GeoDist	0.90	(0.87, 0.94)	0.92	(0.91, 0.94)

Significance level: <0.1 “*”, <0.05 “**”, <0.01 “***”

Table 2.10 Associations of Hospital Acquisition with Access to Respiratory care at the Acquiring Hospitals for Acquisition 1 and 4

	Acquisition 1 OR (95%CI)		Acquisition 4 OR (95%CI)	
Control	Ref	Ref	Ref	Ref
Exposed	1.94	(1.27, 2.95)	0.69	0.33, 1.45
Pre-	Ref	Ref	ref	Ref
Concurrent-	1.03	(0.64, 1.64)	0.65	(0.38,1.10)
Post-	1.03	(0.63, 1.69)	1.08	(0.67, 1.74)
Exposed*Concurrent	**1.70***	**(0.95, 3.06)**	0.69	(0.19, 2.50)
Exposed*Post	1.00	(0.53, 1.90)	**6.85******	**(2.96, 15.88)**
Age >=60 years old	Ref	Ref	Ref	Ref
<1 years	0.70	(0.37, 1.30)	1.05	(0.27, 4,11)
1-17 years old	0.77	(0.48, 1.23)	0.73	(0.30, 1.76)
18-39 years old	0.74	(0.42, 1.28)	1.79	(0.81, 3.98)
40-64 years old	0.68	(0.49, 0.96)	1.30	(0.82, 2.08)
White	Ref	Ref	Ref	Ref
African American	0.31	(0.18, 0.51)	1.47	(0.90, 2.40)
Other races	1.51	(1.06, 2.14)	0.130	(0.05, 0.32)
Hispanic	1.13	(0.77, 1.66)	2.78	(1.42, 5.45)
Medicare	Ref	Ref	Ref	Ref
Self-pay	1.63	(0.98, 2.71)	NA	NA
Private	1.54	(1.12, 2.13)	0.52	(0.31, 0.89)
Medicaid	1.77	(1.11, 2.82)	2.13	(1.18, 3.85)
Other payers	1.74	(0.83, 3.65)	1.65	(0.88, 3.08)
Referral	ref	Ref	Ref	Ref
Transferred	0.70	(0.35, 1.41)	12.82	(8.63, 19.05)
Other sources	1.40	(0.94, 2.09)	NA	NA
Urgent/Emergent	Ref	Ref	Ref	Ref
Elective	4.65	(2.94, 7.34)	0.92	(0.37, 2.32)
Female	1.23	(0.96, 1.58)	0.67	(0.48, 0.93)
GeoDist	0.89	(0.86, 0.93)	0.94	(0.93, 0.96)

Significance level: <0.1 “*”, <0.05 “**”, <0.01 “***”

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3. IMPACTS OF RURAL HOSPITAL ACQUISITIONS ON TREATMENT PATTERNS

3.1 Background

The U.S. hospital market has become more concentrated in recent decades. The number of hospital acquisitions has risen since 2008, with 129 announced hospital "change of control" transactions in 2012 and 118 similar transactions in 2017, which were among the highest in the last 20 years (LeMaster and Jaeger, 2018). According to the American Hospital Association (AHA) annual report, the number of U.S. registered community hospitals has decreased from 5,815 in 2008 to 5,262 in 2019 (American Hospital Association, 2019).

Hospitals in Texas are part of this wave of hospital acquisition. Various types of hospital acquisition transactions in Texas occurred, including mega-hospital system mergers, partnerships among local hospitals, and acquisitions between a local community hospital and a tertiary hospital system. For instance, one recent acquisition in Texas was the combination of Good Shepherd Health System and Christus Health of Dallas in 2017 (Brabham, 2017). All local hospitals in the Good Shepherd Health System now are under the tertiary system of Christus Good Shepherd Medical Center. The CEO of the local hospital at Marshall told the public that the new system would offer an extensive scope of medical services to the local community (Brabham, 2017).

Conceptually, the hospital acquisition between a local community hospital and a tertiary hospital system could influence on the delivery of treatment for patients living in the local community through (1) referrals of patients to the tertiary hospital; or (2) investments in the local hospital. A recent report released by Charles River Associates summarized that hospital acquisition could help to expand the scope and the scale of health care services (Noether and May, 2017). Moreover, hospital leaders usually promise that their main motivation for acquisition is to invest in local hospitals, transfer expertise, provide advanced services, and ultimately enhance health care services for local communities (Brabham, 2017). Meanwhile, competing hospitals in the same market area would respond to the acquisition by employing business strategies. Previous studies focusing on the impact of hospital acquisition on price reported that competing hospitals would raise prices after an acquisition between rival hospitals in the same market (Dafny, 2009). Taken together, as illustrated in Figure 3.1 and 3.2, the hospital acquisition may influence the overall treatment patterns on patients living in the exposed area through two strategies: (1) the tertiary (i.e., acquiring) hospital's market share of patients; (2) the local community (i.e., acquired) hospital's market share of patients. In addition, the competing hospital(s)' market share of patients may also affect treatment patterns.

Empirical studies regarding the impact of hospital acquisition on treatment patterns are mixed. Bazzoli et al. investigated two hospital merging periods: 1983-1988 and 1989-1996, and reported that hospitals reduced service duplication and nursing full-time equivalents (FTEs) but did not invest in acquired hospitals (Bazzoli et al., 2002). Hayford scrutinized the impacts of hospital mergers on an overall treatment pattern and quality by focusing on heart disease patients in California from 1990 to 2006. He found that hospital mergers might be associated with greater treatment intensity but without evidence of higher quality or better health outcomes (Hayford, 2012). The most recent study published in *New England Journal of Medicine* on January 2, 2020 investigated hospital acquisitions from 2009 through 2013 and did not find any conclusive evidence on the effects of hospital acquisition on the clinical performance of acquired hospitals

(Beaulieu et al., 2020). Most of these published studies focused on the effect of hospital acquisition on hospital-level assessment, and did not target patient-level assessment.

The impact of hospital acquisition on the treatment patterns can be influenced by patients' lucrativeness and severity of illness. Due to financial motivations, after acquisition the reorganized hospital system may only target patients with lucrative insurances, rather than all patients from the local community (i.e., "cherry-picking"). As a result, the acquisition may only have a positive influence on better insured patients. For example, researchers also found that Medicare patients might receive more intensive treatment if they were "high-valuation" patients (Bundorf et al., 2004, Kessler and Geppert, 2005). "High-valuation" in the study was defined as high risk, since hospitals could charge more on a Medicare patient who had a higher risk. All previous studies on this topic used Medicare patients as their study samples, and the impact of hospital acquisition has not been explored much in other populations.

In this study, I target cross-market hospital acquisition between a local community hospital (i.e., acquired hospital) and a tertiary hospital (i.e., acquiring hospital) in Texas and evaluate the impact of acquisition on interventional treatment pattern received by patients with four research questions:

Research question 1: How would the proportion of patients receiving interventional treatment among all patients living in the acquisition exposed area change after a hospital acquisition?

***Hypothesis 1*: I expect to observe the proportion of patients, receiving treatment in the acquisition exposed area, to increase after the hospital acquisition relative to the control areas (Figure 3.2).**

This is derived from the assumption that after acquisition, the reorganized hospital system would expand their medical services to the exposed area.

Research question 2: Does the impact of acquisition on interventional treatment received by patients vary depending on health insurance status or severity of illness?

<u>Hypothesis 2.1</u>: In the hospital acquisition exposed area, patients with private health insurance are more likely to receive an interventional treatment relative to patients with Medicaid or lack of insurance.

<u>Hypothesis 2.2</u>: In the hospital acquisition exposed area, patients with higher severity of illness are more likely to receive an interventional treatment relative to patients with lower severity of illness.

These two hypotheses stem from an assumption that the impact of acquisition could be different based upon patients' lucrativeness and severity of illness. To obtain a better financial status, hospitals may tend to prioritize patients with better insurance plans. Meanwhile, I expect that the reorganized hospital system would have a better clinical standardization after acquisition, as hospital leaders have promised. Therefore, patients with major or extreme severity of illness would be more likely to receive an interventional treatment.

Research question 3: How would the acquiring hospital's market share of interventional treatment change after the acquisition?

<u>Hypothesis 3.1</u>: When there are no competing hospitals in the same market area, I expect to observe the acquiring hospital's market share of interventional treatment received by patients living in the exposed area to increase after the acquisition (Figure 2.3 and 3.2).

<u>Hypothesis 3.2</u>: When there is a competing hospital(s) in the same market area, the acquiring hospital's market share of interventional treatment received by patients living in the exposed area would not increase after the acquisition (Figure 2.3 and 3.2).

The acquiring hospital has a better capacity in terms of interventional treatment, and patients' referral process would be streamlined after the acquisition. Therefore, the acquiring hospital's market share is more likely to increase, when no competing hospitals could affect this market. If there is a competing hospital responding to the acquisition in the same market, the competing hospital's market share would increase, which would affect the acquiring hospital's market share of the interventional treatment.

Research question 4: Does the impact of acquisition on interventional treatment received by patients at the acquiring hospital vary depending on health insurance status or severity of illness?

<u>Hypothesis 4.1</u>: Comparing with the control area, the interventional treatment received by patients in the hospital acquisition exposed area is more likely to be performed at the acquiring hospital for patients having better health insurance.

<u>Hypothesis 4.2:</u> Comparing with the control area, the interventional treatment received by patients in the exposed area is more likely to be performed at the acquiring hospital for patients with higher severity of illness.

Patients' health insurance status determines how much can be reimbursed for the interventional treatment conducted in hospitals. I assume the capacity of interventional treatment provided in an acquiring hospital is fixed in the short term. Then, the acquiring hospital tends to prioritize the interventional treatment for patients with better insurance plans after acquisition. In addition, if a clinical standardization has been successfully built between the acquiring and the acquired hospital after their acquisition, this may help patients with more severe illness receive the interventional treatment. Thus, I would observe that the acquiring hospital also prioritizes the interventional treatment for patients with higher severity of illness.

3.2 Methods

3.2.1 Study design

In this retrospective study, I investigate the impact of hospital acquisition on interventional treatment patterns received by patients living in the acquisition exposed area using a Difference-in-Differences (DiD) approach. Under the DiD study design, the "intervention" for this study is defined as cross-market hospital acquisition between a tertiary hospital system (i.e., acquiring hospital) and a local community hospital (i.e., acquired hospital) in Texas from 2008 through 2014. Similarly to the previous section (see section 2.2.1), the study period consists of pre-, concurrent, and post- acquisition periods. Unit of analysis includes both discharge level and ZIP code level, which is accumulated using discharge-level data.

3.2.2 Data

Data used in this study are derived from four sources: Texas Inpatient Public Use Data Files (PUDF), AHA Landscape Changes in U.S. Hospitals files and AHA Annual Survey, the American Community Survey (ACS), and National Bureau of Economic Research (NBER). The PUDF provided by Texas Department of State Health Service (DSHS) are on discharge (patient)-level and contain comprehensive information on inpatients, such as demographic characteristics, clinical features, International Classification of Diseases (ICD) codes for diagnoses and procedures. The AHA Landscape Changes files include annual hospital acquisition information; AHA Annual Survey collects hospital features, such as the number of beds as well as five-digit ZIP code. ZIP code-level information is downloaded directly from ACS and NBER websites.

3.2.2.1 Hospital acquisition

Target hospital acquisitions are identified from AHA Landscape Changes in U.S. Hospitals files. The inclusion criteria are: hospital acquisitions occurring in (1) Texas; (2) between 2008 and 2014; (3) acquisition between an acquiring hospital and an acquired hospital, which means that both of them are general hospitals and the number of beds of an acquiring hospital should be at least double the number of beds of an acquired hospital; (4) cross-market, which requires that the geographic distance between the acquiring and the acquired hospital be greater than 10 miles (fixed- and variable-radius measures for hospital competition market are discussed in the previous section (see Section 2.2.1)). Exclusion criteria include: (1) a hospital acquisition involving at least one psychiatric, rehab, or any other types of specialty hospital; (2) there are hospital closures or openings during the pre-, concurrent, and post- periods for both hospital acquisition exposed and control areas (See section 3.2.2.2). In addition, to study the acquiring hospitals' market share, it is necessary to have a unique hospital identifier/Texas Health Care Information Collection_Identifier (THCIC_ID) for each of the acquiring hospital and the acquired hospital. If the reorganized hospital system submits both the acquiring and the acquired hospital discharge together under the same hospital identifier to the Texas DSHS, then I could not distinguish acquiring or acquired hospital market share using PUDF data. More discussions on the inclusion and exclusion criteria can be found in the previous section (see Section 2.2.2). Four hospital acquisitions are identified using these criteria (see Table 2.1) and the basic characteristics are summarized in Table 3.1.

As described in the previous section (see Section 2.2.2), I also identify competing hospital(s) within the same market as the acquired hospital, which is a general acute hospital(s) and its geographic distance to the acquired hospital of an acquisition is less than 10 miles.

3.2.2.2 Study sample

I focus on patients diagnosed with Coronary Artery Disease (CAD), as it is one of the top causes of hospitalization. CAD patients may receive interventional treatments, which are usually considered as more profitable procedures from a hospital's perspective (McDermott, et al., 2017). The interventional treatment includes coronary angioplasty, or Percutaneous Coronary Intervention (PCI), and coronary artery bypass grafting (CABG). They have been used as an indicator for the treatment pattern of cardiovascular inpatient care in many published studies (Hayford, 2012, Ho and Hamilton, 2000). In this study, I combine both PCI and CABG as the interventional treatment for CAD patients due to a low volume of CABG conducted in one ZIP code area.

3.2.2.2.1 Discharge level

CAD patients are identified using diagnosis codes from International Classification of Diseases, Ninth Revision; Clinical Modification (ICD-9-CM) and International Classification of Diseases, Tenth Revision; and Clinical Modification (ICD-10-CM). Interventional treatments are identified using procedure codes from All Patient Refined Diagnosis Related Groups (APR-DRGs). Detailed codes are displayed in Tables S.5 and S.6.

3.2.2.2.2 ZIP code level

Using a strategy similar to that employed in the previous section (see Section 2.2.2), I identify two sets of ZIP code-areas: hospital acquisition exposed and control areas. Five factors are considered, and Figure 3.2 and 3.3 illustrate the concepts and calculations of these variables on ZIP code level:

(1) Geographic distance;

(2) Median income;

(3) *Proportion* (*Exposed*) and *Proportion* (*Control*): the proportion of CAD patients receiving the interventional treatment in the acquisition exposed and control areas, respectively;

(4) $Market\ share\ (Exposed)_{Acquiring}$ and $Market\ share\ (Control)_{Acquiring}$: the acquiring hospital's market share of interventional treatments received by CAD patients living in the acquisition exposed and control areas;

(5) $Market\ share\ (Exposed)_{Acquired}$ and $Market\ share\ (Control)_{Acquired}$, the acquired hospital's market share of interventional treatments received by CAD patients living in the acquisition exposed and control areas.

Through the previous section, I have obtained two sets of ZIP code areas for acquisition exposed and control areas, which are relatively balanced on median income and geographic distance to the acquiring hospital.

After constructing these variables, $Market\ share\ (Control)_{Acquired}$ is used to verify that the acquired hospital's market share of interventional treatments received CAD patients living in the control area is very small (i.e., < 1%). The parallel assumption between the exposed and control areas is examined using *proportion (Exposed)* versus *Proportion (Control)* and $Market\ share\ (Exposed)_{Acquiring}$ versus $Market\ share\ (Control)_{Acquiring}$, respectively.

In addition, I also construct the competing hospital's market share of CAD patients living in the acquisition exposed area: $Market\ share\ (Exposed)_{Competing}$. Both $Market\ share\ (Exposed)_{Competing}$ and $Market\ share\ (Exposed)_{Acquired}$ are used for the descriptive analysis of this study.

3.2.3 Variables and measures

To capture the impact of hospital acquisition (i.e., "intervention") over time, this study consists of three time periods: pre-, concurrent, and post- acquisition periods. The Acquisition 1 and 4 in this study occurred in 2008 and 2014, so the 2006-2007 and 2015-2016 years of PUDF data are used to reflect the pre- acquisition period for Acquisition 1 and the post- acquisition period for Acquisition 4, respectively.

The discharge data files indicate both year and quarter, while AHA hospital data files only suggest the year of hospital acquisition. It is hard to accurately match the discharge-level information with hospital-level acquisition data on both year and quarter. For example, if a hospital acquisition occurred in the last quarter of 2013, the hospital-level information for concurrent period should be mapped with 2013 Q4, 2014 Q1, 2014 Q2, and 2014 Q3 discharge-level files. However, the AHA data files do not include the quarter of hospital acquisition. To deal with this issue, I expand one quarter to both before and after the year of hospital acquisition. For this study, the pre-, concurrent, post- acquisition periods consist of 7, 6, and 7 quarters, respectively.

On ZIP code-level analysis, the response variables are (1) *Proportion*; and (2) $MarketShare_{Acquiring}$ of the acquisition exposed or control areas. Explanatory variables contain time-fixed effects ($\boldsymbol{time_t}$), fixed exposed/control effects (*intervention*), and their interactions. Pre- acquisition period is the reference group, and two indicators represent the time-fixed effects: concurrent period ($time_1$) as well as post- acquisition period ($time_2$).

For the analysis on discharge level, I also consider two response variables: (1) whether the CAD patients would receive interventional treatment or not, and (2) whether the interventional treatment received by CAD patients would be performed at the acquiring hospital or other hospitals. Both response variables are analyzed as dummy variables indicating whether the observed discharge record (e.g., data captured from the patient stay) includes an interventional procedure or not and whether the procedure is offered by the acquiring hospitals or other hospitals using THCIC_ID.

The main variable of interest is the interaction effect between *intervention* and $\boldsymbol{time_t}$. The models also include time-fixed effects, fixed exposed/control effects (*intervention*), gender, age, ethnicity, race, health insurance status, type of admission, source of admission, geographic distance to the acquiring hospital, and patent's severity of illness. Detailed definitions and values of these variables are listed in the Appendix (see Table S4).

By comparing the exposed and control areas, I identify:

(1) Changes in the proportion of CAD patients receiving the interventional treatment for the concurrent and post- acquisition periods comparing with the pre- period (Research question 1);

(2) Different impact of hospital acquisition on receiving the interventional treatment depending on discharge (i.e., patient)-level health insurance status or severity of illness;

(3) Changes in the acquiring hospital's market share of the interventional treatment received by CAD patients for the concurrent and post- acquisition periods comparing with the pre- period (i.e., Research question 3);

(4) Different impact of hospital acquisition on the interventional treatment being performed at the acquiring hospital (versus at other hospitals) depending on discharge (i.e., patient)-level health insurance status or severity of illness (i.e., Research question 4).

3.2.4 Statistical analysis

As provided in the previous section and Table S.3 in the appendix, to detect a 5% difference in market share using a 2-sided test at a significance level of 0.05 with a power of 0.85, the sample size of ZIP code areas for exposed and control should be at least 73. Therefore, at least two out of the four acquisitions should be combined to achieve the power on ZIP code-level analysis.

For the analysis on ZIP code level, the overall trends in the proportion of CAD patients receiving the interventional treatment and the acquiring hospital's market share of the interventional treatment are plotted between the acquisition exposed and control areas over years to determine whether the parallel trend assumption of DiD is met.

To answer Research Question 1, the impact is estimated using mixed models taking into account ZIP code areas over time:

$$\textit{Proportion of interventional treatment}_{jt} =$$

$$\alpha_0 + \boldsymbol{\alpha_1} \times \textbf{\textit{time}}_{\boldsymbol{t}} + \alpha_2 \times intervention + \boldsymbol{\alpha_3} \times intervention \times \textbf{\textit{time}}_{\boldsymbol{t}} + \gamma_j + \epsilon_{jt} \qquad (3.1)$$

Proportion of interventional treatment$_{jt}$ denotes the proportion of CAD patients receiving the interventional treatment among all CAD patients living in the ZIP code area j during time t. The $\textbf{\textit{time}}_{\boldsymbol{t}}$ consists of two indicators: $time_1$ for the concurrent period (i.e., = 1) and $time_2$ for the post-acquisition period (i.e., = 1), and the pre- acquisition period is the reference group with $time_1=time_2=0$. *Intervention* indicates that whether the ZIP code area j is an acquisition exposed (=1) or control area (=0). The interaction term of $\textbf{\textit{time}}_{\boldsymbol{t}}$ and *intervention* represent the acquisition impact on the proportion of CAD patients receiving the interventional treatment for the concurrent period or post - acquisition period. The coefficients of interest are $\boldsymbol{\alpha_3}$, indicating an increase in the proportion for the concurrent and post- acquisition period when they are estimated to be statistically significant and positive. Additionally, $\boldsymbol{\alpha_1}$ denotes a fixed time effect in control areas, α_2 represents a difference in the proportions between the exposed and control areas for the pre- acquisition period, and γ_j denotes a random effect of ZIP code areas.

To answer Research Question 2, multilevel logistic regression on discharge level is employed, and the model is specified as below:

$$log\left(\frac{Pr(Y_{ijt})}{1\text{-}Pr(Y_{ijt})}\right)=$$

$$\beta_0+\boldsymbol{\beta_1}\times\boldsymbol{time_t}+\beta_2\times intervention+\boldsymbol{\beta_3}\times intervention\times\boldsymbol{time_t}+\boldsymbol{\beta_4}\times\ \boldsymbol{payers}+\boldsymbol{\beta_5}\times\ \boldsymbol{payers}\times\boldsymbol{time_t}$$

$$+\boldsymbol{\beta_6}\times\ \boldsymbol{payers}\times intervention+\boldsymbol{\beta_7}\times\boldsymbol{time_t}\times\ \boldsymbol{payers}\times intervention+\boldsymbol{\beta_8}\cdot\boldsymbol{X_j}+\beta_9\cdot D_j+\gamma_j+\epsilon_{ijt} \qquad (3.2)$$

Y_{ijt} indicates whether the patient i from ZIP code area j receives interventional treatment (i.e., = 1) or not (i.e., = 0) when he/she is hospitalized during the acquisition time period t.
Covariates $\boldsymbol{time_t}$ and *intervention* have the same interpretation as in the model above. ***Payers*** is a categorical variable for health insurance status: Medicare (i.e., reference group), private insurance, Medicaid, and lacking of insurance. The three-way interaction would not be equal to 0 when there are different impacts of acquisition on receiving the interventional treatment or not among various types of health insurance. I examine whether this three-way interaction term is statistically significant. If it is not significant, I would remove it from the model, which suggest that no statistical differences are observed in the impacts of hospital acquisition on receiving the

interventional treatment. Then, I would examine the two-way interaction term between $\boldsymbol{time_t}$ and *intervention*, which represents an overall acquisition impact regardless of types of insurance plan. $\boldsymbol{X_j}$ denotes a vector of demographic and clinical characteristics of patient i, including age group, gender, and severity of illness; γ_j indicates random effects of ZIP code areas.

I also evaluate impact of hospital acquisition on receiving the interventional treatment or not by patient's severity of illness. The model is similar with the one above, and the term $payers$ is replaced with the severity of illness in the two and three way-interaction terms. The three-way interaction would not be equal to 0 when there are statistically different impacts of acquisition on receiving the interventional treatment for patients with various levels of severity illness.

To explore Research Question 3, the basic model is similar to the model (3.1) and written as below:

$$Market\ share_{jt\_Acquiring} =$$

$$\alpha_0 + \boldsymbol{\alpha_1} \times \boldsymbol{time_t} + \alpha_2 \times intervention + \boldsymbol{\alpha_3} \times intervention \times \boldsymbol{time_t} + \gamma_j + \epsilon_{jt} \qquad (3.3)$$

$Market\ share_{jt\_Acquiring}$ represents the acquiring hospital's market share of interventional treatment received by CAD patients living in the ZIP code area j during time t. And other terms and coefficients share similar interpretations with the first model.

To answer Research Question 4, I use the model below, which is similar to the model on page 74, except for the response variable:

$$log\left(\frac{Pr\left(Trt_{ijt}\right)}{1\text{-}Pr\left(Trt_{ijt}\right)}\right)=$$

$$\beta_0+\boldsymbol{\beta_1}\boldsymbol{\times time_t}+\beta_2\times intervention+\boldsymbol{\beta_3}\times intervention\times\boldsymbol{time_t}+\boldsymbol{\beta_4}\boldsymbol{\times payer}+\boldsymbol{\beta_5}\boldsymbol{\times payer\times time_t}$$

$$+\boldsymbol{\beta_6}\boldsymbol{\times payer}\times intervention+\boldsymbol{\beta_7}\boldsymbol{\times time_t\times payer}\times intervention+\boldsymbol{\beta_8}\boldsymbol{\cdot X_j}+\beta_9\cdot D_j+\gamma_i+\epsilon_{ijt} \qquad (3.4)$$

The response variable Trt_{ijt} indicate whether patient i's interventional treatment is performed at the acquiring hospital (i.e., = 1) or not (i.e., = 0) during the acquisition time period t, and the patient i lives in ZIP code area j. Other terms are similar to the ones on page 69.

All analyses are conducted using SAS Version 9.4. (Cary, NC) and statistical significance level is considered to be 0.05 unless specified.

3.3 Results

3.3.1 The impact of the hospital acquisition on the proportion of CAD patients receiving the interventional treatment

CAD patients' characteristics have been summarized in the previous section (see Section 2.3.1), and the number of patients who received an interventional treatment is shown in Table 3.2 by each acquisition. On average, there is a total of 51.4% and 52.1 % CAD patients receiving the interventional treatment in the exposed and control areas. As displayed in Figure 3.4 and Table 3.3, there are no significant increases or decreases in the proportion over the concurrent or post-acquisition periods when combining all acquisitions. Yet, the impact is positive for the concurrent period for Acquisition 1 and 4 at the significance level of 0.1. In particular, the estimated increase of the concurrent period is 7.76 (p-value=0.06, Table 3.4).

On discharge-level, no statistically significant differences are found after Acquisition 2 and 3 (see Table 3.5). For Acquisition 1 and 4, the impact of hospital acquisitions on receiving the interventional treatment is positive for the post- acquisition period, which suggests that CAD patients living in the exposed area are more likely to receive the interventional treatment after Acquisition 1 and 4 relative to the control areas. Furthermore, patients with higher severity of illness are more likely to obtain the intervention after Acquisition 4 [OR (95% CI) = 2.56 (1.07, 6.14)].

3.3.2 Descriptive results for acquired and the competing hospitals' market shares of interventional treatment in the exposed area

As shown in Figure 3.5 (a), the two acquired hospitals' market shares are relatively stable through the pre-, concurrent, and post- acquisition periods (Acquisition 1 and 4). In particular, the acquired hospital market shares for Acquisition 1 are approximately 5% for all three periods, and the acquired hospital market shares for Acquisition 4 are all zero until the last three quarters.

The acquired hospitals from Acquisition 2 and Acquisition 3 have relatively higher market shares of the interventional treatment before their acquisitions (see Figure 3.5 (b)). For Acquisition 2, the acquired hospital's market share is stable over the three periods while for Acquisition 3 its acquired hospital's market share decreases from 35.0% to 21.9%. Moreover, the competing hospitals' market shares increase from 4.49% to 13.32% and 46.3% to 60.60% for Acquisition 2 and Acquisition 3, respectively (see Table 3.6).

3.3.3 The impact of the hospital acquisition on acquiring hospitals' market share of the interventional treatment

Figure 3.6 displays the acquiring hospitals' market shares between the exposed and control areas for each acquisition. There is no significant difference in the concurrent or post- acquisition period without stratifying for the competing hospital in the same market as the acquired hospital. When focusing on Acquisition 1 and 4, in which there is no competing hospital in the same market, the acquiring hospitals' market shares of the interventional treatment increases by 10.4% (see Table 3.7).

3.3.4 Impacts of hospital acquisition on the interventional treatment being performed at acquiring hospitals on discharge level

The impact of hospital acquisition on the interventional treatment being performed at the acquiring hospital is positive for Acquisition 1 and 4, and the ORs (95% CI) are 5.12 (1.96, 13.39) and 2.04 (1.70, 2.43), respectively (Table 3.8). For Acquisition 3, the treatment is more likely to be received at the acquiring hospital for CAD patients with minor severity of illness [ORs (95% CI) = 10.45 (7.79, 14.03)] while is less likely to be received at the acquiring hospital for CAD patients with major severity of illness [ORs (95% CI) = 0.04 (0.02, 0.07)].

3.4 Discussion

I investigate the cross-market hospital acquisition between an acquired hospital and an acquiring hospital that occurred in Texas from 2008 through 2014. The results for Research Questions 1-4 indicate that (1) there is a positive impact of Acquisition 1 and 4 on the proportion of CAD patients receiving the interventional treatment in the hospital acquisition exposed area; (2) for Acquisition 4, CAD patients with a higher severity of illness living in the acquisition area are more likely to receive the interventional treatment; (3) when there is no competing hospital in the same market as the acquired hospital, the impact of hospital acquisition on the acquiring hospital's market share of CAD patients is positive; (4) the impact of hospital acquisition on the interventional treatment being performed at acquiring hospitals is different by each hospital acquisition and patients' severity of illness. Key findings have been summarized in Table 3.9.

The impact of acquisition on the proportion of CAD patients receiving the interventional treatment is positive for Acquisition 1 and 4, though it is not statistically significant at the 0.05 significance level. The positive impact is consistent with previous studies. Hayford also found that after hospital acquisition the utilizations of bypass surgery and angioplasty increased for hospital acquisitions that occurred in California from 1990 through 2006 (Hayford, 2012). On the contrary, there is no the positive impact observed for Acquisition 2 and 3. These results imply that when there is no substitute hospital, CAD patients living in the acquisition exposed area are more likely to receive the interventional treatment after the acquisition. If the substitute hospital is available, then no significant impact is observed. The increase in the proportion might also be attributed to the acquiring hospitals' financial incentive for higher reimbursement rates from patients with private insurance plans. However, for Acquisition 1 and 4, I could not tell whether CAD patients would prefer to receive the treatment or if they have no other choice, since no alternative hospital is available.

I only observe a significant increase in the acquiring hospital's market share of CAD patients when there is no competing hospital in the same market as the acquired hospital. This finding suggests that the impact of acquisition on the acquiring hospital's market is more substantial when the acquired hospital market is less competitive. A similar pattern has been found from an investigation of hospital mergers on hospital costs and prices. Connor et al. reported that the impact of hospital merger on price reduction was smaller in a less competitive market (Connor et al., 1998).

The results on the discharge-level analysis suggest that the impact of acquisition on the interventional treatments being performed at the acquiring hospital is different by each acquisition and by patients' characteristics. Previous studies reported that acquiring hospitals only referred patients with remunerative insurance plans, and did not select patients based on severity of illness (Nakamura et al., 2007). The "cherry-picking" results observed from Acquisition 3 in this study are consistent with the previous research, and this strategy is not found from Acquisition 4. From an ownership perspective, the two hospitals in Acquisition 3 are nongovernment not-for-profit (Church operated), while the two hospitals in Acquisition 4 are government owned (State and Hospital district). The different ownerships might affect acquisition visions and strategies, and therefore the acquisition impact on patients is different.

The results of this study should be interpreted carefully in line with the following limitations. First, if the change in the proportion of the market share is smaller than 5%, this study does not have large enough sample size to detect a difference. Nevertheless, the discharge-level results provide an alternative perspective, which has sufficient observations for each acquisition. Next, standard indicators for hospital competition status are HHI and the number of competing hospitals in the exposed areas, but both of them are not appropriate based upon empirical data from this study. Therefore, I use the indicator of competing hospitals in the acquired hospital market to measure hospital competition status. Future studies should choose proper measurements based upon both theory and empirical evidence. Lastly, the findings from this study should not be used for any casual inference. For example, I observe the increases in the competing hospitals' market shares of CAD patients living in the exposed areas for Acquisition 2 and 3 over years but do not investigate whether the increasing trends are related with the acquisitions or other events. These findings should not be generalized into any causal inferences or other scenarios.

In short, the impact of hospital acquisition on the interventional treatment patterns received by CAD patients is different by each acquisition and patients' characteristics. This suggests heterogeneity in hospital acquisitions and their impacts on patients' treatment patterns.

3.5 Figures

Figure 3.1 A Conceptual Framework of the Impact of Hospital Acquisition Between a Tertiary Hospital (Acquiring Hospital) and a Local Community Hospital (Acquired Hospital) on the Treatment Pattern Received by Patients who Living in the Acquisition n Exposed Area

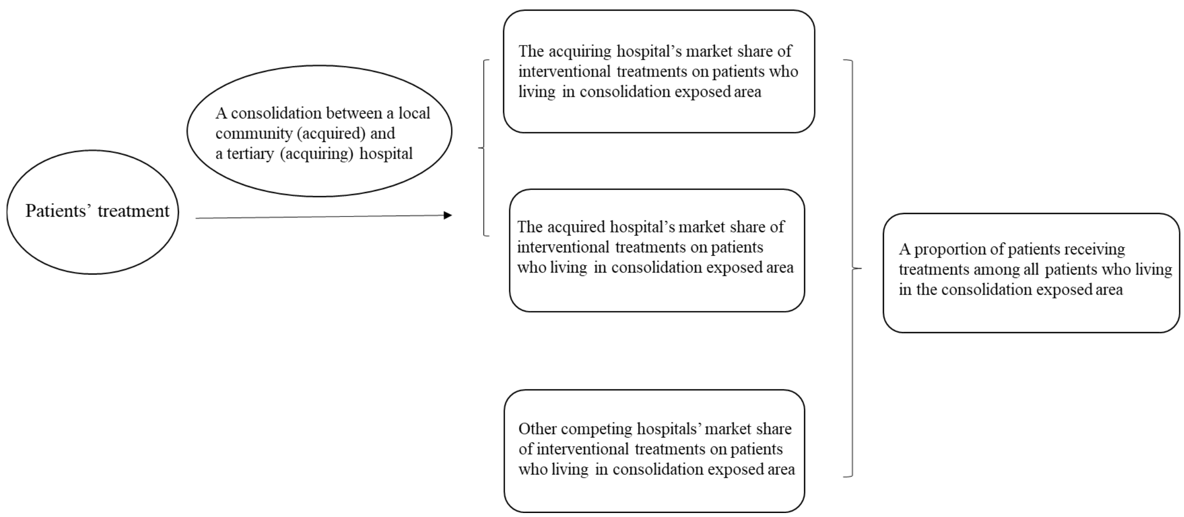


Figure 3.2 An Illustration of Main Variables Constructed in This Study

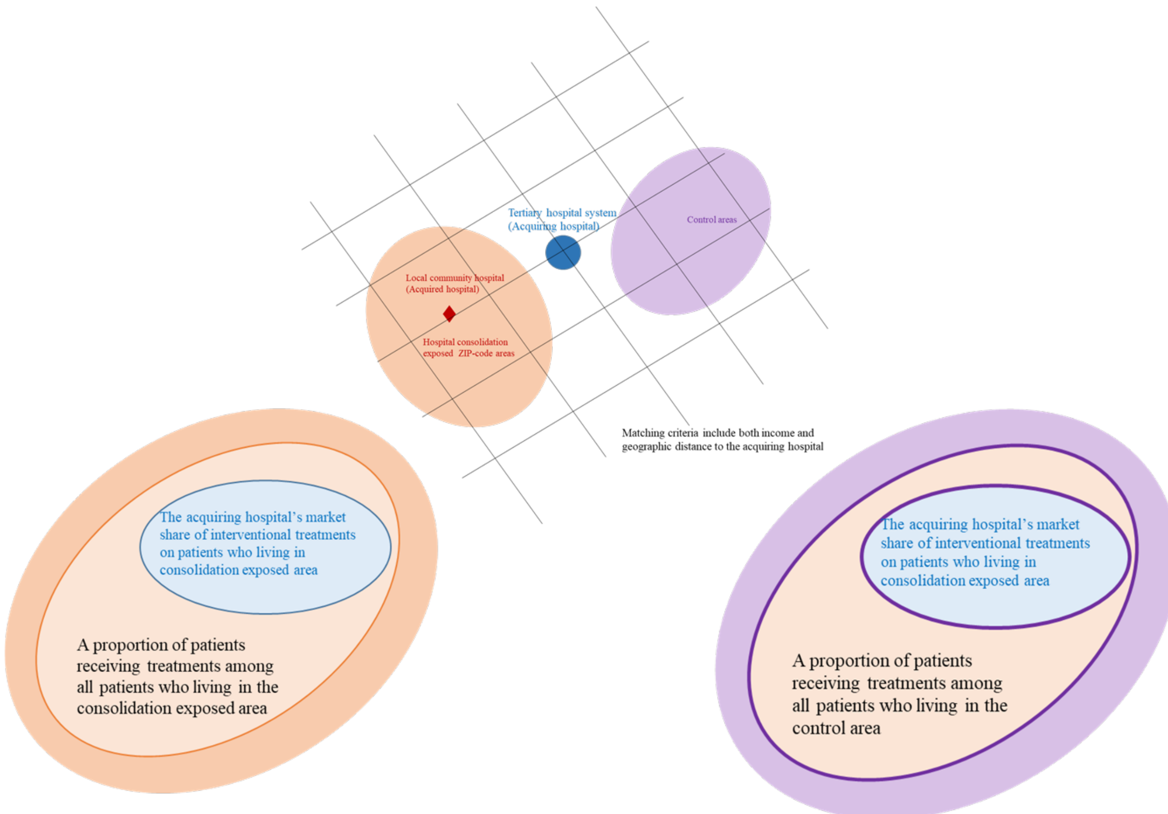
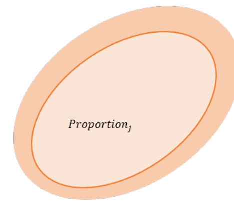
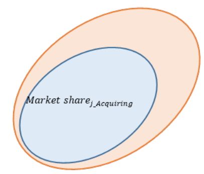


Figure 3.3 An Illustration of ZIP Code-level Variables Constructed in This Study Using an Exposed Area as an Example

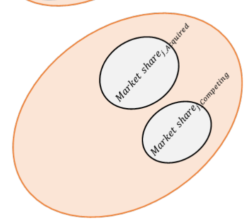
$$Proportion_j = \frac{\text{The number of CAD inpatients receiving the interventional treatment from the ZIP code area j}}{\text{The total number of CAD inpatients from a ZIP code area j}}$$



$$Market\ share_{j\_Acquiring} = \frac{\text{The number of interventional treatments performed at the acquiring hospital}}{\text{The total number of interventional treatments from a ZIP code area j}}$$



$$Market\ share_{j\_Acquired} = \frac{\text{The number of interventional treatments performed at the acquired hospital}}{\text{The total number of interventional treatments from ZIP code area j}}$$



$$Market\ share_{j\_Competing} = \frac{\text{The number of interventional treatments performed at the competing hospital}}{\text{The total number of interventional treatments from ZIP code area j}}$$

Figure 3.4 Trends in the Proportions of CAD Patients Receiving the Interventional Treatment between Acquisition Exposed and Control Areas

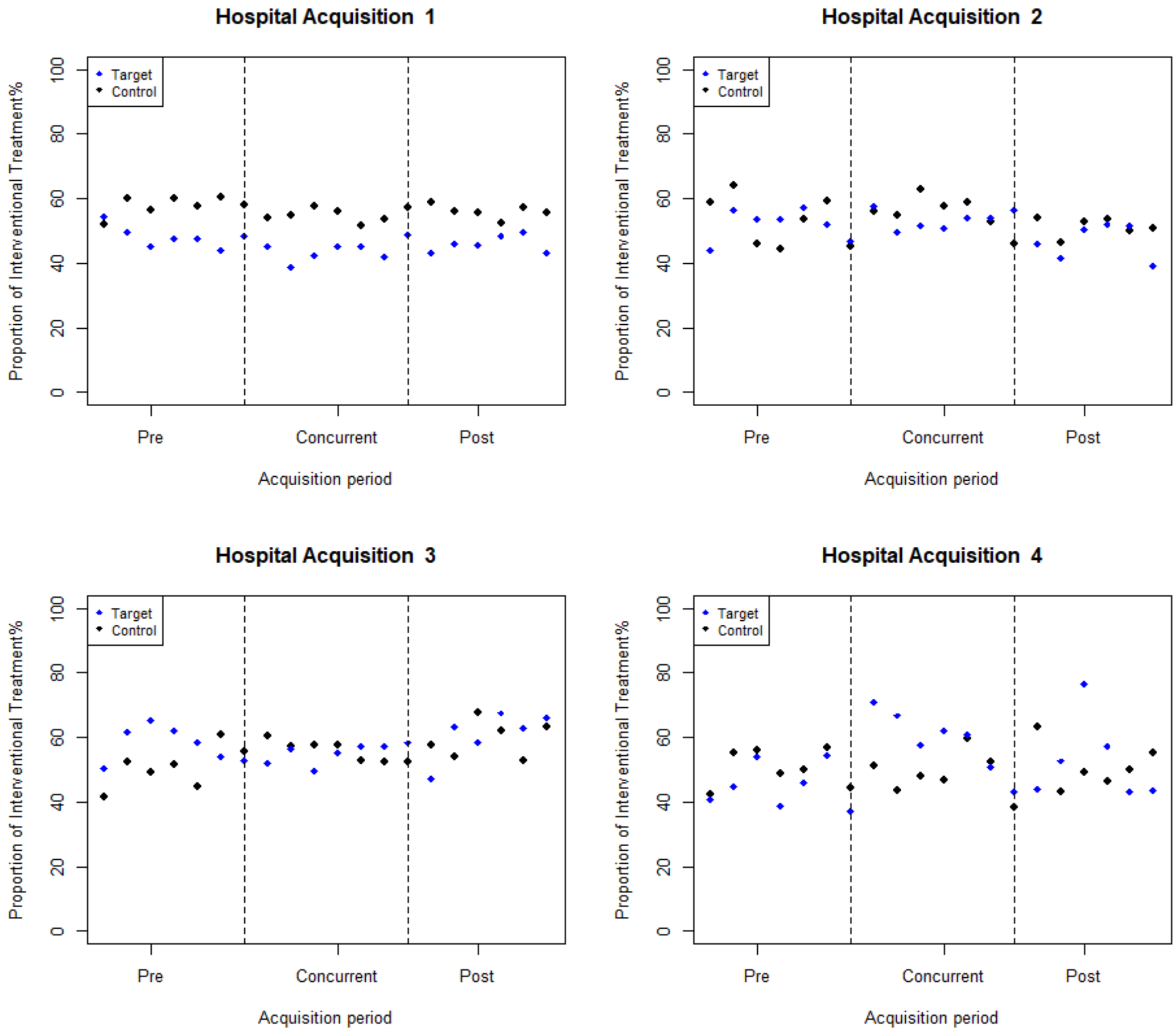


Figure 3.5 Trends in Acquiring, Acquired, and Competing Hospitals' Market Shares of the Interventional Treatment between the Acquisition Exposed and Control Areas

(a) Figure 3.5A There was no competing hospital in the same market as the acquired hospital

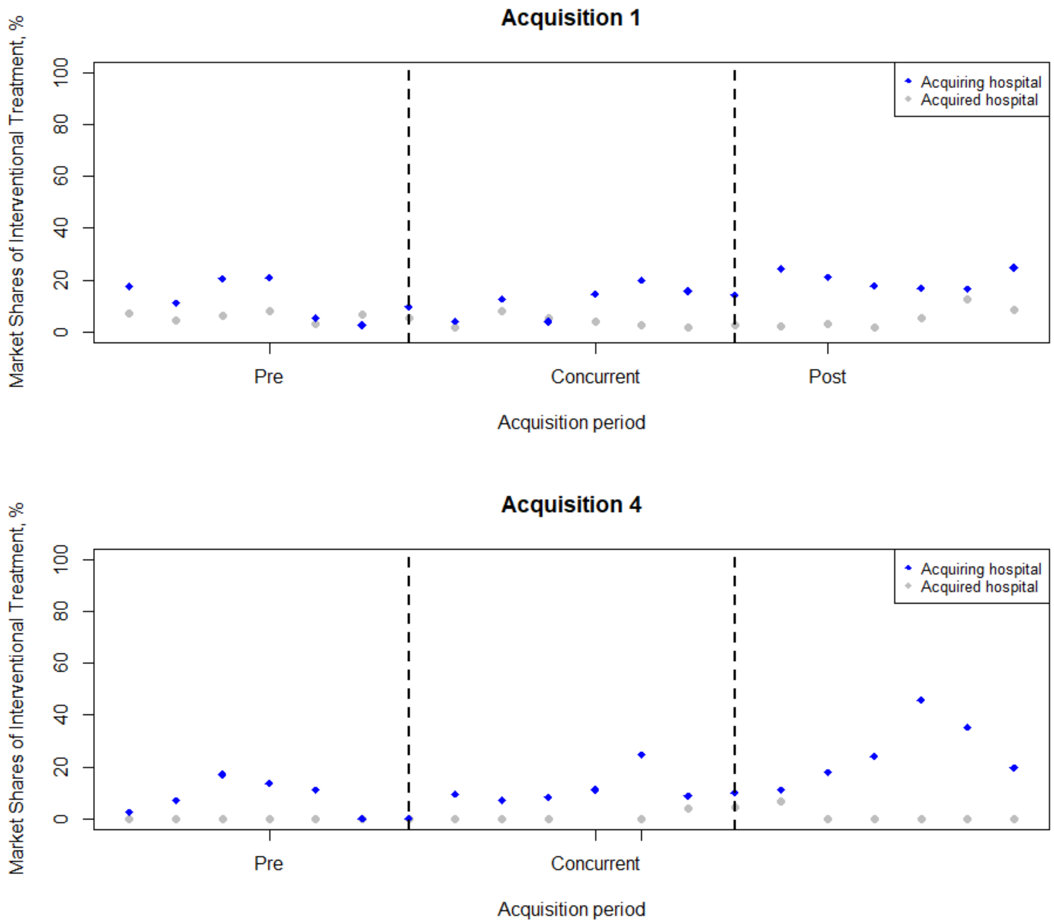
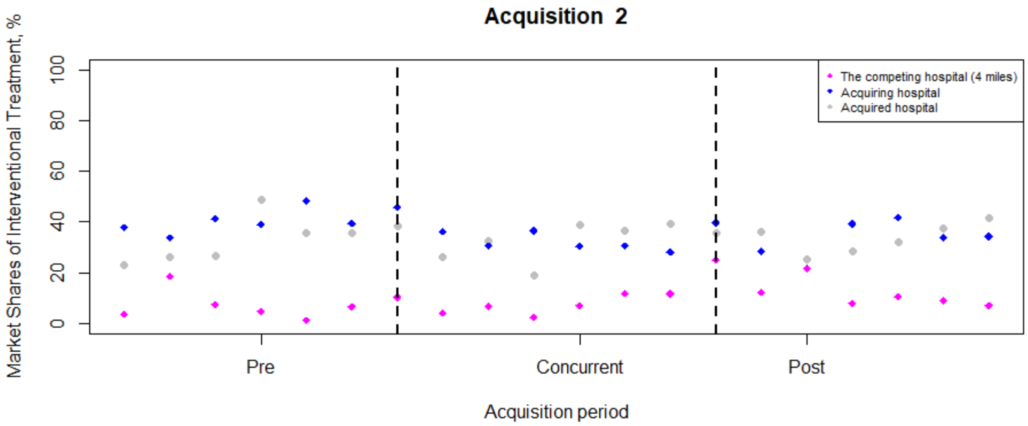


Figure 3.5 Continued

(b) Figure 3.5B. There was a competing hospital in the same market as the acquired hospital



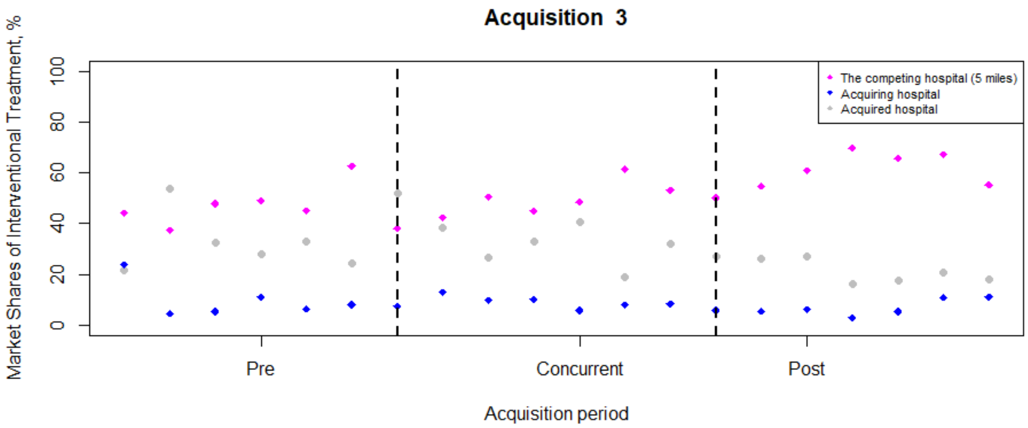
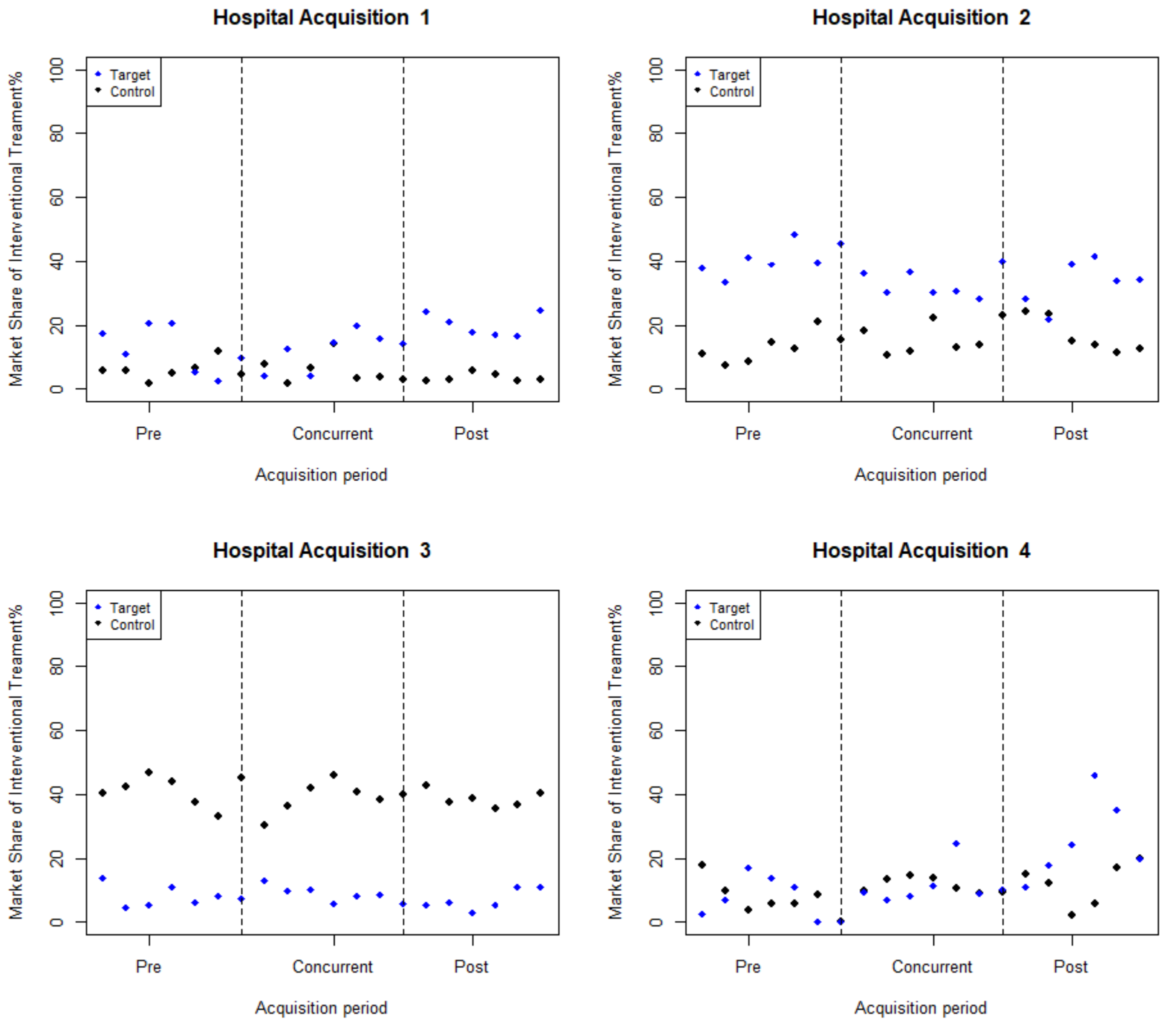


Figure 3.6 Trends in Acquiring Hospitals' Market Shares of the Interventional Treatment Between Hospital Acquisition n Exposed and Control Areas



3.6 Tables

Table 3.1 Hospital Features of Acquired and Acquiring Hospitals in This Study

Acquisition ID	Hospital Name	Acquisition	Total number of beds	Cardiac intensive care beds
1	East Houston Regional Medical Center	Acquired	131	0
1	Bayshore Medical Center	Acquiring	355	10
2	Mainland Medical Center	Acquired	201	0
2	Clear Lake Regional Med Center	Acquiring	404	10
3	CHRISTUS Hospital-St. Mary	Acquired	202	NA
3	CHRISTUS Hospital-St. Elizabeth	Acquiring	456	16
4	Angleton Danbury Medical Center	Acquired	51	0
4	University of Texas Medical Branch Hospitals	Acquiring	397	0

NA: The information is missing in AHA annual survey database

Table 3.2 The Number of CAD Patients Receiving Interventional Treatment by Acquisition Exposed or Control Area and Each Hospital Acquisition

	Exposed	Control
Acquisition 1	1474 (46.35)	2422 (51.95)
Acquisition 2	1653 (50.11)	1750 (50.79)
Acquisition 3	1773 (57.29)	1331 (54.26)
Acquisition 4	772 (52.80)	1677 (51.63)

Table 3.3 The Impact of Hospital Acquisition on the Proportion of CAD Patients Receiving the Interventional Treatment on ZIP Code Level without Stratifying Competing Hospitals Co-located in the Acquired Hospital Market

	Coefficient	S.E.	p-value
Acquisition Exposed	1.73	1.83	0.196
Concurrent Period	0.66	1.89	0.361
Post Period	-2.38	1.83	0.719
Acquisition Exposed *Concurrent Period	1.53	2.67	0.570
Acquisition Exposed *Post Period	-0.05	2.59	0.985

Table 3.4 The Impact of Hospital Acquisition on the Proportion of CAD Patients Receiving the Interventional Treatment on ZIP Code Level for Acquisitions Without Competing Hospitals in the Acquired Hospital Market (Acquisition 1 and 4)

	Coefficient	S.E.	p-value
Acquisition Exposed	-7.52	2.85	0.01
Concurrent Period	-1.69	2.93	0.57
Post- Acquisition Period	-1.42	2.81	0.62
Acquisition Exposed *Concurrent Period	***7.76 ****	***4.19***	***0.06***
Acquisition Exposed *Post- Consolidation Period	3.72	4.01	0.35

Significance level: <0.1 "*", <0.05 "**", <0.01 "***"

Table 3.5 Impacts of Hospital Acquisition on CAD Patients Receiving the Interventional Treatment on Discharge Level

		OR	95%CI	
Acquisition 1	Concurrent* Exposed	0.98	0.78	1.24
	Post* Exposed	***1.42****	***1.11***	***1.80***
Acquisition 2	Concurrent* Exposed	0.84	0.65	1.07
	Post* Exposed	0.83	0.65	1.06
Acquisition 3	Concurrent* Exposed	***0.65****	***0.50***	***0.86***
	Post* Exposed	0.97	0.74	1.27
Acquisition 4	Concurrent* Exposed	***1.51***	***1.08***	***2.11***
	Post* Exposed	***1.48***	***1.08***	***2.01***

Significance level: <0.1 "*", <0.05 "**", <0.01 "***"

Table 3.6 Acquired and Competing Hospitals' Market Shares of the Interventional Treatment in the Hospital Acquisition Exposed Areas, %

		Acquisition 1	Acquisition 2	Acquisition 3	Acquisition 4
Acquired Hospital	Pre-	5.84	33.45	34.97	0
	Concurrent	4.17	31.97	31.55	0.64
	Post-	5.11	33.74	21.92	2.34
Competing Hospital	Pre-	NA	7.49	46.34	NA
	Concurrent	NA	7.23	50.19	NA
	Post-	NA	13.32	60.59	NA

Table 3.7 The Impact of Hospital Acquisition on the Acquiring Hospitals' Market Shares of Interventional Treatment on ZIP Code Level Without Competing Hospital in the Same Market, %

	Coefficient	S.E.	p-value
Acquisition Exposed	3.41	2.48	0.17
Concurrent Period	2.56	2.58	0.33
Post Period	1.00	2.48	0.69
Acquisition Exposed *Concurrent Period	-0.76	3.65	0.83
Acquisition Exposed *Post Period	***10.44****	***3.51***	***<0.01***

Significance level: <0.1 "*", <0.05 "**", <0.01 "***"

Table 3.8 Impacts of Hospital Acquisition on the Interventional Treatment Being performed at Acquiring Hospitals

	Acquisition 1 OR (95%CI)			Acquisition 4 OR (95%CI)		
Control	ref	ref	ref	ref	ref	ref
Acquisition Exposed	2.75	1.51	5.02	1.02	0.38	2.72
Pre-period	ref	ref	ref	ref	ref	Ref
Concurrent period	0.95	0.51	1.77	2.41	1.27	4.57
Post-period	0.46	0.20	1.09	2.93	1.61	5.33
Acquisition* Concurrent period	1.19	0.54	2.64	1.27	0.40	4.00
Acquisition* (Post-period	***5.12****	***1.96***	***13.39***	***2.04****	***1.70***	***5.83***
>=65 years	ref	ref	ref	ref	ref	ref
40-64 years	0.53	0.36	0.77	1.68	1.07	2.65
White	ref	ref	ref	ref	ref	ref
African American	0.40	0.22	0.70	1.42	0.86	2.35
Other races	1.46	0.91	2.37	0.09	0.04	0.21
Hispanic	1.51	0.92	2.50	3.02	1.61	5.66
Medicare	ref	ref	ref	ref	ref	Ref
Self-pay	2.51	1.30	4.85	NA	NA	NA
Private	2.28	1.50	3.49	0.38	0.24	0.62
Medicaid	2.49	1.08	5.74	1.50	0.70	3.20
Other payers	2.97	1.29	6.85	1.15	0.64	2.07
Minor illness	ref	ref	ref	ref	ref	Ref
Moderate	1.23	0.85	1.78	1.24	0.80	1.93
Major	1.15	0.75	1.78	0.87	0.52	1.44
Extreme	0.53	0.25	1.12	0.43	0.17	1.08
Referral	ref	ref	ref	ref	ref	Ref
Transferred	0.04	0.01	0.29	0.78	0.48	1.27
Other sources of admission	1.56	0.98	2.50	NA	NA	NA
Elective	ref	ref	ref	ref	ref	Ref
Urgent/Emergent	2.03	1.24	3.33	1.56	1.03	2.37
Female	0.99	0.71	1.38	0.82	0.57	1.16

Table 3.9 Key Response Variables and Findings in This Study

Research Question	Response Variable	Findings
	ZIP Code Level	
1	*Proportion:* the proportion of the interventional treatment received by CAD patients in the acquisition exposed or control area	An increase in the proportion is found for concurrent period of Acquisition 1 and 4.
3	$Market\ share_{Acquired}$: the acquiring hospital's market share of interventional treatments received by patients who living in the acquisition exposed and control area	An increase in the $Market\ share_{Acquired}$ is found after Acquisition 1 and 4.
	Discharge Level	
2	Y_{ijt}: whether the patient *i* who living in ZIP-code area j receive interventional (=1) or not (=0)	Positive impacts of hospital acquisition on receiving the interventional treatment are observed after Acquisition 1 and 4.
4	Trt_{ijt}: whether a patient *i* who received interventional treatment and living in ZIP-code area is treated at an acquiring hospital (=1) or not (=0)	Positive impacts of hospital acquisition on the interventional treatment being performed at acquiring hospitals are observed after Acquisition 1 and 4; The treatments for patients with less severe illness are more likely to be performed at the acquiring hospital after Acquisition 3.

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4. AN APPLICATION OF A BAYESIAN ESTIMATION METHODOLOGY TO INPATIENT OBSTETRIC SERVICES OFFERED BY RURAL HOSPITALS IN TEXAS

4.1 Background

After the implementation of the Patient Protection and Affordable Care Act (ACA), rural hospitals face several unprecedented challenges and the fate of many remain unclear. All over the country, 121 rural hospitals have closed from 2010 to January 2020, and 40% of the rest are closing certain inpatient care services, according to a report from the North Carolina Rural Health Research and Policy Analysis Center (North Carolina Rural Health Research Program, 2014). Numerous concerns have been raised from the public, hospital stakeholders, and policy makers, such as a shortage of inpatient care services and limited access to care in rural communities (Bowman, 2019; United States Government Accountability Office, 2018).

Low case volumes and limited health care resources are two of the main challenges faced by rural hospitals. On the one hand, due to low case volumes and low reimbursement rates, it is difficult for a rural hospital to support as many fixed costs as a full-size hospital (United States Government Accountability Office, 2018). On the other hand, local residents in rural areas are more likely to have chronic conditions and need access to fundamental medical services, though the volume is much lower than in urban areas (American Hospital Association, 2019). Therefore, many rural hospitals are trying to find a “right-size” facility for their communities. Some rural hospitals have ceased providing inpatient services, and others have converted to alternative care sites, such as emergency, primary care, and skilled nursing facilities (Thomas et al., 2015). The National Advisory Committee on Rural Health and Human Services encourages further studies to assess utilizations of core medical services for rural clinics, as well as support rural hospital planning and conversion to meet the needs of local communities (National Advisory Committee on Rural Health & Human Services, 2015). Yet, there are few empirical studies focusing on this field.

In fact, it is very challenging to delineate the utilization of medical services provided by rural hospitals using classical statistics that have been applied to describe high-volume hospital utilization. First, the relevant data may not be available, especially for rural hospitals. In Texas, for example, the Texas Department of State Health Services (DSHS) regularly releases Public Use Data Files (PUDF). However, about 20% of rural hospitals had not been included in these data files before 2015, since rural hospitals were not required to report their inpatient discharges information to the state agency (Texas Department of State Health Services, 2016). Another challenge is small area estimation (National Quality Forum Rural Health Committee, 2015). To achieve an adequately precise estimate, it is necessary to have enough homogeneous samples from a certain population. For an estimation based upon samples from small areas, it is challenged by low-volume, small practice size, and population heterogeneity. For instance, the low-volume and population heterogeneity issues in rural hospitals lead to unstable estimations of health care utilizations. A published study reported that the newborn delivery volume of a low-volume hospital might be below 10 or greater than 110 per hospital in 2011 (Kozhimannil et al., 2016). As a consequence, scholars have limited options available to explore the inpatient services provided by rural hospitals as well as to help guide policy for rational resource allocation at rural hospitals. At present, given the current uncertain fate of rural hospitals, it is crucial to learn more about the inpatient services offered by these facilities.

It is very fortunate that Bayesian models for Small Area Estimation are appropriate for this type of analysis (Ghosh and Rao, 1994; Pfeffermann, 2002). The approach was developed many years ago and has previously been applied in relevant fields, such as economics, epidemiology, and sociology (Isaki, 1990). The basic idea behind Bayesian inference was proposed approximately three centuries ago, but was not adopted widely until the 1980s (Fienberg, 2006). Its estimation approach is based upon likelihood inference (Box, 1980). In brief, the basic Bayesian model assumes that data y have a distribution $L(y|\theta)$ determined by parameters, and the parameters have a prior distribution $g(\theta)$. The posterior distribution $\pi(\theta|y)$, represents the updated distribution of the parameters in light of the data. The posterior is such that

$$\pi(\theta|y) \propto L(y|\theta) \cdot g(\theta),$$

and $L(y|\theta)$ is called the likelihood function.

Bayesian hierarchical models can reflect heterogeneity of parameters across several populations (Hoff, 2009). Bayesian hierarchical modeling approach has been adopted by the Centers for Medicare & Medicaid Services (CMS) for hospital performance evaluation (Davidson et al., 2007). In particular, the current CMS approach employs one Gaussian distribution to evaluate hospital utilization and performance, which uses so-called shrinkage to support risk adjustment for case-mix and stabilization of the estimated Standardized Mortality Rate (SMR). This strategy is suitable for moderate or large hospitals but may not be appropriate for small volume hospitals (e.g., rural facilities) (Ash et al., 2012). The main reason for the inappropriateness is that the Bayesian hierarchical modeling with one Gaussian distribution assumes that the various means come from one cluster, which might not be a valid assumption for hospitals having large, moderate, and small volumes of patients. The Committee of Presidents of Statistical Societies (COPSS) suggested a hierarchical, mixed-effects approach for the national-level model to CMS to remedy the low information context in 2012 (Ash et al., 2012). Yet, this approach has not been commonly adopted in health services research, and no study has applied the mixture of distributions into hospital utilization estimation.

In this study, I follow the recommendation from COPSS to estimate the utilization of inpatient health care provided by rural hospitals, and focus on newborn delivery care. Approximately 500,000 babies are born in rural hospitals every year, and newborn delivery is one of the top three procedures among all inpatient admissions in rural hospitals (Stranges et al., 2010). Meanwhile, rural counties in the U.S. are losing hospital obstetric services, and providers in rural areas are trying to assess this need in local communities (Hung et al., 2017). As of January 2018, only 42% of rural hospitals in Texas offer newborn delivery services and the number could keep shrinking, according to the Texas Organization of Rural and Community Hospitals (Paavola, 2018). It is important to have an accurate estimate of the demand for newborn delivery services at rural hospitals to support a rational allocation of limited health care resources.

Two goals of this study are to:

(1) Identify factors affecting the number of inpatient newborn deliveries provided by small hospitals in rural areas of Texas;

(2) Predict the number of inpatient newborn deliveries at the rural hospitals using the Bayesian Poisson hierarchical modeling approach.

This study's resulting estimations might offer empirical evidence for the utilization of the newborn delivery care provided by rural hospitals.

4.2 Methods

4.2.1 Data sources

In this study, I use three data sources to collect inpatient discharge-, hospital-, and county-level information. Texas Inpatient Public Use Data Files (PUDF), received from Texas Department of State Human Services (DSHS), provide inpatient demographic, geographic, admission, diagnosis, procedure, and discharge information. The inpatient discharges information for small hospitals or hospitals in rural areas is not available until 2015 in Texas (Texas Department of State Health Services, 2016). This study take advantage of the most recent available datasets (i.e., 2015, 2016, and 2017) and focus on inpatient newborn delivery care offered by the rural hospitals. The number of licensed beds as hospital-level predictor is derived from the American Hospital Association (AHA) Survey. County-level female population is downloaded from American Community Survey (https://www.census.gov/programs-surveys/acs/).

4.2.2 Target hospitals and population

I focus on hospitals in rural areas of Texas, which are defined as hospitals "located in a county with a population less than 35,000" (Texas Department of State Health Services, 2016). Small hospitals with limited hospitalizations (i.e., the quarterly number of discharges was less than 50) are excluded from the analysis, as the Texas PUDF suppress their information. In all, there are 25 rural hospitals identified in this study, and Figure 4.1 shows the geographic locations of these rural hospitals. I use the All Patient Refined Diagnosis Related Groups (APR-DRGs) to identify newborn deliveries, and detailed delivery APR-DRGs codes are listed in Table S7.

4.2.3 The main outcome and predictors of interest

The outcome of interest is the quarterly number of inpatient newborn deliveries at each hospital for the three years 2015, 2016, and 2017. Predictors included are the number of licensed beds, the number of females aged 20-35 in the county where the rural hospital is located, and quarters of a year to capture potential seasonal effects (i.e., Q1-Q4). In particular, the number of females is rescaled for regression analysis by dividing by 1,000.

4.2.4 Regression models

In this study, I employ both restricted maximum likelihood estimation (REML) for multilevel Poisson regression and Bayesian estimation for Poisson hierarchical model to predict the number of inpatient newborn deliveries for each hospital, and compare the prediction results using a cross-validation approach.

4.2.4.1 Multilevel Poisson regression

The Poisson distribution is a classical model for count data, and the mean and variance of the Poisson distribution are known to be equal:

$$E(Y) = Var(Y) = \lambda .$$

A generalized linear model for the mean of a Poisson random variable can be written as:

$$g(\lambda) = log\lambda = X'\beta .$$

A multilevel model is considered to account for hospital random effects.

Let Y_{ij} be the number of newborn deliveries in hospital j and quarter i, where i = 1, 2, 3, 4. For example, Y_{1j} is the total number of hospital j deliveries in the first quarter of 2015, 2016 and 2017. Then our model assumes that Y_{ij} given a_j has a Poisson distribution with mean λ_{ij}, where

$$log\,\lambda_{ij} = \lambda + a_j + X_{ij}'\beta ,$$

λ is an overall effect, a_j is a random effect due to hospital j, and X_{ij} is a vector of covariates including dummy variables that account for a possible quarterly effect. A more detailed model definition is given in the next section.

4.2.4.2 Model specifications

Multilevel Poisson regression models are defined as follows:

Full model:

$$log\,\lambda_{ij} = \beta_0 + a_j + \beta_1 X_{11,j} + \beta_2 X_{12,j} + \beta_3 X_{2,j} + \beta_4 X_{11,j} X_{2,j} + \beta_5 X_{12,j} X_{2,j} + \beta_{6,j} Q_2 + \beta_7 Q_3 + \beta_8 Q_4$$

Reduced model 1:

$$log\,\lambda_{ij} = \beta_0 + a_j + \beta_1 X_{11,j} + \beta_2 X_{12,j} + \beta_3 X_{2,j} + \beta_4 X_{11} X_{2,j} + \beta_5 X_{12,j} X_{2,j}$$

Reduced model 2:

$$log\,\lambda_{ij} = \beta_0 + a_j + \beta_1 X_{11,j} + \beta_2 X_{12,j} + \beta_3 X_{2,j}$$

λ_{ij}: is the average number of newborn deliveries at rural hospital j during quarter i;

a_j: is a random intercept reflecting hospital effects;

$X_{11,j}$ and $X_{12,j}$ represent the medium bed count (24-49) and the large bed count (50-99) of hospitals j, and the small bed count (<24) is the reference group;

$X_{2,j}$ denotes the number of females per 1000 between the ages of 20 and 35 in the county where the hospital j is located;

Q_2, Q_3, and Q_4 are indicator variables for quarters, using the first quarter (Q_1) as the reference;

β_1, β_2 *and* β_3 represent fixed effects of the hospital bed counts and number of females per 1000 between the ages of 20 and 35;

β_4 *and* β_5 denote the interaction effects between the bed counts and the number of females;

β_6, β_7 *and* β_8 indicate seasonal effects of Q_2, Q_3, and Q_4;

All parameters were estimated using the REML approach for the multilevel Poisson regression models above.

4.2.4.3 Bayesian Poisson Hierarchical Model

In Bayesian inference, the Poisson hierarchical full model is written as:

$$Y_{ij} \sim \ Poisson\left(\lambda_{ij}\right)$$

$$\lambda_{ij} = exp\ (\beta_{0j}+\beta_1 X_{11,j}+\beta_2 X_{12,j}+\beta_3 X_{2,j}+\beta_4 X_{11,j} X_{2,j}+\beta_5 X_{12,j} X_{2,j}+\beta_6 Q_2+\beta_7 Q_3+\beta_8 Q_4).$$

The Bayesian Poisson hierarchical model is equivalent to the Multilevel Poisson model (4.2.4.2),

with $\beta_{0j} = \beta_0 + a_j$, $E(a_j) = 0$,

and $exp\ (\beta_0)$ represents an overall mean for hospitals whose bed count is below than 24, when the quarter is 1. Interpretations of other parameters and coefficients are the same as the multilevel models above. As specified in 4.2.4.2, the reduced Model 1 drops the three terms that indicate quarter effects, and reduced Model 2 eliminates the two interaction terms.

The basic framework of Bayesian estimation is introduced in the background. Posterior distributions of parameters, $\pi(\theta|y)$, are obtained via priors and a likelihood function from the empirical data. The likelihood function in this case is expressed as:

$$L\left(\lambda_{ij}|y_{ij}\right) = \prod_{j=1}^{25}\prod_{i=1}^{4}\frac{\lambda_{ij}^{y_{ij}} exp^{-\lambda_{ij}}}{y_{ij}!} \propto \prod_{j=1}^{25}\prod_{i=1}^{4}\lambda_{ij}^{y_{ij}} \cdot exp^{-\lambda_{ij}} = \prod_{j=1}^{25}\prod_{i=1}^{4}\{exp[\, log\left(\lambda_{ij}^{y_{ij}}\right)] \cdot exp^{-\lambda_{ij}}\}$$

$$= \prod_{j=1}^{25}\prod_{i=1}^{4} exp\left[y_{ij} \cdot log\left(\lambda_{ij}\right) - \lambda_{ij}\right],$$

where λ_{ij} is defined above.

Moreover, β_{0j} is assumed to come from a mixture of two normal distributions, i.e.,

$$\beta_{0j} \sim \pi N(\theta_1, \sigma^2) + (1-\pi)N(\theta_2, \sigma^2)$$

$$\alpha \equiv (\pi, \theta_1, \theta_2, \sigma^2),\ \theta_1 \leq \theta_2\ .$$

To distinguish parameters in regression models from parameters in $\boldsymbol{\alpha}$, π, θ_1, θ_2, *and* σ^2 are called hyper-parameters in this study. As Hoff suggested, prior distributions should be as minimally informative as possible, if it is not going to represent real prior information about the parameters (Peter Hoff, 2009). By following Hoff's rule, non-informative uniform priors were employed.

Assuming the independence of parameters and hyper-parameters, then the posterior would be:

$$\boldsymbol{p\ (\beta_0, \beta, \alpha, z \,|\, y) \propto p\ (\, y \,|\, \beta_0, \beta, \alpha, z) \times p\ (z \,|\beta_0, \beta, \alpha) \times p\ (\beta_0, \beta, \alpha)}$$

$$= \boldsymbol{p\ (y \,|\, \beta_0, \beta) \times p\ (\beta_0 \,|\, z,}\ \theta_1,\ \theta_2,\ \sigma^2\boldsymbol{) \times p\ (\beta) \times p\ (z \,|\, \pi) \times p}\ (\pi,\ \theta_1, \theta_2,\ \sigma^2\boldsymbol{)}$$

$$\propto \boldsymbol{p\ (y \,|\, \beta_0, \beta) \times p(\beta)} \times \prod_{j=1}^{25} \frac{1}{\sigma} \phi[\frac{\beta_{0j} - (\theta_1 - \theta_2)\, z_j - \theta_2}{\sigma}] \times \prod_{j=1}^{25} \pi^{z_j} (1-\pi)^{[1-z_j]}$$

$$\times I_{(0,1)}(\pi) \times p(\theta_1, \theta_2) \times p(\sigma^2),$$

$\boldsymbol{\beta_0}$ *is a vector with* $\boldsymbol{\beta_0} = \left(\beta_{01}, \ldots, \beta_{0j}, \ldots \beta_{025}\right)$;

$\boldsymbol{z}$ *is a vector with* $\boldsymbol{z} = (z_1,\ \ldots,\ z_j,\ \ldots,\ z_{25}\ )$**.** This is a latent variable that indicates which mixture components $\left(\beta_{01}, \ldots, \beta_{0j}, \ldots \beta_{025}\right)$ come from: $z_j=1$ *and* $z_j=0$ indicate that β_{0j} is drawn from $N(\theta_1, \sigma^2)$ and $N(\theta_2, \sigma^2)$, respectively;

$\boldsymbol{\beta}$ is a vector with $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_8)$. They are the covariates' coefficients.

Priors used for $\pi,\ \theta_1, \theta_2,\ \sigma^2,$ *and* $\boldsymbol{\beta}$ are

$p(\pi) \sim beta\ (1,\ 1),$

$p(\theta_1, \theta_2) \propto e^{-\frac{\theta_1^2}{2\tau^2}} \cdot e^{-\frac{\theta_2^2}{2\tau^2}} \cdot I(\theta_1, \theta_2),$ *where* τ *is the variance of* θ_1 *and* θ_2,

$p(\sigma) \sim inverse\ gamma\ (\frac{v_0}{2},\ \frac{v_0}{2}\sigma_0^2)$, and $\boldsymbol{\beta} \propto$ constant non-informative prior.

4.2.4.4 Model estimation

Monte Carlo Markov Chain (MCMC) sample methods (Gibbs steps and Metropolis-Hastings algorithm) are used to construct the posterior distribution (Hoff, 2009). It is not possible to identify full conditional distributions for every parameter for our model. Thus, Gibbs steps are used for hyper-parameters π, (θ_1, θ_2), σ^2, and their full conditional distributions are binomial, truncated normal, and inverse-gamma distributions, respectively. The Metropolis-Hastings algorithm is used for sampling parameters in the model, and the proposal distribution for $\boldsymbol{\beta_0}$ is such that the components are independent and each component has

$$\beta_{0j} \sim N\left(\tilde{\beta}_{0j}, \tilde{\sigma}_j^2\right),\ j = 1, \ldots 25$$

$$\tilde{\beta}_{0j} = \log \bar{y}_j - X_j' \hat{\beta},\ \tilde{\sigma}_j^2 = \frac{c}{\bar{y}_j}$$

$\bar{y}_i$ and $\boldsymbol{X_j}$ are the average count and covariates for hospital j, respectively;

The variation is derived using Taylor series expansion, and c is a constant value, which is set to be 3 in this analysis to produce good mixing.

As other parameters are assumed to have fixed effect, by following Hoff's suggestion, the proposal distribution for $\boldsymbol{\beta}$ is

$$N\left(\boldsymbol{\beta}^{(s)},\ \hat{\sigma}^2 (\boldsymbol{X}'\boldsymbol{X})^{-1}\right),$$

where $\boldsymbol{\beta}^{(s)}$ is the current values in iteration s, and $\hat{\sigma}^2$ is the sample variance of $\log(y_{i,j}+1/2)$.

Initially, 10,000 iterations are used, and trace plots are used to verify convergence. Sample autocorrelation function (ACF) is employed to identify autocorrelation arising in MCMC. A thinning strategy is used to reduce the autocorrelation. Every 10th value is used for each parameter.

4.2.4.5 Model comparison

Model selection is a trade-off between parsimony and goodness-of-fit. There are various criteria for model selection, and the Posterior Bayes factor (PBF) is used in the study (Aitkin Murray, 1991). To compare models with likelihood L_1 and L_2, the PBF is

$$Posterior\ Bayes\ factor = \frac{\int L_1(y|\lambda_1)\ \pi_1(\lambda_1|y)\ d\lambda_1}{\int L_2(y|\lambda_2)\ \pi_2(\lambda_2|y)\ d\lambda_2}$$

A guide for levels of evidence is indicated in Table S.8 (L. Held and M. Ott, 2018).

In addition, I use the Bayesian information criterion (BIC):

$$BIC = -2log(L) + (p+2)\ log\ (n),$$

where L is the likelihood evaluated at its maximum for a given model (Full model, Reduced model 1, or Reduced model 2);

n represents the number of observations and *p* is the number of parameters. The model with a lower BIC value is considered to be better (Neath and Cavanaugh, 2012).

4.2.4.6 Cross-Validation and Prediction

I randomly sample 3 out of 12 (25%) observations from each hospital, which leads to a test dataset with 75 observations and a training dataset with 225 observations. The posterior predictive distribution obtained from the posterior distributions is

$$p\,(y^{new}/y) = \int p\,(y^{new}\,|\,\lambda_j)\,p\,(\lambda_j\,|\,y)\,d\,\lambda_j\ .$$

Mean squared prediction error (MSE) is used to compare predictions from REML and Bayesian modeling methods.

4.3 Results

4.3.1 Exploratory data analysis results

There are 25 rural hospitals included in this study, and 72% of them have a medium bed count (24-49). The bed count frequency and proportion are summarized in Table 4.1. Figure 4.2 shows the histogram and empirical distribution of the number of newborn deliveries from each rural hospital, and the range is 1-122 per quarter.

Figure 4.3 displays the number of newborn deliveries by hospital bed count. As this figure indicates, there seems to be a bimodal pattern of the number of newborn deliveries at the rural hospitals. Figure 4.4 is a scatter plot of the number of newborn deliveries at a rural hospital and the number of females ages between 20-35 in the county where this rural hospital is located. The plot suggests a positive correlation between the explanatory variable and the response variable. Since the data are collected over time, there is a concern about possible autocorrelation in the data. Autocorrelation function plots are created for each hospital, and no significant autocorrelations are observed (Figure 4.6). Quarter indicators are included in the full model to account for potential seasonal effects.

To diagnose the convergence of MCMC algorithm, trace plots and ACF plots are constructed and displayed. Figure 4.7 suggests that the MCMC chain has converged to its stationary distributions, but its samples are autocorrelated. A thinning strategy is used to reduce the autocorrelation from MCMC samples, and it is determined that every 10th value should be used from each MCMC sequence.

4.3.2 Model selection

Both results from BIC and Posterior Bayes Factor support the parsimonious model with interaction terms. The BIC values from three multilevel Poisson models (i.e., full model, reduced model 1, and reduced model 2) are 2392.7, 2386.5, and 2389.1, respectively. For the hierarchical Poisson models, the posterior Bayes Factor 1 (i.e., full model versus reduced model 1) is 0.23, which indicates substantial evidence against the full model; the posterior Bayes Factor 2 (i.e., reduced model 1 versus reduced model 2) is 15.93, implying that there is strong evidence against the reduced model 2. Thus, the reduced model 1 is selected for further predictions.

4.3.3 Associations from REML and Bayesian inference

Table 4.2 summarizes estimated coefficients of the multilevel Poisson model, and all predictors as well as their interactions are statistically significant. Overall, the number of newborn deliveries in the rural hospitals with medium or large bed count would be higher compared with hospitals with fewer beds. Given a rural hospital bed count, if the county that this hospital is located in has a higher female proportion, the number of newborn deliveries at the hospital would be higher.

Table 4.3 and Table 4.4 include 95% credible intervals of hyper-parameters and parameters. The 95% credible intervals of interactions between the number of females and median bed count as well as large bed count are (1.80, 1.85) and (1.80, 1.89), respectively. Though the estimated coefficients from REML and Bayesian inference are consistent, there are shrinkages on the random intercepts from Bayesian modeling method (see Figure 4.8).

4.3.4 Cross-validation and prediction

The prediction results are shown in Figure 4.9, and the purple-colored points represent the average of three true values of the numbers of newborn deliveries given at the 25 hospitals. The red-colored points indicate predicted values from the Bayesian modeling method, and blue-colored points are predicted values from the REML estimation approach. As shown in Figure 4.9, when the true values are much higher than the mean, both estimations have higher MSE, but the MSE of predicted values from Bayesian estimation are always lower than the MSE from REML. The MSE from the Bayesian hierarchical Poisson model is 360.1, while the MSE from multilevel Poisson model is 511.1.

4.4 Discussion

In this study, Bayesian inference is leveraged to estimate hyper-parameters and parameters in hierarchical Poisson models, and results are compared with estimated coefficients using conventional REML estimation approach. Both hospital bed count and the number of 20-35 years old females are positively associated with the number of newborn deliveries at rural hospitals. Moreover, the prediction of newborn delivery services from the Bayesian method has lower MSE than the REML approach.

In recent decades, the number of rural hospital closures is rapidly increasing, and there are fewer rural hospitals providing obstetric care, which could lead to a rural maternity care crisis. For example, one study reported that more than half of rural US counties had no hospital obstetric services in 2014 (Hung et al., 2017). The rural hospital closures might have an influence on access to obstetric care for women living in the nearby areas. Previous research found that the effect of rural hospital closures on obstetrics and gynecology care was substantial (DesHarnais et al., 1998). This study find a positive association of the newborn delivery utilization with the number of females in the 20-35 age group, implying that the influence of the rural maternity care crisis on access to obstetric services might be more significant for rural communities with a higher proportion of females of reproductive age. It is essential for these rural communities to find alternative solutions and improve the access to obstetric and newborn delivery care.

Rural hospitals are always challenged by limited health care resources and the needs of local communities. Due to low volumes and long driving distances, it is very hard for rural hospitals to support the costs of equipment and to recruit healthcare providers to the extent that a full-size hospital would. In this low-volume situation, it is important to rationally allocate resources. The results of this study suggest that characteristics of rural areas and features of rural hospitals can be used for medical services assessments and predictions. Studies in the United Kingdom also employed a similar approach to predict the medical service utilizations and to facilitate hospital reorganizations for small residential areas in the U.K. (Congdon, 2000, 2001). The Bayesian estimation approach may provide an accurate prediction of the core medical services needed by rural communities and help with the rational allocation of limited resources.

There are some limitations in this study. First, I only focus on the estimation of newborn delivery services, and future studies should explore other types of medical services. For example, relative to urban areas, there is a higher proportion of the senior population living in rural areas, where emergency cardiovascular care is crucial. Moreover, this study only include rural hospitals whose bed counts are less than 100 in the analysis, and the findings could not be extrapolated into other types of hospitals. In addition, I could not leverage the geographic distance information based upon patients' residential ZIP codes and hospital ZIP codes, and this is because most of patients' ZIP codes have been suppressed for patient confidentiality.

Many stakeholders have pointed out that new health care delivery models should be developed for rural areas to support the need of local communities and the rational allocation of health care resources (Wishner, et al., 2016). The findings of this study indicate that the Bayesian estimation approach leveraging both demographic characteristics of counties and features of rural hospitals would provide rigorous statistical evidence for both the need assessment and the rational allocation in rural areas.

4.5 Figures

Figure 4.1 Geographic Locations of Rural Hospital in This Study

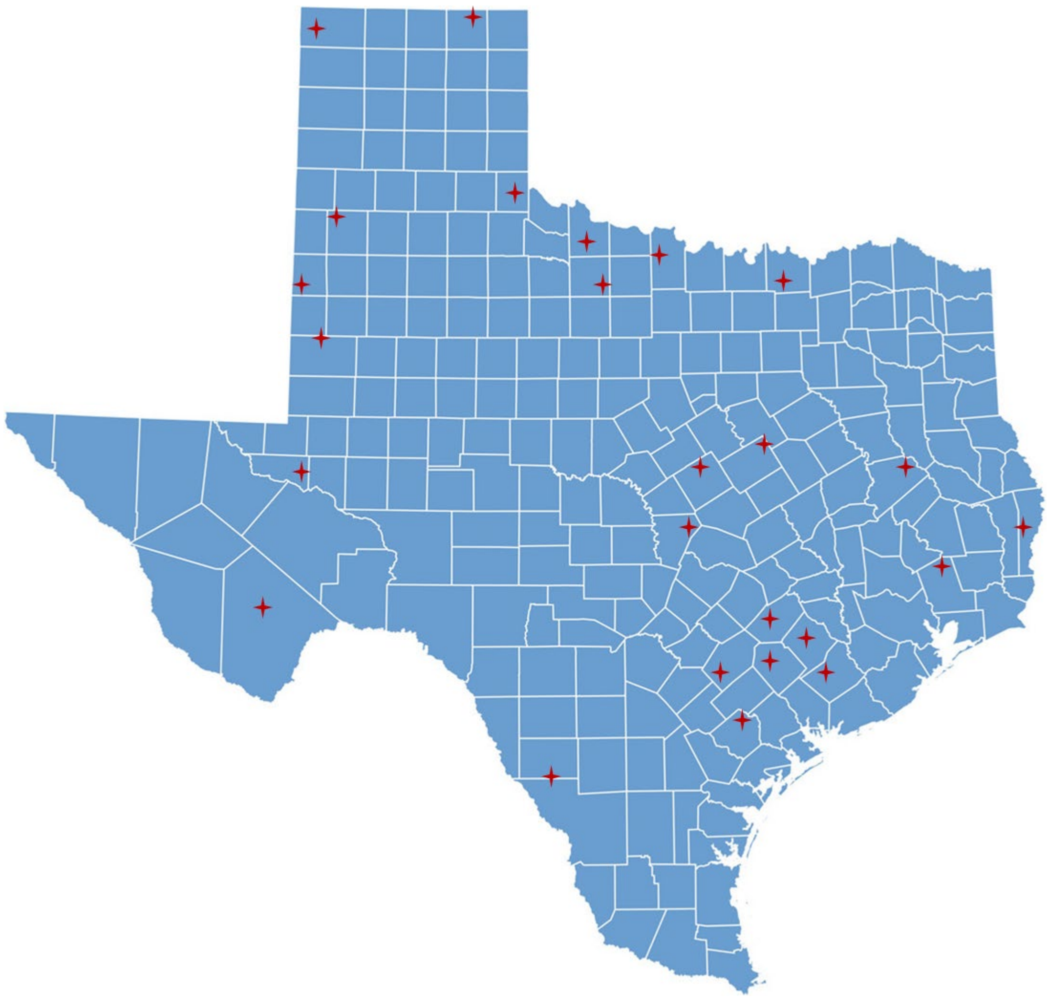


Figure 4.2 Histogram and Empirical Distribution of the Number of Newborn Deliveries from Each Hospital

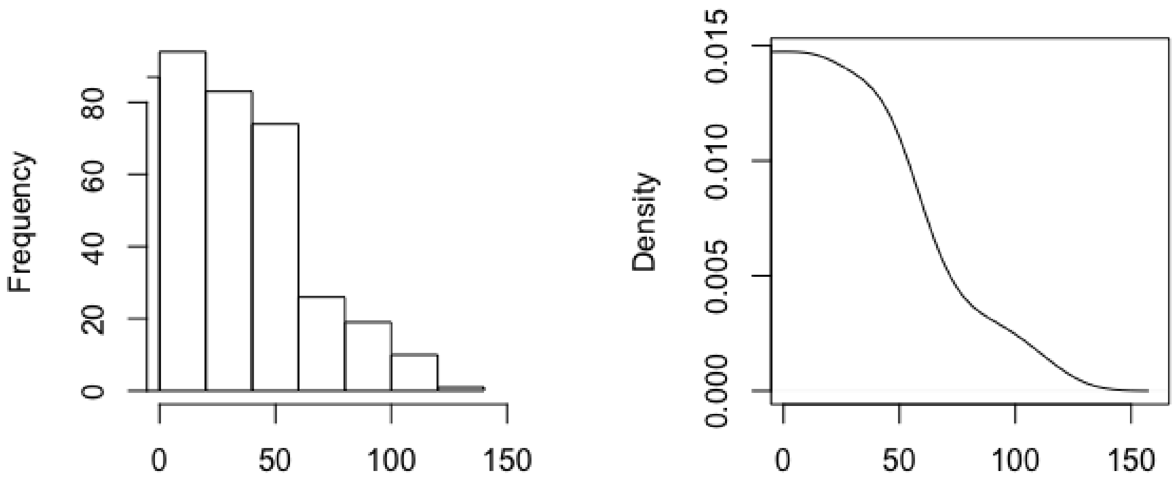


Figure 4.3 Histograms of the Number of Newborn Deliveries Given in One Hospital by Bed Count

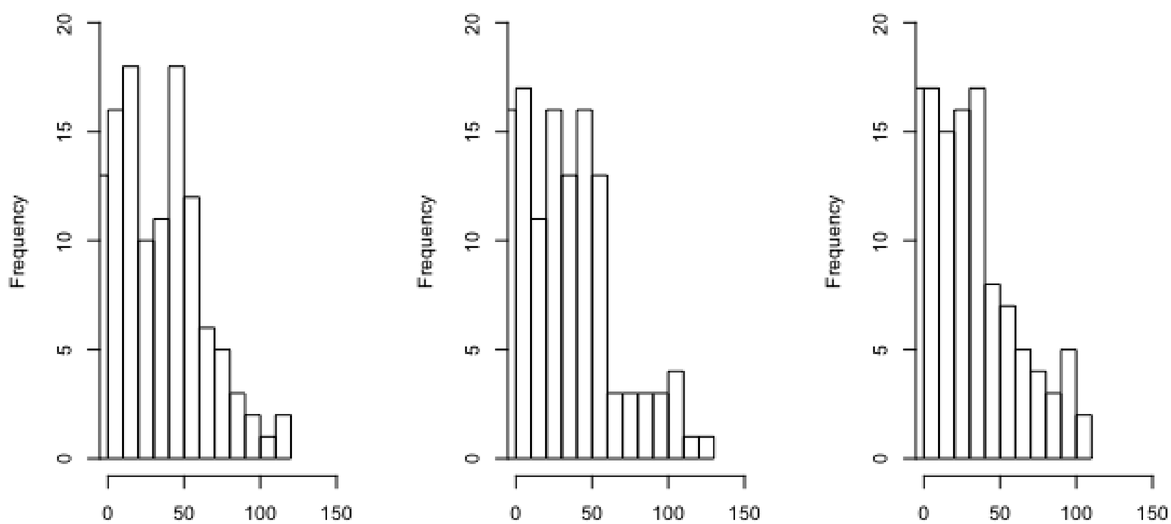


Figure 4.4 A Scatterplot between the Number of Females per 1,000 (20-35 years old) in the County Where Each Rural Hospital is Located (X-axis) and the Number of Newborn Deliveries Given in the Hospital (Y-axis)

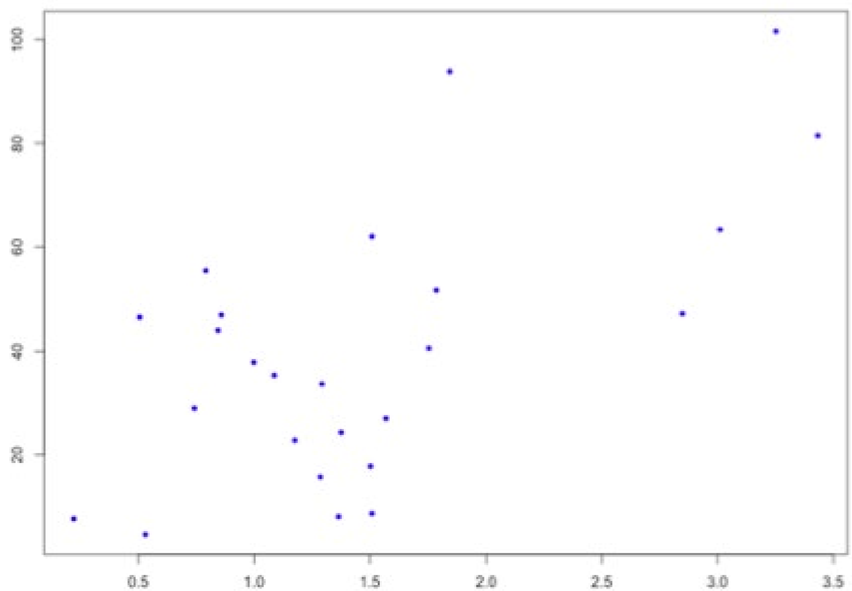


Figure 4.5 Autocorrelation Function Plots by Hospitals

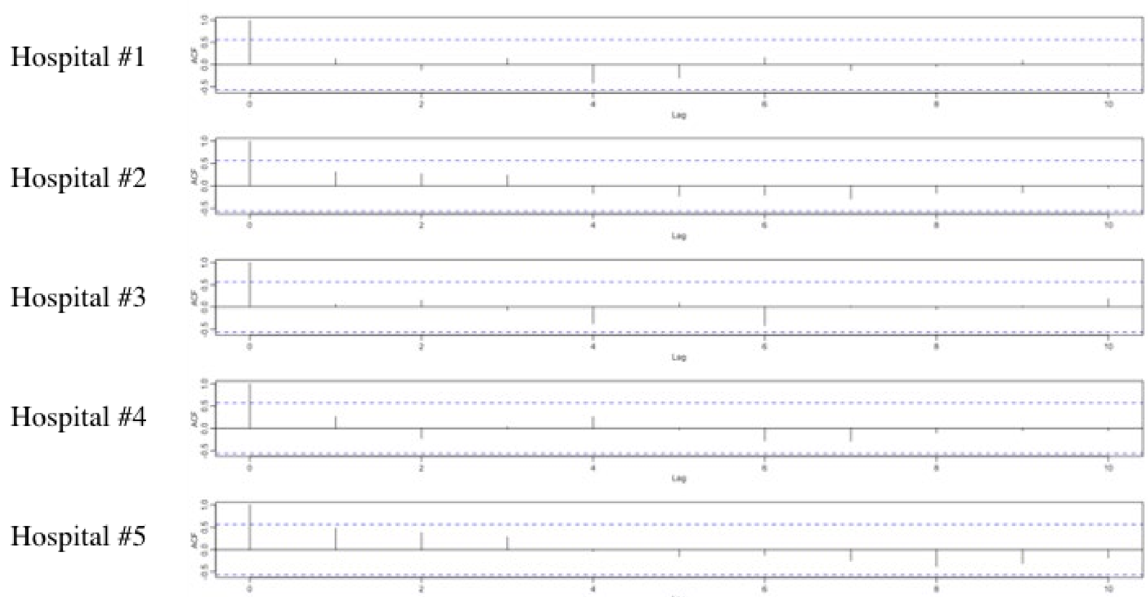
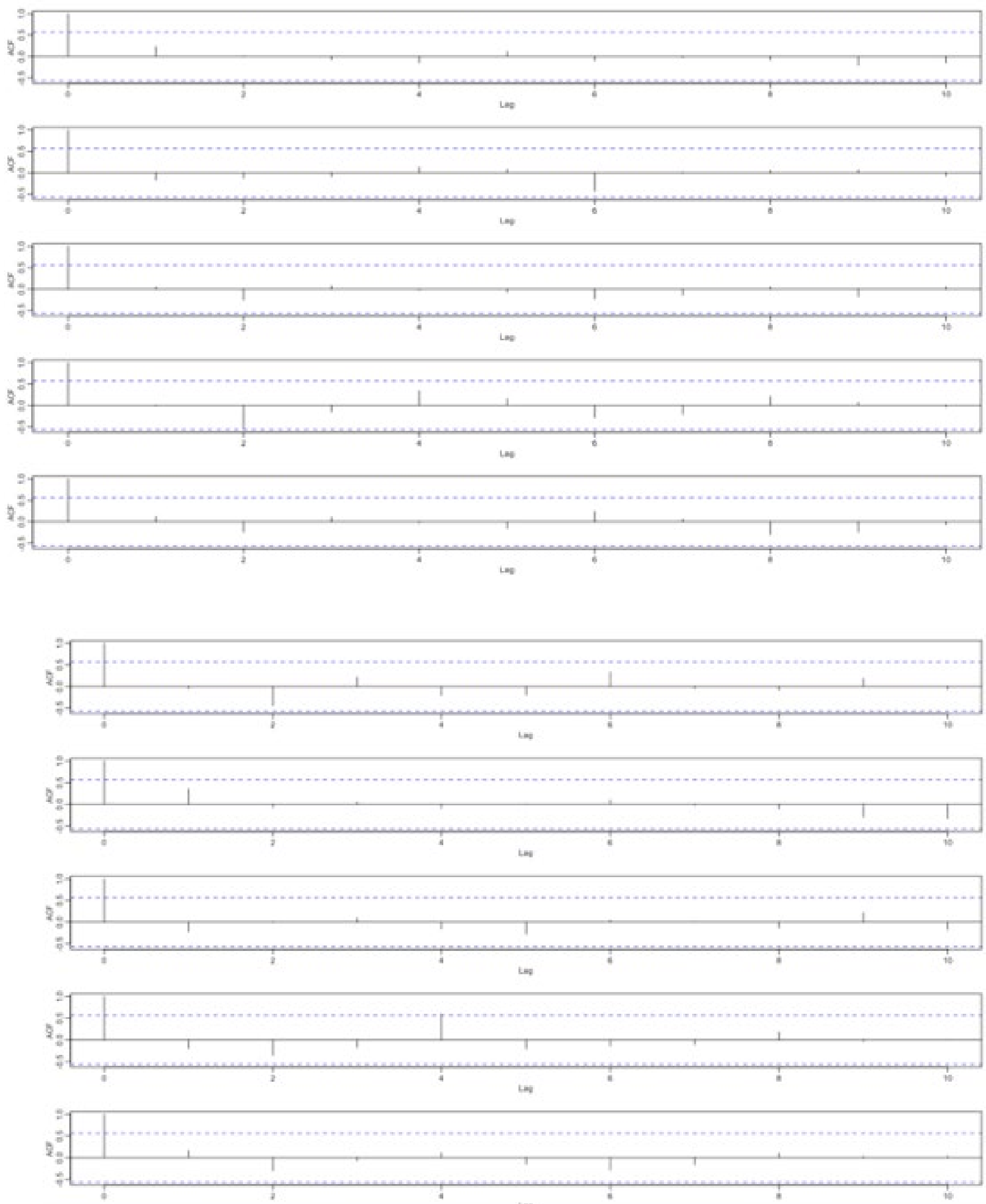


Figure 4.5 Continued



Hospital #6

Hospital #7

Hospital #8

Hospital #9

Hospital #10

Hospital #11

Hospital #12

Hospital #13

Hospital #14

Hospital #15

Figure 4.5 Continued

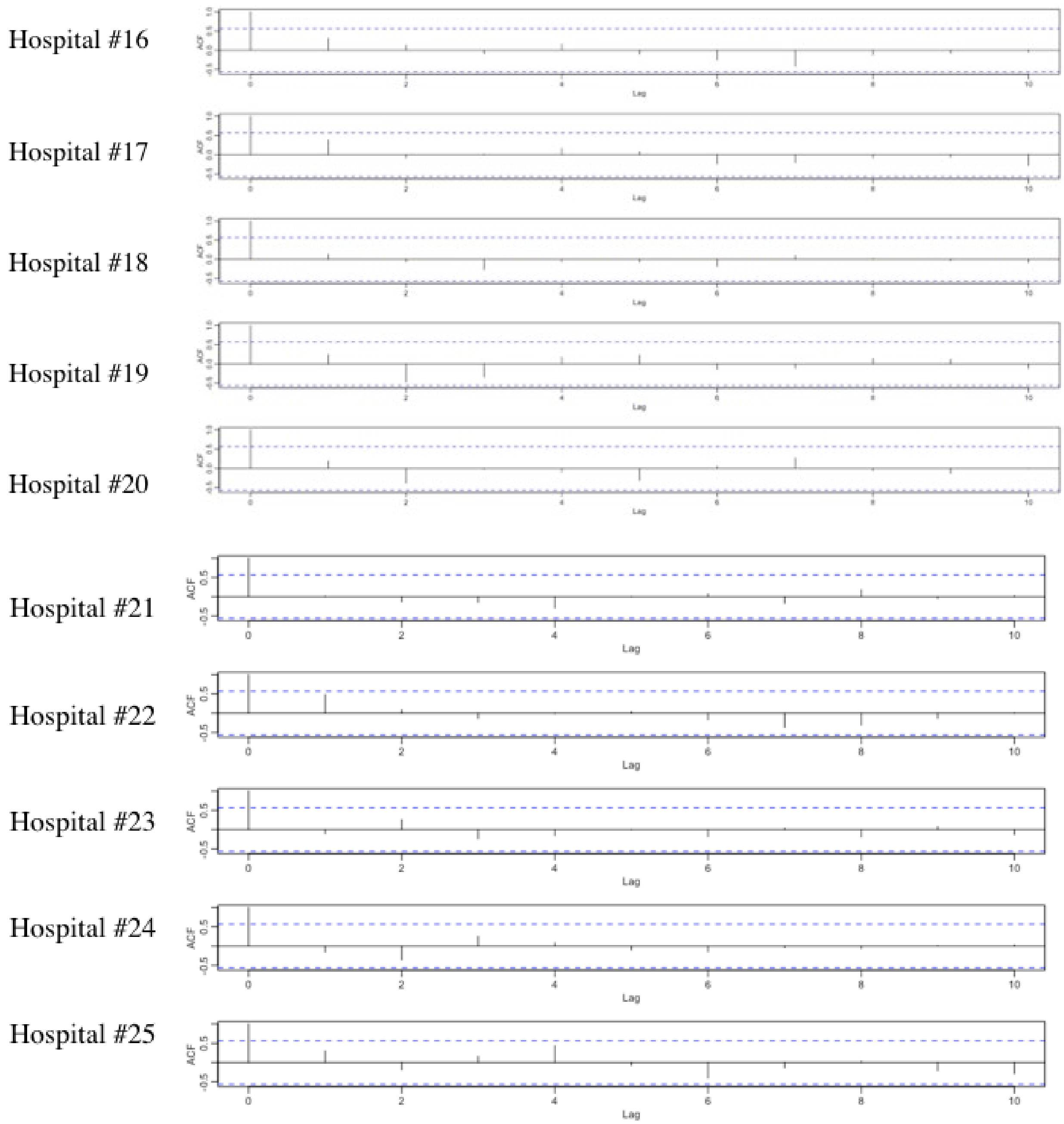


Figure 4.6 Number of Newborn Deliveries over Twelve (Left) or Four (Right) Quarters by Each Hospital

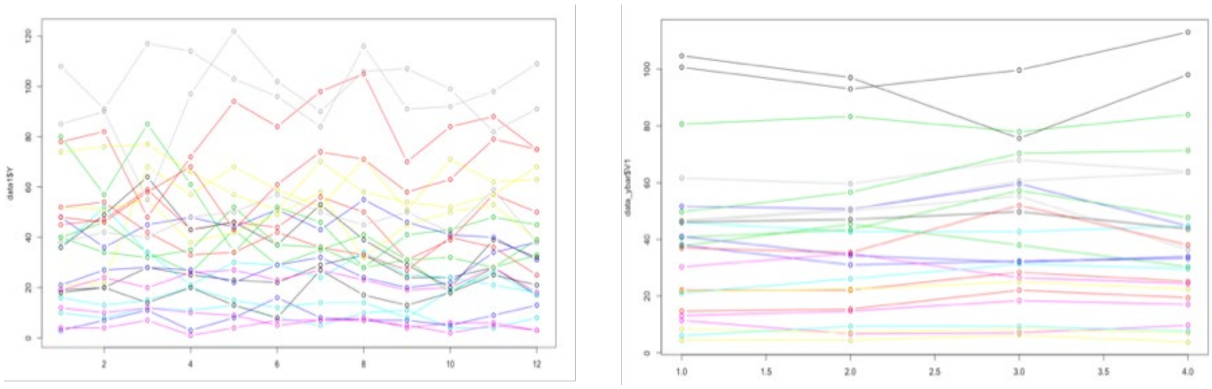


Figure 4.7 Trace Plots and ACF Plots of β_{0j} (j=1, 5, 10, 15, 20, 25)

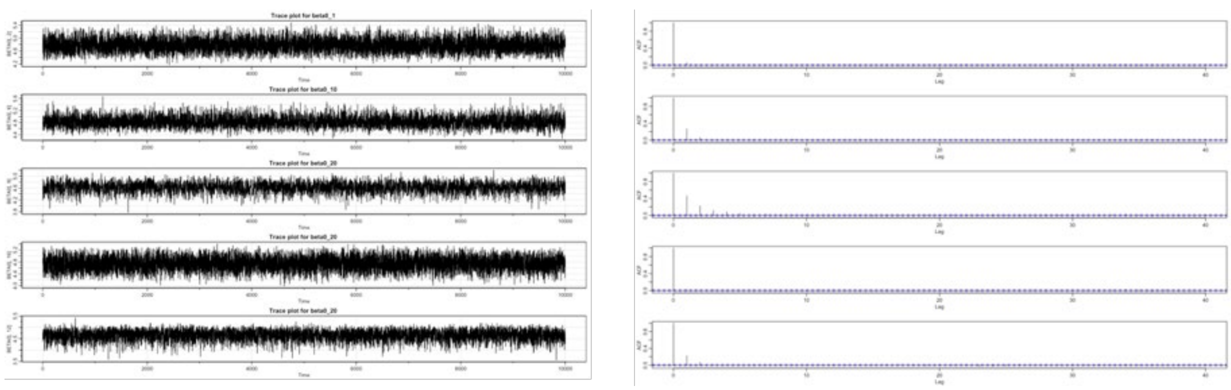
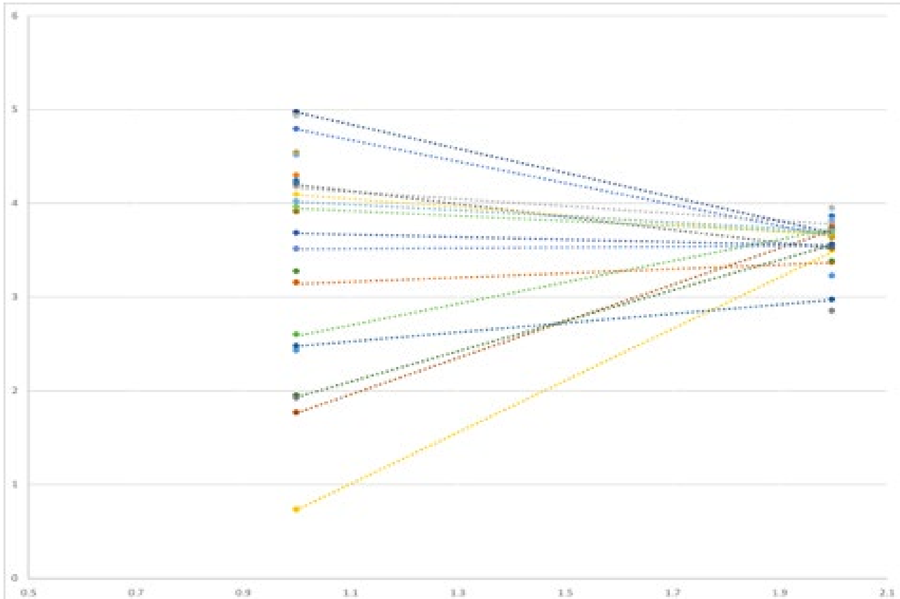
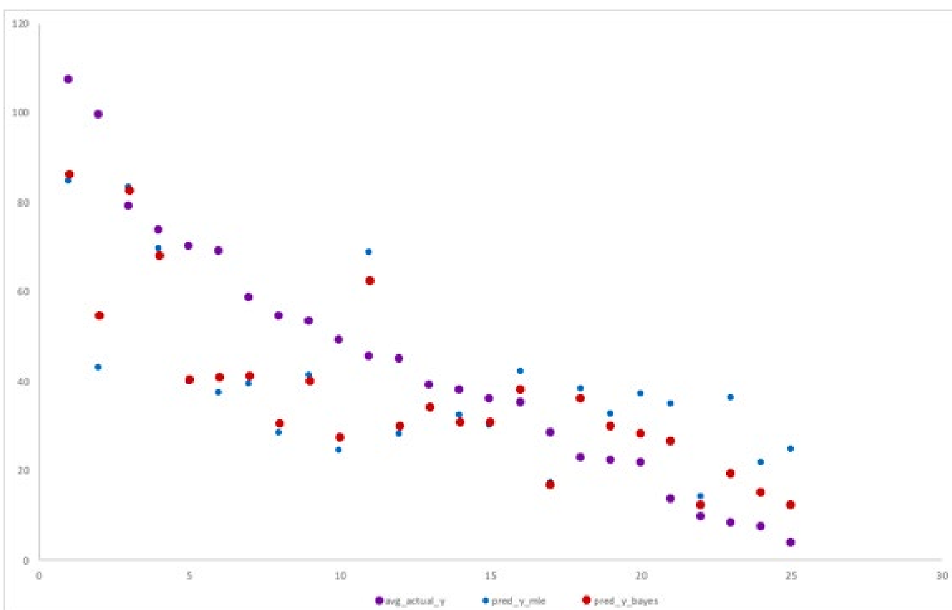


Figure 4.8 Shrinkage: Restricted Maximum Likelihood (REML) Estimates Are Pulled Severely Towards to the Mean



MLE estimates Bayesian estimates

Figure 4.9 Comparison of Averages of Three Actual Values and Averages of Predicted Values



4.6 Tables

Table 4.1 The Frequency and Percentage of Hospital Bed Count in This Study

Indicator variable (Bed size)	**n (%)**
Small (6-24)	4 (16)
Medium (25-49)	18 (72)
Large (50-99)	3 (12)

Table 4.2 Coefficients and 95% Confidence Intervals Using Restricted Maximum Likelihood Estimation (REML).

	Coefficients	**95% CI**
Bed count (Medium)	-1.810	(-1.988, -1.632)
Bed count (Large)	-1.774	(-2.038, -1.509)
The number of females per 1,000 (20-35 years old)	-1.406	(-1.578, -1.234)
Bed count (Medium)* the number of females per 1,000 (20-35 years old)	1.823	(1.649, 1.996)
Bed count (Large)* the number females per 1,000 (20-35 years old)	1.832	(1.646, 2.018)

Table 4.3 95% Credible Intervals of Hyperparameters Using Bayesian Inference

Credible Interval	**95% Credible Intervals**
theta 1	(-0.643, 3.075)
theta 2	(1.023, 4.665)
π	(0.256, 0.697)
σ^2	(19.377, 45.232)

Table 4.4 95% Credible Intervals of Parameters Using Bayesian Inference

Predictors	**95% Credible Interval**
Bedsize (Medium)	(-1.841, -1.769)
Bedsize (Large)	(-1.851, -1.678)
The number of females per 1,000 (20-35 years old)	(-1.423, -1.367)
Bedsize (Medium)* The number of females per 1,000 (20-35 years old)	(1.803, 1.845)
Bedsize (Large)* The number of females per 1,000 (20-35 years old)	(1.801, 1.890)

4.7 References

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5. CONCLUSIONS

5.1 Summary

This dissertation investigates the impact of rural hospital acquisition on access to tertiary care and treatment patterns, as well as predicts the utilization of health care services at rural hospitals in Texas. The findings of this research indicate that the impact of acquisition is different for each acquisition configuration, hospital market competition status, and patient characteristics. The Bayesian estimation approach might provide a more accurate prediction of health care utilization to support a rational allocation of limited health care resources at rural hospitals.

The next step for this research is to replicate this analysis in other states and examine the corresponding results. This would increase sample sizes and allow the models to detect a smaller difference or identify different impacts from various hospital markets. The Bayesian estimation approach should be applied to estimate other key medical services utilizations at rural hospitals. It would provide more evidence for resource allocation at rural hospitals.

APPENDIX A

Supplemental Tables

Table S 1 Inclusions of Hospital Acquisitions Occurred in Texas from 2008 through 2014 Obtained from American Hospital Association data files §

Local Community Hospital (Acquired Hospital)	**Tertiary Hospital (Acquirer Hospital)**	**Types of Mergers or Acquisitions**	**Inclusion**
Angleton Danbury Medical Center	University of Texas Medical Branch	Cross-market acquisitions between a tertiary and a local hospital	1
East Houston Regional Med Ctr	Bayshore Medical Center	Cross-market acquisitions between a tertiary and a local hospital	1
Mainland Medical Center	Clear Lake Regional Medical Center	Cross-market acquisitions between a tertiary and a local hospital	1
CHRISTUS Hospital-St. Mary	CHRISTUS Hospital-St. Elizabeth	Cross-market acquisitions between a tertiary and a local hospital	1
St. David's Rehabilitation Center	St. David's Medical Center	Rehabilitation hospital	0
Kindred Hospital Tarrant County-Fort Worth Southwest	Kindred Hospital-Fort Worth West	Long term hospital	0
CHRISTUS St. Michael's Health System	CHRISTUS St. Michael Health System	All discharges from two facilities submitted together to Texas Department of State Health Services	0
Cornerstone Hospital of Houston - Bellaire	Cornerstone Hospital of Houston at Clearlake	Long term hospital	0
North Texas Community Hospital	Wise Regional Health System	All discharges from two facilities submitted together to Texas Department of State Health Services	0
Midland Memorial Hospital	Midland Memorial Hospital	Intra-market mergers	0
Solara Hospital Harlingen-Brownsville Campus	Solara Hospital Haringen	Long term hospital	0
CHRISTUS Santa Rosa Hospital - New Braunfels	CHRISTUS Santa Rosa Health System	Another hospital acquisition in exposed areas in study periods	0
Methodist Texsan Hospital	Methodist Hospital	Specialty hospital	0
Heart Hospital of Austin	St. David's medical Center	Specialty hospital	0
CHRISTUS Santa Rosa Children's Hospital	CHRISTUS Santa Rosa Hlth Care	Children hospital	0
Triumph Hospital Northwest	Kindred Hospital North Houston	Long term hospital	0

Table S 1 Continued

Local Community Hospital (Acquired Hospital)	Tertiary Hospital (Acquirer Hospital)	Types of Mergers or Acquisitions	Inclusion
Padre Behavioral Hospital	Corpus Christi Medical Center	Psychiatric hospital	0
Regency Hospital of North Dallas	Select Specialty Hospital-Dallas	Long term hospital	0
DePaul Center	Providence Health Center	Psychiatric hospital	0
St. David's Georgetown Hospital	St. David's medical Center	Another hospital acquisition in control areas in study periods	0
Metropolitan Methodist Hospital	Methodist Hospital	Intra-market consolidation	0
Lifecare Hosp of Fort Worth	LifeCare Hospitals of Dallas	Long term hospital	0
LifeCare Hospitals of Plano	LifeCare Hospitals of Dallas	Long term hospital	0
Edinburg Regional Med Center	South Texas Health System	Intra-market consolidation	0
McAllen Medical Center	South Texas Health System	Intra-market consolidation	0
Del Sol Medical Center	Las Palmas Del Sol Healthcare	Intra-market consolidation	0
King's Daughters Hospital	Scott and White Memorial Hospital	Intra-market consolidation	0
Mem Hermann Southwest Hosp	Memorial Hermann Northwest Hospital	Intra-market consolidation	0
Select Specialty Hospital	Select Specialty Hospital	Rehabilitation hospital	0
Select Specialty Hospital	Select Specialty Hospital	Rehabilitation hospital	0
Alliance Hospital	Odessa Regional Medical Center	Intra-market consolidation	0
RehabCare Rehab Hospital	HealthSouth Rehab Hospital	Rehabilitation hospital	0
Memorial Hermann Southeast	Memorial Herman NW Hospital	Intra-market consolidation	0
McKenna Memorial Hospital	Christus Santa Rosa Hlthcare	Another hospital acquisition in exposed areas in study periods	0

§ There were four hospital acquisitions included in this dissertation research (Section 2 and 3)

Table S 2 International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) Used in Section 2 and 3 §

Target conditions	ICD-9-CM Diagnosis Codes	ICD-9-CM Description
Newborn care	V27.0	Outcome of delivery, single liveborn
	V30.0	Single liveborn
Respiratory care		
	480	Viral pneumonia
	481	Pneumococcal pneumonia
	482	Other bacterial pneumonia
	483	Pneumonia due to other specified organism
	484	Pneumonia in infectious diseases classified elsewhere
	485	Bronchopneumonia, organism unspecified
	486	Pneumonia, organism unspecified
	490	Bronchitis, not specified as acute or chronic
	491	Chronic bronchitis
	492	Emphysema
	494	Bronchiectasis
	496	Chronic airway obstruction, not elsewhere classified
Cardiovascular care		
	410	Acute myocardial infarction
	411	Other acute and subacute forms of ischemic heart disease
	412	Old myocardial infarction
	413	Angina pectoris
	414	Other forms of chronic ischemic heart disease

§ 2.2.2 and 3.2.2

Table S 3 Power and Sample Size Used in Section 2 and 3 §

ZIP code areas for market shares (means)	Effect size	Power	Alpha	Sample size
	10	0.85	0.05	19
	10	0.9	0.05	22
	8	0.85	0.05	29
	8	0.9	0.05	34
	5	0.85	0.05	73
	5	0.9	0.05	85
	3	0.85	0.05	201
	3	0.9	0.05	235
Patient Discharges for proportions (p2/p1)	2	0.85	0.05	93
	2	0.9	0.05	108
	1.5	0.85	0.05	335
	1.5	0.9	0.05	391
	1.25	0.85	0.05	1251
	1.25	0.9	0.05	1464

§ 2.2.4 and 3.2.4

Table S 4 Definitions and Values of Variables Used Section 2 and 3 §

Variables	Definitions	Values	Data sources
	ZIP code level analysis		
Acquisition	An indicator of a patient living in hospital acquisition exposed or control areas	1: Acquisition exposed area; 0: control area	PUDF
Time	The time periods involving in hospital acquisition	0: pre- period; 1: concurrent period; 2: post-period	AHA
Rival	An indicator of am existed competing hospital within 10 miles of the local community hospital (acquired hospital)		PUDF
	Discharge level analysis		
PAT_AGE	Age of patient on date of discharge	0-26; Each value indicates an age group (For example, 03 indicates 5-9 years old)	PUDF
SEX	Patients' gender	M: Male; F: Female	PUDF
RACE	Patients' race	1: American Indian/Eskimo/Aleut; 2: Asian or Pacific Islander; 3: Black; 4: White; 5: Other	PUDF
ETHNICITY	Patients' Hispanic origin	1: Hispanic; 2: Not Hispanic	PUDF
Health insurance	Patients' primary source of payment	0: Self-pay; 1: Private insurance; 2: Medicare; 3: Medicaid; 99: Others	PUDF
Admiss_cate	Types of admission	1: Emergency; 2: Urgent; 3:Elective; 4: Newborn; 5: Trauma Center	PUDF
Admiss_source	Source of admission	1: Referral; 2: Transferred	PUDF
GeoDis	Geographic distance from the tertiary hospital	Miles	PUDF and NBER
Acquisition	An indicator of a patient living in hospital acquisition exposed or control areas	1: Consolidation exposed area; 0: control area	PUDF
Time	The time periods involving in hospital acquisition	0: pre- period; 1: concurrent period; 2: post-period	AHA

§ 2.2.3 and 3.2.3

Table S 5 International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) Used in Section 3 §

ICD-9-CM	ICD-9-CM description
410	Acute myocardial infarction
411	Other acute and subacute forms of ischemic heart disease
412	Old myocardial infarction
413	Angina pectoris
414	Other forms of chronic ischemic heart disease

§ 3.2.2

Table S 6 All Patient Refined Diagnosis Related Groups Used in Section 3 §

APR-DRG	APR-DRG Description
165	Coronary Bypass w Cath
166	Coronary Bypass w/o Cath
174	Percut CV Procs w AMI
175	Percut CV Procs w/o AMI
191	Cardiac Cath Exc Ischem Disease
192	Cardiac Cath for Ischem Disease

§ 3.2.2

Table S 7 Medicare Severity-Diagnosis Related Group (MS-DRG) Codes Used in Section 4 §

Delivery MS-DRG codes	**Interpretation**
765	Cesarean section W CC/MCC
766	Cesarean section W/O CC/MCC
767	Vaginal delivery W sterilization &/OR D&C
768	Vaginal delivery W O.R. PROC except sterilization &/OR D&C
774	Vaginal delivery W Complication Diagnoses
775	Vaginal delivery W/O complicating diagnoses

§ 4.2.2

Table S 8 The Proposed Classification Scheme for Bayes Factor by Jeffreys (1961) §

Values of Bayes factor (Null versus Alternative)	Interpretation
>100	Decisive evidence for H0
30-100	Very strong for H0
10-30	Strong for H0
3-10	Substantial for H0
0.3-3	Not worth more than a bare mention
0.1-0.3	Substantial for H1
0.03-0.1	Strong for H1
0.01-0.03	Very strong for H1
<0.01	Decisive evidence for H1

§ 4.2.3