HOSPITAL SURVIVABILITY AND GOVERNMENT POLICIES: THE 2010 AFFORDABLE CARE ACT

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Abstract

This dissertation investigates the impact of the U.S. Affordable Care Act (ACA) of 2010 on hospital survivability. To this end, I study two policy changes in the ACA. The first is the Hospital Readmission Reduction Program (HRRP), which ties the Centers for Medicare & Medicaid Services (CMS) payments to hospital readmission rates. A hospital's readmission rate thus becomes an important financial and healthcare delivery indicator. Hence, in the first project of this dissertation, I test the financial viability of hospitals based on readmission rates. Then, using Simar and Wilson's two-stage data envelopment analysis (DEA), I test the impact of two dimensions of quality—experiential quality and clinical quality—on hospitals' financial viability. Results indicate that hospitals that offer higher quality care are more efficient at achieving financial viability. Additionally, the results demonstrate that excelling in both dimensions has had additional benefits for hospitals.

The second policy change explored is the ACA's Medicaid coverage expansion. I examine its impact on hospital closures. This policy expands Medicaid coverage to all adults with incomes lower than 138% of the U.S. federal poverty level. However, based on constitutional arguments against the ACA, the U.S. Supreme Court in 2012 ruled that states could opt out of the mandate. The heterogeneous adoption by states enables researchers to conduct a natural experiment by providing a control group. Therefore, I adopt a difference-in-differences analysis framework with fixed effects using a Poisson regression to test whether the ACA-mandated Medicaid coverage expansion impacted hospital closures. Results show that the mandate reduced the number of hospital closures in states that complied with the mandate by 54% as compared to states that did not. Then, I explore hospital-level operational drivers that contributed to the hospital closure crisis. Results demonstrate that the mandate increased patient revenue and perceived quality of care, while no evidence showed that the mandate affected the number of patient discharges, number of employees, and hospital operating expenses. Furthermore, my results suggest that Medicaid expansion increased hospital revenue not by increasing the number of patients, but rather by decreasing hospitals' amount of uncompensated care.

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Chapter 1

1 Introduction

1.1 The Affordable Care Act

This dissertation investigates the impact of the 2010 U.S. Affordable Care Act (ACA) on hospital closure rates in the United States.

On March 23, 2010, President Barack Obama signed the ACA into law. It was the greatest overhaul of the U.S. healthcare system since the introduction of the Medicaid and Medicare programs (healthcare for senior citizens, and for low-income individuals and families, respectively) in 1965 by President Lyndon Johnson. The ACA's mission is to provide high-quality and affordable healthcare to every American. The ACA has three primary goals: (1) Make affordable health insurance available to more people; (2) expand the Medicaid program to cover all adults with income below 138% of the Federal Poverty Level; And (3) support innovative medical care delivery methods designed to lower the costs of healthcare generally.

For the majority, the ACA meant health insurance for those who could not afford one, yet it is a comprehensive health reform that impacts hospitals, physicians, and individuals alike. Silvers (2013) explains the three main drivers of the ACA as:

> (1) The private insurance market needed reform, particularly for individuals and parents of children who had to pay for their own insurance and had to deal with the bureaucracy of insurance companies without the support of large companies,

(2) Medicaid (health insurance for low-income individuals and families) coverage needed to be expanded to every low-income individual so that those who could not afford health insurance could access healthcare services, and

(3) How doctors made medical decisions needed a change.

It was a tough struggle for the Obama administration to push the ACA though the US House and Senate, but it succeeded. On this, Obama said (The White House, 2016). However, the ACA has been the center of controversy since its inception. Politicians accused the ACA of being the cause of rural hospital closures (Blunt, 2015), some Americans believed that the ACA was paid for by hard-working people but benefited lazy people (Luhby, 2017). Although President Trump's attempts to repeal the ACA over his four years in office were unsuccessful, the Republicans' efforts to repeal the ACA will likely continue into the future. This effort is funded in part by the insurance industry, which stands to lose billions of dollars if the ACA is expanded to all U.S. citizens (e.g., single-payer or nationalized government-funded health insurance) as a basic right. Thus, investigation of the ACA's effects is an important topic for Americans and has implications for nations considering funding healthcare as a basic human right.

Nearly 12 years have passed since the Affordable Care Act (ACA) became law, which offers us opportunity to investigate its initial outcomes for several reasons. First, discussions surrounding the ACA's costs and effectiveness have overlooked the ACA's impact on hospitals. Its effects on hospitals have been largely overlooked with its costs and benefits to individuals and families have taken center stage. Yet, hospital survival is a vital issue in the United States, especially because annual hospital closure rates have been growing, and were characterized as a 'public crisis' in 2018, when hospitals were closing at a 30-a-year pace (Flanagan, 2018; Coleman-Lochner and Hill, 2020). Hence, this dissertation fills an important gap in the literature on the ACA by focusing on its effects on U.S. hospitals, large and small.

Secondly, from a timing perspective, the 2010 ACA is old enough that rich data is now available. In addition, the fact that 12 states opted out of one of the ACA mandates, the Medicaid expansion mandate which expands Medicaid coverage to all adults with incomes lower than 138% of the U.S. federal poverty level, creates a control group for a Difference-in-Differences (DID) analysis.

This dissertation investigates two aspects of the ACA by focusing on the impacts of two specific changes to hospitals brought by the ACA. The first change is the Hospital Readmission Reduction Program (HRRP). In 2012, the HRRP, under the ACA policy changes, tied a portion of hospital reimbursements to readmission rates. Under these changes, hospitals that have high readmission rates could lose up to 3% of the Centers of Medicaid and Medicare Services (CMS) reimbursements (HRRP, 2019). In Chapter 2, the first issue I explore is whether these changes had any impact on the financial viability of hospitals.

The second change I investigate is the expansion of Medicaid coverage under the ACA. Medicaid is the basic healthcare coverage provided only to low-income children and their parents who meet federal poverty guidelines, pregnant people, and disabled people prior to the ACA. However, with the goal to provide health insurance to every citizen who cannot afford insurance, the ACA mandated that the states expand the Medicaid coverage to adults who earn less than 138% of the federal poverty level (FPL). In Chapter 3, I examine the second project and its effect of this policy change on hospital closures.

1.2 Investigation 1: Does quality help the financial viability of hospitals? A data envelopment analysis approach

In investigation 1, “Does quality help the financial viability of hospitals? A data envelopment analysis approach”, I analyze the impact of the HRRP under the ACA. In 2012, the HRRP, under the ACA, tied a portion of hospitals’ CMS reimbursements to their readmission rates, making the financial viability of hospitals reliant on keeping their readmission rates low. I examine the financial viability of U.S. hospitals by investigating the impact of clinical and experiential quality as its determinants. I measure clinical quality as hospitals' compliance with the evidence-based treatment and experiential quality based on patients' perception of the service they received. I adopt Simar and Wilson's two-stage bootstrap truncated regression approach. Specifically, I use data envelopment analysis (DEA) in the first stage to estimate efficiency scores. Then, I employ a truncated regression estimation with the double-bootstrap method to test the significance of the quality variables. Given the financial problems recently experienced by U.S. hospitals, where approximately 8% of U.S. hospitals are facing permanent closure (Flanagan, 2018), I chose readmission rates and costs as the outputs to investigate how hospitals can lower readmission rates while minimizing their costs, as under the HRRP, high readmission rates lower hospitals' government reimbursements for services, making both variables crucial outcome goals. The results indicate that both higher clinical quality and higher patient ratings of their experiences are significantly associated with higher financial viability of the hospitals studied. Furthermore, I show that focusing on these two quality dimensions together have additional benefits.

1.3 Investigation 2: The Affordable Care Act and Hospital Closures: A Difference-in-Differences Analysis

For Project 2, "The Affordable Care Act and Hospital Closures: A Difference-in-Differences Analysis", I examine the impact of the Medicaid coverage expansion mandate in the ACA on hospital closures in the United States. States' adoption of the Medicaid coverage expansion mandate in the ACA since the implementation of the ACA created an opportunity for a natural experiment by creating a control group of states that chose not to comply with the ACA-mandated Medicaid coverage expansion. As of December 2020, 38 states complied with the ACA-mandated Medicaid coverage expansion, leaving 12 states that have still not complied. Thus, I adopt a DID analysis framework with fixed effects using a Poisson regression. First, I establish that there are no other differences that could have affected the results between states that complied with the ACA-mandated Medicaid coverage expansion and states that did not. This is necessary to achieve valid results. The results show that the Medicaid expansion mandate decreased hospital closures by 54% in states that complied with the mandate compared to states that did not. In addition, I provide evidence that the choice to expand was a political one. Then, I explore the hospital-level drivers Medicaid expansion and found that expansion increased the hospitals' patient revenue and perceived quality but had no effect on hospital patient expenses, number of patient discharges, and number of employees. These findings suggest that the mandate reduced hospital closures. The main operational driver behind this effect has been identified as the increase in patient revenue due to the reduction of uncompensated care as no increase in patient volume was observed.

Chapter 2

2 Does quality help the financial viability of hospitals? A data envelopment analysis approach

2.1 Introduction

Introduced in 2012, the Obamacare policy changes tied a portion of hospital reimbursements to readmission rates. These changes have been controversial. Under these changes, hospitals which do not achieve a certain readmission rate might lose up to 3% of their reimbursements from the government under the Hospital Readmissions Reduction Program (HRRP, 2019). These changes have been blamed for some hospitals having to close, ultimately leaving citizens without access to appropriate care (Catron, 2017). Thus, it is imperative to investigate readmission rates.

Quality of care has been shown in the literature to reduce readmission rates (Boulding et al., 2011; Stukel et al., 2012; Batt et al., 2018). This statement alone seems sufficient to encourage hospitals to invest in their quality of care as a way of improving readmission rates. However, while quality of care has been shown to reduce readmission rates, this generally comes with increased costs (Venkataraman, 2015; Senot et al., 2016). Hospitals might decide to focus on attracting more patients to benefit from economies of scale to reduce costs (Gaynor et al., 2005; Vitaliano, 1987). This might also help them improve their quality while reducing their costs through learning by doing (Choi et al., 2017). However, for hospitals, this is not always an easy option, as it is difficult to increase the number of patients they treat (Gaynor et al., 2005). Hence, in light of the recent policy changes, their financial situation depends not only on their costs but also on their readmission rates. This means that hospitals are left in a conundrum in terms of how they should approach their quality of care given these fiscal concerns. On one hand, a hospital suffering financial problems might struggle to allocate sufficient resources to improve quality levels because of concerns about the impact on its costs. On the other hand, it might have to allocate more resources to improve its quality so that it can receive full reimbursement from the government on which its financial viability depends. In this study, this conundrum is addressed and how quality of care affects this problem is investigated by looking at two key dimensions of healthcare quality: clinical quality and experiential quality.

Applications of data envelopment analysis (DEA) in healthcare have focused primarily on hospitals' efficiencies in terms of the number of patients they treat given available resources (e.g., Araujo et al., 2014; Lindlbauer and Schreyogg, 2014; Chowdhury and Zelenyuk, 2016; Fragkiadakis et al., 2016). However, the recent review by Kohl et al. (2019) of DEA papers in healthcare that focus on hospitals, emphasizes the importance of considering healthcare quality and the recovery of patients. The authors highlight that the lack of studies of quality of care and recovery of patients that provide insightful information to policymakers, represents a significant gap in the healthcare literature. In this study, using 30-day unplanned readmission rates and costs as the outputs, I address this gap. Furthermore, I define financial viability as hospitals' ability to achieve high levels of care (i.e., low readmission rates) while reducing costs, and how efficiently hospitals can achieve financial viability given their resources and number of patients is investigated. I also, investigate how the two dimensions of healthcare quality, experiential and clinical quality, influence this efficiency.

For this investigation, I apply the two-stage procedure (DEA + truncated regression, bootstrapped) of Simar and Wilson (2007) to examine the determinants of hospital efficiency. This is explained in more detail in Section 2.4.5. The results provide two important contributions. First, as far as the authors are aware, this is the first study to investigate hospitals' efficiencies in terms of financial viability using the number of patients as an input and cost and readmission rates as outputs, given the number of patients and resources they have. Second, the results show that both experiential and clinical quality significantly increase hospitals' efficiencies when low costs and readmission rates are a concern. These results provide important insights for both academics and managers, which I discuss in more detail in Section 2.6.

2.2 Background and Literature Review

2.2.1 Quality of Care

Dimensions of quality of care was first introduced by Donabedian (1966). He introduced three categories to divide healthcare. These categories are structural, process and outcome quality. Structural quality refers to resources that hospitals have such as equipment and technical capability. Process quality is defined as delivering proper treatment. Finally, outcome quality is defined as whether the desired health outcome was achieved. Donabedian's categorization was the first framework to define quality of care. According to Keßler and Heidecke (2017) this framework is often complimented by a fourth dimension called 'quality of experience'. This fourth dimension refers to patients' perception of delivery of care during their interactions with the provider.

However, this is not the only accepted framework in the literature. More recently, the Institute of Medicine defined the quality of care as "the degree to which health services for individuals and populations increase the likelihood of desired health outcomes and are consistent with current professional knowledge." and introduced six dimensions (IOM, 2001). According to the IOM healthcare should avoid harm to patients (*safe*), provide services that are based on scientific evidence to all those who would benefit from them (*effective*), provide respectful service that is centered around each individual's needs (*patient-centered*), reduce harmful wait times and delays (*timely*), avoid waste of any kind (*efficient*), and be consistent in quality to everyone regardless of their individual characteristics (*equitable*). The World Health Organization (WHO) accepts a very similar framework to IOM's. However, in addition to the six dimensions introduced by the IOM, WHO recently included being integrated as the seventh dimension. This dimension refers to health services that ensure that people receive appropriate care according to their needs throughout their lives (2016). Despite different frameworks, recent research focusing on healthcare quality has identified that the nature of healthcare quality is bidimensional (Chandarasekaran et al. 2012; Senot et al., 2016; Nair et al., 2018). I follow the recent literature and study the bidimensional nature of quality which is discussed in the following section.

2.2.2 Bidimensional Nature of Healthcare Quality

Recent literature suggests that the quality of care consists of two distinct dimensions. These two dimensions are clinical quality and experiential quality. Clinical quality is the result of the technical service provided by hospitals, which is usually based on the results of medical procedures (Chandrasekaran et al., 2012). It is associated with evidence-based clinical practices and identifying the quality of care by focusing on "what" is delivered (Elsaleiby, 2015). Experiential quality is the result of the non-technical service delivery experienced by patients during their interactions with the healthcare service (Marley et al., 2004; Chandrasekaran et al., 2012). It is associated with responding to patients' needs and expectations and identifying quality by focusing on "how" the service is delivered (Elsaleiby, 2015).

2.2.3 Recovery of Patients

Though a number of measures might be chosen depending on data availability, readmission rate has been commonly used to measure the outcome of care and the recovery of patients in the healthcare literature (e.g., Chan et al., 2012; Bayati et al., 2014; Kim et al., 2015; Helm et al., 2016). This trend continues in the DEA applications (e.g., Chua et al., 2011; Fiallos et al. 2017; Chowdhury and Zelenyuk, 2016). Mortality rate is another choice, however it has been rarely used in the DEA literature (e.g., Nayar et al., 2013; Karagiannis and Velentzas, 2012), instead researchers chose readmission rate as the determinant of the level of hospital care (Liu et al., 2018). Moreover, the policy changes that threaten the financial viability of hospitals target readmission rates, hence I use readmission rate as the output of care variable. The readmission rate is defined as 30-day hospital-wide unplanned readmissions by discharged patients.

2.2.4 Healthcare Quality and DEA

A plethora of research used DEA to examine hospital performance. However, as Kohl et al. (2019) emphasize, the literature lacks studies of quality of care and recovery of patients. To my knowledge, although there are studies that focus on either quality of care or recovery of patients, no study investigates them together as explained in detail in this section. Table 1 reports a selection of studies that included either at least one dimension of healthcare quality or recovery of patients. As can be seen in the Table 1, most studies that focus on these variables work with only one of them. Laine et al. (2005) and Nayar and Ozcan (2008) are examples of studies that included only clinical quality. Almeida et al. (2015) on the other hand, is an example of studies which only used experiential quality. There are only a few studies that accounted for both dimensions of healthcare quality (Roth et al., 2019; Navarro-Espigares and Torres, 2011; Highfill and Ozcan, 2016). Those that focused on readmission rates only included readmission rates but not a dimension of healthcare quality (Guatam et al., 2013; Chua et al., 2011; Fiallos et al., 2017; Chowdhury and Zelenyuk, 2016). Ferrier and Trivitt (2013) is an exception to this as they use measures for both clinical quality and recovery of patients by including mortality rates, but they do not study experiential quality.

Moreover, studies usually try to find a way to incorporate quality into efficiency calculations. In other words, they try to control for quality while investigating the hospital performance. This method is neither suited for getting interpretable results about quality's impact on hospital performance nor is it the goal. Only a few studies aim to investigate the association between quality of care and hospital performance (Mancuso and Valdmanis, 2016; Chowdhury and Zelenyuk, 2016). While Mancuso and Valdmanis (2016) find a positive association between quality of care and hospital performance, they do not consider recovery of patients and they do not include quality in the hospital performance calculation which can be a misleading performance assessment (Fiallos et al., 2017). Chowdhury and Zelenyuk (2016), on the other hand, include recovery of patients in the regression, but they do not include either dimension of quality of care in their analysis. Their analysis does not demonstrate a significant relationship.

This study addresses this gap in the literature in two ways. First, to the authors' knowledge, this is the first study to incorporate both dimensions of quality of care and recovery of patients using DEA to analyze hospital performance. Second, while I include recovery of patients in the DEA outputs in the form of readmission rates, I use two dimensions of quality of care in the second stage regression so that I can find interpretable results of their impact on hospital performance.

Table 1: Previous Studies of DEA in Healthcare That Include At least One of Recovery of Patients, Clinical Quality, Experiential Quality

Year	Authors	Country	Model	DMUs	Recovery of Patients	Clinical Quality	Experiential Quality	Included in DEA
2005	Laine et al.	Finland	DEA	114	No	Yes	No	No
2008	Nayar and Ozcan	USA	CRS-I	53	No	Yes	No	Output
2011	Chua et al.	Australia	DEA-I + Truncated Regression	58	Yes	No	No	Output
2011	Navarro-Espigares and Torres	Spain	VRS-I	27	No	Yes	Yes	Output
2012	Karagiannis and Velentzas	Greece	CRS-O	8	Yes	No	No	No
2013	Guatam et al.	USA	VRS-I + Readmission Rate	28	Yes	No	No	No
2013	Ferrier and Trivitt	USA	VRS-O + VRS-I	1074	Yes	Yes	No	Output
2013	Nayar et al.	USA	VRS-I	371	Yes	No	No	Output
2013	Nedelea and Tannin	USA	VRS-I + Truncated regression	186	No	Yes	No	Output
2015	Almeida et al.	Portugal	VRS-O	37	No	No	Yes	No
2016	Chowdhury and Zelenyuk	Canada	CRS-O + Truncated regression	113	Yes	No	No	No
2016	Highfill and Ozcan	USA	CRS-I	207	No	Yes	Yes	No
2016	Mancuso and Valdmanis	Italy	CRS-I + OLS regression	20	No	Yes	No	No
2017	Fiallos et al.	Canada	VRS	20	Yes	No	No	Output
2019	Roth et al.	USA	VRS-I + Regression	793	No	Yes	Yes	No

2.2.5 Impact of Quality of Care

The impact of clinical and experiential quality on costs and the readmission rate has been studied, with researchers demonstrating the complicated nature of these dimensions. Experiential quality has been shown to be associated with higher costs in hospitals due to its resource-intensive nature (Bechel et al., 2000; Senot et al., 2016). However, Thorne et al. (2005) argue that experiential quality might have cost benefits through efficient diagnosis and care, because of the better communication it provides. Furthermore, Boulding et al. (2011) find that experiential quality is associated with lower readmission rates in hospitals. This means that since hospitals' reimbursements depend on their readmission rates, they might need to improve their experiential quality to receive their full reimbursements from the government. Though this improvement might look costly at first, they will experience cost benefits of this investment through more efficient diagnosis and communication. Hence, I expect experiential quality to improve hospital financial viability. Thus, I hypothesize the following:

H1: Experiential quality will be associated with higher hospital financial viability.

Similarly, although Senot et al. (2016) find a positive association between clinical quality and costs, the relationship between cost and clinical quality might be a more reversed u-shaped one as shown in Weech-Maldanado et al. (2006) and Kruse and Christensen (2013) with increasing costs at the lower range of quality but decreasing costs associated with higher quality after a threshold. The reason being because of hospitals needing an initial investment in their clinical quality which pays off after a certain threshold through increased process efficiency and reduced errors. This is further supported by Jha et al., (2009) and Nair et al. (2013)'s not finding a positive association between costs and clinical quality on average. Improved process and fewer errors mean clinical quality reduces readmission rates (Lawson et al., 2013; Chandresekaran et al., 2016). Hence, just like experiential quality, I expect clinical quality to improve hospital financial viability.

H2: Clinical quality will be associated with higher hospital financial viability.

Senot et al. (2016) show the complimentary nature of two dimensions of quality. Once hospitals excel at both clinical and experiential quality, they observe additional benefits. Hospitals that can follow routines and reduce errors can free up more resources needed for interactions with patients. Thus, improvement in clinical quality will result in additional benefits through improvements in experiential quality. Therefore, I hypothesize:

H3: Combined quality will be associated with higher hospital financial viability.

2.3 Methodology

This section first discusses the data sources for each variable. Then, I introduce the variables used in this research and explain how each of them is calculated along with the assumptions made. Finally, the mathematical approach is explained in detail.

2.3.1 Data

The data for this study are obtained from five sources, detailed below, from the Centers of Medicaid and Medicare Services (CMS), which is the federal agency of the U.S. Department of Health and Human Services that administers the Medicare program and Medicaid, the Children's Health Insurance Program, and health insurance portability standards. The unit of analysis is U.S. acute care hospitals. There were 3424 acute care hospitals listed in the CMS in 2014. This extensive data set covers all hospitals in the United States and contains hospital-level information on quality measures, costs, and hospital characteristics. I use *CMS Cost Reports*[1] to manually extract the Medicare costs, number of beds, number of discharges, and number of employees for each hospital. *CMS Impact Files*[2] are used to extract the control variables such as wage index, OPDSH (Operating Disproportionate Share Hospital Payment Adjustment) factor, teaching intensity, and location of the hospital. I use the *Timely and Effective Care*[3] files to calculate the clinical quality values. *Hospital Consumer Assessment of Healthcare Providers and Systems*[4] surveys are used to extract experiential quality and the

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[1] https://www.cms.gov/Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/Cost-Reports

[2] https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS

[3] https://healthdata.gov/dataset/timely-and-effective-care-hospital

[4] https://data.medicare.gov/data/hospital-compare

Readmissions, Complications and Deaths[5] file is used to collect the readmission rates. I use the data reported in 2014 for 2013, the first year after the implementation of readmission rate reimbursement changes. Readmission rates are reported with a one-year lag, for which I account. I remove any hospital that has missing values for any of the variables. This leaves 2997 of the 3424 hospitals in the system for the analysis. Table 2 reports the descriptive statistics for the variables used in this study.

Table 2: Descriptive Statistics of the Input, Output and Environmental Variables Used in the DEA Model

	Variable	Description	Mean	Median	Standard Deviation
Inputs	Beds	Natural Logarithm of the Number of Beds	4.946	4.997	0.901
	Employees	Natural Logarithm of the Number of Employees	6.652	6.664	1.019
	Discharges	Natural Logarithm of the Number of Discharges	-8.660	-8.778	1.106
Outputs	Readmission Rate	Negative Logit Form of the Hospital-Wide Readmission Rate	1.690	1.696	0.080
	Cost	Negative Natural Logarithm of Total Operating Costs	-16.858	-16.954	1.174
Environmental Variables	WageIndex	Wage Index	0.985	0.934	0.188
	OPDSH	Operating Disproportionate Share Hospital Payment Adjustment Factor	0.031	0.026	0.031
	ODummy	Location Dummy for Outer Urban Areas	0.329	0.000	0.470
	LDummy	Location Dummy for Larger Urban Areas	0.409	0.000	0.492
	TeachInt	Teaching Intensity	0.066	0.000	0.163
	CQ	Clinical Quality	3.378	3.315	1.045
	EQ	Experiential Quality	0.945	0.926	0.255
	CQ * EQ	Interaction of Clinical and Experiential Quality	0.000	0.000	0.363

[5] https://data.medicare.gov/data/hospital-compare

2.3.2 Variables

2.3.2.1 Input and Output Variables

The choice of inputs and outputs is guided by previous DEA applications in healthcare as well as other studies in the operations management literature used in the healthcare context. In the competitive environment in the United States, any increase in costs or reduction in reimbursements might jeopardize a hospital's financial stability. As my investigation focuses on hospitals' financial viability, my two outputs are total Medicare operating costs and the 30-day hospital-wide readmission rate, on which hospitals' financial viability depends due to the recent changes in hospital reimbursement policy. Costs are usually used as an input in DEA healthcare applications (e.g., Linna et al., 2006; Magnussen and Nyland, 2008; Czypionka et al., 2014). However, in the healthcare literature, they are often considered as an operational output (Nair et al., 2013). Moreover, since hospitals try to lower their costs, as do most other organizations, costs are more fitting as an output variable in this investigation of financial viability. I take the negative natural logarithm of costs, as shown in Equation (1), since costs are an undesirable output (Seiford and Zhu, 2002). In this study, I use total Medicare inpatient operating costs $C_i`$ for hospital i collected from Medicare cost reports and convert this to:

$$C_i = -\ln (C_i`) \tag{1}$$

I use readmission rates to include recovery of patients in the analysis. Readmission rates are not only the main goal of healthcare providers, but also an important output on which hospitals' financial viability depends under the new reimbursement model in the United States. Readmission rates are reported as a percentage of binary variables that report whether a patient has been readmitted to a hospital, unplanned, within 30 days of his/her discharge. For instance, a readmission rate of 15 means that 15% of discharged patients from that hospital were readmitted to a hospital (when they were not supposed to) within 30 days of their discharge. Because of this, I convert readmission rates into their logit forms in accordance with statistical theory (Collett, 2003) and to ensure consistency with the other environmental variables used in the truncated regression, clinical and experiential quality. I also take the negative of the value because a lower readmission rate means better care and thus the goal is to minimize this value, since it is an undesirable output similar to costs (Seiford and Zhu, 2002). Equation (2) shows how I convert the readmission rate into its logit form for hospital i, where RA_i` is the reported hospital-wide readmission rate:

$$RA_i = -\ln\left(\frac{RAi`}{1-RAi`}\right) \quad (2)$$

I choose three input variables, two of which are the number of beds and number of full-time employees. These are two of the most common input variables in DEAs. As the final input variable, I deviate from most DEA studies. The number of discharges is commonly used as an output by many researchers to represent the outcome of hospital efficiency in terms of the number of patients treated. However, to achieve better financial viability, hospitals need lower readmission rates and lower costs while treating the same number of patients. Research shows that the number of patients is more fixed than we hope it to be. Since the rural population lacks options and the urban population tends to choose the closest hospital to their location, hospitals actually experience relatively constant volume (Gaynor and Vogt, 2000). Hence, I use the number of discharges as an input variable. Similar to costs and the readmission rate, I use the negative number of discharges since it is better to treat more patients. I take the natural logarithm of all the input and output variables to ensure consistency with the readmission rates and process quality variables.

2.3.2.2 Environmental Variables

My two independent variables are clinical quality and experiential quality. Clinical quality measures examine whether a hospital follows evidence-based treatment guidelines. To measure clinical quality, I use the metrics reported in the Timely and Effective Care files. These are reported as binary variables, similar to the readmission rate for each evidence-based treatment. The number of patients that have received the appropriate treatment out of the number of patients eligible to undergo the treatment is reported along with the number of cases. This proportion refers to the percentage of patients who received treatment. For instance, one of the measured treatments is whether heart attack patients were given aspirin at discharge. If the reported value is 90, this means that the hospital gave aspirin to 90% of its heart attack patients at discharge. These values are interpreted as the higher the percentages are, the higher the clinical quality of the hospital. Two exceptions to this rule are PC_01, which tracks the percentage of newborns whose deliveries were scheduled early, and VTE_6, which tracks the incidence of potentially preventable blood clots. For these two measurements, the lower the percentages are, the higher the clinical quality of the hospital. Thus, to account for this difference, I convert these values into their inverse forms by subtracting them from 100. To compute a hospital's overall clinical quality using these measures, I deviate from previous research that has adopted a weighted average approach (Nair et al., 2018; Theokary and Ren, 2011). Instead of calculating the weighted average, I opt for the unweighted average of the measures of each condition. Then, I take the average of each condition. This approach aims to avoid favoring more common treatments or conditions. For instance, VTE_1 and VTE_6 are two of the six measurement items for Blood Clot Prevention and Treatment (see the Appendix A). In the Southeast Alabama Medical Center, for example, the sample size for measuring VTE_6 is 26 patients, while it is 433 for measuring VTE_1. The weighted average approach would favor VTE_1 because of its large sample size compared with VTE_6, which I want to avoid. Therefore, I first calculate clinical quality for each condition by taking the averages of each measure for that condition (Equation (3)). Then, I once again take the average of all the conditions to calculate the hospital's overall clinical quality (Equation (4)). Finally, I convert this into its logit form following prior studies (Senot et al., 2016; Chandrasekaran et al., 2012) and statistical theory (Collett, 2003) to satisfy distributional assumptions such as normality and homoscedasticity (Equation (5)). Measures that have fewer than 25 eligible patients are excluded from the study in accordance with CMS guidelines. Since I use the hospital-wide readmission rate in the DEA, I use all the inpatient clinical care measures reported in the same year. I use 31 measures for the seven conditions reported by the CMS are used. These are reported and explained in more detail in the Appendix A. Specifically, clinical quality (CQ_i) is given by

$$CQ_{ik} = \frac{\sum_{m=1}^{n} CQ_{im}}{n} \tag{3}$$

$$CQ`_i = \frac{\sum_{k=1}^{7} CQ_{ik}}{7} \tag{4}$$

$$CQ_i = -\ln\left(\frac{CQi`}{1-CQi`}\right) \tag{5}$$

where m is the clinical care measure, i is the hospital identifier, and n is the number of measures for hospital i and condition k.

To evaluate experiential quality, I use the data from the Hospital Consumer Assessment of Healthcare Providers and Systems surveys. From the survey, I use the six items that reflect patients' perceptions of healthcare quality following previous research (Nair et al., 2018; Senot et al., 2016). In this survey, patients answer questions such as whether doctors explained things to them in a way that they could understand and whether they received help as soon as they wanted. The answers to these items are reported as Never, Sometimes, Usually, or Always. The sixth item is reported as either Yes or No (see the Appendix A). Following previous research (Senot et al., 2016), I measure experiential quality as the average of the percentage of patients whose response was "Always" to the first five items and "Yes" to the sixth item. These are interpreted as the higher the percentages are, the higher the experiential quality of the hospital. For instance, scoring 80% on the nurse communication measure means that 80% of the patients in that hospital that took the survey said that nurses "Always" communicated well with patients. Following CMS guidelines, I remove cases that have fewer than 100 responses and take the average of the six measures (Equation (6)). Similar to clinical quality, I calculate the logit form of experiential quality to satisfy distributional assumptions (Equation (7)). Thus, experiential quality for hospital i (EQ_i) is calculated as

$$\text{EQ`}_{\text{i}} = \frac{\sum_{m=1}^{6} \text{EQ}_{\text{im}}}{6} \tag{6}$$

$$\text{EQ}_{\text{i}} = -\ln\left(\frac{EQi`}{1-EQi`}\right) \tag{7}$$

where m is the survey item and i is the hospital identifier.

Finally, to test for the impact of excelling in both dimensions of quality on a hospital's financial viability, I calculate the interaction term between clinical and experiential quality by first multiplying them by each other (Equation (8)) and then controlling for the multiplication (Equations (9) and (10)) to capture the impact of the two dimensions in addition to their primary effects:

$$\text{(CQ*EQ)`}_{\text{i}} = \text{CQ}_{\text{i}} * \text{EQ}_{\text{i}} \tag{8}$$

$$\text{(CQ*EQ)`}_{\text{i}} = \alpha + \beta_1 * \text{CQ}_{\text{i}} + \beta_2 * \text{EQ}_{\text{i}} + \varepsilon_{\text{i}} \tag{9}$$

$$\text{(CQ*EQ)}_{\text{i}} = \varepsilon_{\text{i}} \tag{10}$$

I also use, two location dummies and three control variables to control for factors that might affect the results. Location has been shown to impact hospital efficiency in previous studies (e.g. Chowdhury and Zelenyuk, 2016). Thus, I add location dummies to control for the disadvantages rural hospitals might experience. For instance, rural hospitals are known to serve smaller populations which limits the demand to their services and makes it more difficult for them to benefit from the economies of scale (Mascovice and Rosenblatt, 2000; and Gaynor et al., 2005). In addition, rural hospitals lack trained and experienced personnel (Lutfiyya et al., 2007; Escarce and Kapur, 2009). This might affect their efficiencies as well as quality levels. Rural populations also tend to be older and in general poorer in health with lower income (James et al., 2007) which might lead to more costly treatments and higher readmission rates despite investment in quality levels. This means that rural hospitals might not be able to convert the investments in quality levels to financial benefits as well as hospitals in outer and large urban areas. Hence, I use outer urban and large urban as my two dummy variables, where rural is the base dummy variable.

My three control variables are wage index, OPDSH factor, and teaching intensity. I use wage index to control for the higher wages some hospitals might pay because of their location or for other reasons. Wage index has been used as a proxy for local cost of living in the literature (Pizzini 2006; Hsia et al., 2011). This might impact hospitals' cost and therefore might affect how much they can benefit from quality improvements. In addition, higher wages go hand in hand with more experienced and better trained employees and resources (King and Lewis, 2017). Hospitals paying higher wages will be able to hire more talented employees. More resources and more educated employees might affect hospitals' ability to learn and convert their focus on quality into better outcomes. Hence, I include wage index in the analysis. OPDSH factor reflects the hospital's propensity to treat uninsured and Medicaid patients who often require more resources (Coughlin and Liska, 1998) which might impact efficiency. In addition, Medicaid and uninsured patients on average have lower incomes which is associated with poorer health conditions (Wagstaff, 2002) which might make it more difficult for hospitals to benefit from quality because it is more challenging to treat such patients. Teaching intensity is calculated using the resident-to-bed ratio (Sloan et al., 2001) and is included to control for hospitals that allocate more resources to teaching activities which require additional tasks that teaching hospitals need to manage compared to non-teaching hospitals. Teaching status has been reported to be associated with better clinical quality than non-teaching hospitals (Allison et al., 2000). However, at the same time, they tend to offer lower patient experience than non-teaching hospitals. (Shahian et al., 2012). In addition to this disparity in dimensions of quality, their costs tend to be higher than non-teaching hospitals (Koenig et al., 2003), because they are able to attract talented physicians due to their focus on research and treatment of rare diseases (Theokary and Ren, 2011). Kim (2010) also identifies teaching status as a characteristic that puts hospitals in financial distress. Therefore, teaching hospitals might struggle more with patient experience compared to non-teaching hospitals and it might be more difficult for them to convert improvement in quality into financial benefits given the disadvantageous position that they are already in compared to non-teaching hospitals.

2.3.3 DEA

This study analyzes the relationship between hospital quality and hospital efficiency using two of the most significant metrics from a hospital perspective, costs and readmission rates, and Simar and Wilson's (2007) two-stage DEA approach. DEA is a non-parametric method used in operations research to evaluate the efficiency of decision-making units (DMUs). A DMU is regarded as the entity responsible for converting inputs into outputs in DEA (Thanassoulis et al., 2008). My DMUs in this study are hospitals. DEA was first introduced by Charnes et al. (1978), who measure efficiency by assuming constant returns to scale. This was later extended by Banker et al. (1984) using variable returns to scale (VRS) to create a more flexible model. Because healthcare organizations often operate at an inefficient scale due to several factors such as imperfect competition and financial constraints (Lindlbauer et al., 2016), the VRS assumption is adopted herein. This approach requires a choice of either input or output orientation. In this study, an output-oriented VRS approach is used based on the assumption that hospitals already have a certain number of beds, employees, and patients, which are relatively difficult to change (Rego et al., 2010) and that they aim to lower their costs and readmission rates given these inputs. Since I investigate how quality might affect how efficient hospitals are in converting their inputs into achieving these outputs, an output-oriented model is deemed more suitable. In an output-oriented model, the DEA results are greater than 1, where 1 is the most efficient hospital and any value greater than 1 is how much a hospital is inefficient compared with the frontier. For instance, if the result of the analysis is 1.25 for hospital i, it means that that hospital is 25% less efficient than the frontier. In other words, the greater the score for a hospital is, the more inefficient the hospital.

DEA is chosen because this study focuses on measuring the efficiency of hospitals. It is also suitable for analyzing both recovery of patients and cost at the same time. One disadvantage of DEA is that it does not provide directions as to how to improve efficiency. Another disadvantage of DEA is that it is difficult to perform statistical tests with the results. Yet, Simar and Wilson's (2007) two-stage DEA approach addresses these problems of DEA. This methodology allows us to find interpretable results that can provide direction to managers and policymakers. Hence, I adopt Simar and Wilson's (2007) method in the analysis to account for the shortcomings of DEA.

The analysis is performed in R using the "rDEA" package (Simm and Besstremyannaya, 2016). I first calculate the DEA efficiency scores for all the DMUs in the data set using Equation (11), where ϑ is the efficiency scores for each DMU, the x_is are the input variables, the y_rs are the output variables, and the λs are the unknown weight variables over which the optimization is made:

$$
\begin{aligned}
&\text{Max } \vartheta \\
&\text{s.t.} \\
&\textstyle\sum_{j=1}^{n} \lambda_j \, x_{ij} \le x_{io} && , \text{All } i \\
&\textstyle\sum_{j=1}^{n} \lambda_j \, y_{rj} \ge \vartheta y_{ro} && , \text{All } r \\
&\textstyle\sum_{j=1}^{n} \lambda_j = 1 && \qquad (11) \\
&\lambda_j \ge 0 && , \text{All } j
\end{aligned}
$$

2.3.4 Quartile Analysis

After I calculate the efficiency (ϑ) of each hospital, I divide hospitals into four groups based on their quality levels to compare the impacts of quality: Low Experiential Quality/Low Clinical Quality, Low Experiential Quality/High Clinical Quality, High Experiential Quality/Low Clinical Quality, and High Experiential Quality/High Clinical Quality. For these groups, I take the highest and lowest quartiles of each quality dimension, and group the hospitals based on them accordingly. For instance, hospitals in the highest quartile in both clinical and experiential quality are grouped into High Experiential Quality/High Clinical Quality.

I use this methodology as a preliminary analysis to better visualize the impact of quality. However, I adopt Simar and Wilson's (2007) two-stage bootstrap methodology with truncated regression for more detailed insights. This also allows me to control for other variables such as location and teaching. Moreover, it does not make the assumption that at least one hospital from the data set is efficient, which may not be the case.

2.3.5 Bootstrapped Truncated Regression

Simar and Wilson's (2007) two-stage bootstrap methodology with truncated regression overcomes the unknown serial correlation complicating the two-stage analysis. I use 500 replications in the first stage and 2000 replications in the second stage; both are sufficient numbers according to Simar and Wilson's recommendations. Overall, I use three inputs and two outputs in the DEA and eight Z variables in the truncated regression. Specifically, the following regression specification is assumed and tested:

$$\hat{\vartheta}i = \alpha + z_i \beta + \varepsilon_i \qquad i = 1,\ldots,n \qquad (12)$$

In Equation (12), $\hat{\vartheta}$ is the efficiency score for hospital i, ε_i is the error term of the regression that is assumed to be normally distributed with right truncation at $-z_i\beta$, α is the intercept or constant term, z_i is a vector of the environmental variables for DMU i that are expected to affect hospital efficiency, and β is a vector of the parameters to be estimated. However, $\hat{\vartheta}$ are serially correlated with the ε_is in Equation (12). While the correlation among the ε_is disappears asymptotically, standard inference methods are invalid (Nedelea and Fannin, 2013).

Simar and Wilson's (2007) "Algorithm #1" is a parametric bootstrap of the truncated regression used to provide a valid inference in the second-stage analysis. Although this single bootstrap procedure improves inference in the regression, it does not correct for the DEA estimator bias.

To address this issue, Simar and Wilson (2007) suggest using a bootstrap procedure to obtain bias-corrected DEA estimates of efficiency and employ them as the dependent variable in the second-stage regression:

$$\hat{\hat{\vartheta}}_i = \alpha + z_i \beta + \varepsilon_i \qquad i = 1, \ldots, n \qquad (13)$$

where $\hat{\hat{\vartheta}}_i = \hat{\vartheta}_i - \text{bias}(\hat{\vartheta}_i)$ is the bias-corrected estimator of efficiency and $\text{bias}(\hat{\vartheta}_i)$ is the bootstrap bias estimate of $\hat{\vartheta}_i$. To provide a valid inference about β, a second bootstrap procedure must be applied to the truncated regression in Equation (13), which Simar and Wilson (2007) refer to as "Algorithm #2." The specific steps of the double-bootstrap procedure used in this study are listed below:

1. Estimate ϑ_i using Equation (11).

2. Estimate $\hat{\beta}$ in the truncated regression in Equation (12).

3. Loop over the next four steps (a→d) 500 times to obtain a set of bootstrap estimates $B_i = \{\hat{\vartheta}_{ib}^*\}_{b=1}^{500}$

    a. For each $i = 1, \ldots, n$, draw ε_i from the $N(0, \hat{\sigma}_\varepsilon^2)$ distribution with right truncation at $z_i\beta$.

    b. For each $i = 1, \ldots, n$, compute $\vartheta_i^* = z_i \hat{\beta} + \varepsilon_i$.

    c. Again, for all $i = 1, \ldots, n$, set $x_i^* = x_i \hat{\vartheta}_i / \vartheta_i^*$ and $y_i^* = y_i$.

    d. Estimate $\hat{\vartheta}_i^*$ for all $i = 1, \ldots, n$ using x_i^* and y_i^* in the DEA estimator.

4. Compute the bias-corrected estimator $\hat{\hat{\vartheta}}_i$ using the bootstrap estimates B_i and original estimate $\hat{\vartheta}_i$ for all $i = 1, \ldots, n$.

5. Estimate the truncated regression of $\hat{\hat{\vartheta}}_i$ on z_i to obtain the $(\hat{\hat{\beta}}, \hat{\hat{\sigma}})$ estimates.

6. Loop over the next three steps (a→c) 2000 times to obtain a set of $\Delta = \{(\hat{\beta}^*, \hat{\sigma}_\varepsilon{}^*\}_{b=1}^{2000}$.

   a. For each $i = 1, \ldots, n$, draw εi from the $N(0, \hat{\hat{\sigma}})$ with right truncation at -$z_i\beta$.

   b. Compute $\vartheta_i{}^{**} = z_i\hat{\hat{\beta}} + \varepsilon_i$ again for each $i = 1, \ldots, n$.

   c. Estimate the truncated regression of ϑi^{**} on z_i, yielding the estimates $(\hat{\hat{\beta}}^*, \hat{\hat{\sigma}}^*)$

7. Use the bootstrap values in Δ and original estimates $(\hat{\hat{\beta}}, \hat{\hat{\sigma}})$ to construct estimated confidence intervals for each element of β. Construct the confidence interval $(1-\alpha)$ for β_j using Equation (14).

$$\Pr[-b^*_{\alpha/2} \leq (\hat{\hat{\beta}}_j{}^* - \hat{\hat{\beta}}_j) \leq -a^*_{\alpha/2}] \approx 1-\alpha \qquad (14)$$

Summary of my methodology is explained in Figure 1. Analysis part 1 gives me the results in Table 3. Table 4 shows the results from analysis part 2 and Figure 2 compares these two analyses. Table 5 reports the findings from analysis part 3.

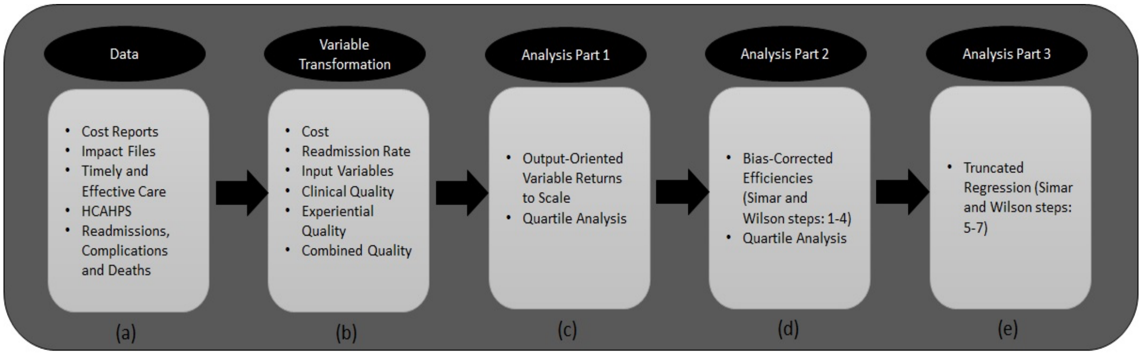

Figure 1: Summary of Methodology

2.4 Findings

Table 2 summarizes the sample descriptive statistics for all the input, output, and environmental variables used in the analysis along with their descriptions. I analyzed 2997 hospitals in the United States. I then grouped these hospitals based on their quality levels as explained in Section 3.4. Table 3 presents the descriptive statistics of the estimated efficiency scores for each quality quartile.

A comparison of the quartiles using the results from the output-oriented VRS efficiency scores from the DEAs shows that hospitals benefit from improving either quality dimension. However, the major difference is seen in hospitals that achieve both high experiential and clinical quality. On average, those hospitals are 12.1% less efficient than the efficient (frontier) units. On the contrary, hospitals that have low quality levels on both quality dimensions are on average 19.2% less efficient than those on the frontier. Hospitals that achieve high quality on only one of the quality dimensions still seem to perform better than low quality hospitals. However, hospitals that have better experiential quality, but low clinical quality are 16% less efficient and hospitals with better clinical quality and low experiential quality are 16.7% less efficient than the frontier on average. Moreover, although both dimensions offer relatively small improvements separately, the largest benefits of better quality seem to be observed in hospitals that excel on both dimensions.

Table 3: Descriptive Statistics of the Estimated Efficiency of U.S. Hospitals Using the DEA Approach

Quality	Mean	Median	Std. Deviation	Min	Max
Low Experiential/Low Clinical Quality	1.192	1.193	0.054	1.000	1.354
Low Experiential/High Clinical Quality	1.167	1.170	0.055	1.000	1.326
High Experiential/Low Clinical Quality	1.160	1.160	0.047	1.000	1.299
High Experiential/High Clinical Quality	1.121	1.124	0.067	1.000	1.332

To make valid inferences about the impacts of quality as an environmental variable on hospital efficiencies, I use Simar and Wilson's (2007) two-stage bootstrapped truncated regression method that removes bias from the efficiency scores. Table 4 reports the results of the bias-corrected efficiency scores for each quartile and Table 5 compares each quartile as well as the original and bias-corrected efficiency scores. Although the bias-corrected efficiency scores are larger than the former, the interpretation of the results is similar. It can be seen that hospitals that achieve higher experiential quality are more efficient regardless of the clinical quality level providing support for my first hypothesis. Experiential quality helps hospitals improve their efficiencies from 1.224 to 1.191 in hospitals with low clinical quality and from 1.201 to 1.154 in hospitals with high clinical quality. Similarly, high clinical quality seems to be associated with better efficiency providing support for my second hypothesis. While clinical quality helps hospitals boost their efficiencies from 1.224 to 1.201 in low experiential quality hospitals, it aids hospitals enhance their efficiencies from 1.191 to 1.154 in high experiential quality hospitals. Finally, the most efficient hospitals are the ones achieving high quality in both dimensions providing support for the third and last hypothesis.

Table 4: Descriptive Statistics of the Bias-Corrected Estimated Efficiencies of U.S. Hospitals

Quality	Mean	Median	Std. Deviation	Min	Max
Low Experiential/Low Clinical Quality	1.227	1.224	0.050	1.107	1.393
Low Experiential/High Clinical Quality	1.205	1.201	0.053	1.093	1.366
High Experiential/Low Clinical Quality	1.194	1.191	0.042	1.075	1.333
High Experiential/High Clinical Quality	1.160	1.154	0.057	1.065	1.362

Table 5: Bias-Corrected and Naive Efficiency Scores

		Clinical Quality	
		Low	High
Experiential Quality	Low	1.224 (1.193)	1.201 (1.170)
	High	1.191 (1.160)	1.154 (1.124)

Table 6 reports the results of the truncated regression. As the output from the DEA for efficiencies is right truncated, the values are greater than 1, where the smaller the value is, the more efficient the hospital. This causes the regression coefficients to have negative values. In other words, the negative coefficients mean that the variable increases efficiency.

Table 6: Results of the Second-Stage Bootstrapped Truncated Regressions[6]

Variable	Model 1	Model 2	Model 3
Intercept	1.203***	1.274***	1.274***
Wage Index	-0.002	-0.009	-0.009
OPDSH	0.314***	0.195***	0.196***
ODummy	-0.025***	-0.019***	-0.019***
LDummy	-0.013***	-0.009***	-0.009***
Teaching	0.059***	0.063***	0.063***
CQ		-0.005***	-0.005***
EQ		-0.048***	-0.049***
CQ * EQ			-0.006**

The results of the regression reinforce my inferences from the quartile analysis. First, both clinical and experiential quality are significantly associated with the high efficiency of hospitals ($\beta_{clinical} = -0.004$, $p<0.01$; $\beta_{experiential} = -0.045$, $p<0.01$). Hence, hypothesis 1 and hypothesis 2 are supported. Further, achieving these two quality dimensions together also provides hospitals with additional advantages, as shown by the significance of the interaction term ($\beta_{interaction} = -0.006$, $p<0.05$). This shows that hypothesis 3 is also supported. The results also provide some insights into the impact on efficiency of location and teaching intensity of hospitals. Urban hospitals are more efficient at achieving lower costs and readmission rates than rural hospitals regardless of whether they are located in outer or large urban areas, as both dummy variables are significant and the sign of the coefficient is negative ($\beta_{outer} = -0.019$, $p<0.01$; $\beta_{large} = -0.009$, $p<0.01$). Teaching intensity and OPDSH, on the contrary, seem to put pressure on hospitals to lower costs and readmission rates, as it is significantly associated with lower efficiency scores ($\beta_{teaching} = 0.063$, $p<0.01$; $\beta_{OPDSH} = 0.196$, $p<0.01$).

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[6] *** 99% significance, ** 95% significance, * 90% significance.

500 bootstrap replications in the first stage and 2000 bootstrap replications in the second stage were used.

2.5 Discussion

This research investigates hospitals' ability to efficiently achieve both a better level of care and lower costs and shows the part that clinical and experiential quality play in this efficiency. In particular, I explore the efficiencies of U.S. hospitals from a different perspective. While the majority of DEA studies consider cost as an input and patient volume as an output, on the premise that hospitals need to treat as many patients as possible at as low cost as possible, my perspective treats cost as an output variable and patient volume as an input variable for two reasons. First, as previous research has found, patient volume is, in most cases, a relatively constant variable, whereas costs result from operations given hospitals' inputs. This means that hospitals try to lower their costs by focusing on their operations and being more efficient given their numbers of patients. Second, as the main goal of this research is to investigate a hospital's financial viability, two variables directly associated with hospitals' financial conditions, namely costs and readmission rates, were used as output variables. This approach bridges a gap in the literature, as the changes that tie a portion of hospital reimbursements to readmission rates put readmission rates next to costs in the list of financial problems for the hospital. Lower readmission rates have become not only a desired outcome of care but also a financial priority. This perspective allowed me to examine a hospital's ability to achieve better financial outcomes and discover how each quality metric affects this efficiency.

The results show that both clinical quality and experiential quality improve the efficiency of hospitals. The efficiency scores from both the DEA quartile approach and the bootstrap methodology of Simar and Wilson (2007) provides similar results. The quartile analysis shows that hospitals that have the lowest efficiency scores have the lowest quality on each dimension. Indeed, they are on average 7.1% (19.2 – 12.1) less efficient than hospitals that attain high levels of both clinical and experiential quality. Hospitals that only focus on one quality dimension are still more efficient than hospitals that trail on both dimensions. Both quality dimensions seem to be increasing efficiency equally significantly. These findings support my hypotheses. However, focusing on both together enhances efficiency even more, as can be seen from the truncated regression. Hence, all my hypotheses are supported by my findings. These results are interesting, because despite its well-known benefits on care outcomes, such as readmission rates, the literature is not set on cost implications of quality (e.g. Bechel et al., 2000; Thorne et al., 2005; Weech-Maldanado et al. 2006; Kruse and Christensen, 2013; Senot et al., 2016). This study takes one step further and investigates impacts of quality on both cost and readmission rates together given hospital resources. I find that not only improvements in quality have positive implications on this efficiency, but also there are additional benefits in focusing on both dimensions of quality together. Simar and Wilson (2004) argue that it is possible that none of the DMUs in the data set fall on the efficient frontier. A hypothetical DMU might exist at the frontier even though no real observation has reached that point. The bootstrapping method addresses this concern. As can be seen in Figure 2, this is the case in my data set, as none of the hospitals is at the efficient frontier for performance. The most efficient hospital in my data set is still 6.5% less efficient than the frontier. In addition, my results suggest that both the OPDSH factor, i.e. hospitals' propensity to treat uninsured and Medicaid patients, and teaching intensity of hospitals reduce efficiency. Impact of the OPDSH factor is not surprising. Given that uninsured and Medicaid patients tend to have lower incomes and hence in general be in poorer health (Wagstaff, 2002), their treatments tend to be more costly with worse outcomes which naturally harm hospital efficiency. Teaching intensity, on the other hand, yielded rather unexpected results. I find that teaching intensity reduces the efficiency of hospitals. Teaching intensity's association with high costs is well documented (Koenig et al., 2003; Kim, 2010), however, they also provide high clinical quality (Allison et al., 2000) and with their ability to hire more talented, experienced employees, one would expect them to learn and benefit more from quality improvements. This negative association might be because of the additional structural and operational requirements needed by a teaching hospital. Such hospitals might need to focus on these additional responsibilities, which might make it more difficult or more costly than it is for others to improve quality.

Finally, I find that both outer and large urban areas increase efficiency compared to rural hospitals. This finding makes sense given many disadvantages that rural hospitals deal with such as an inability to attract better employees or certain characteristics of the rural population (e.g., Mascovice and Rosenblatt, 2000; Hartley, 2004; Gaynor et al., 2005; Reschovsky and Staiti, 2005; Lutfiyya et al., 2007; James et al., 2007; Escarce and Kapur, 2009; Cleland et al., 2012).

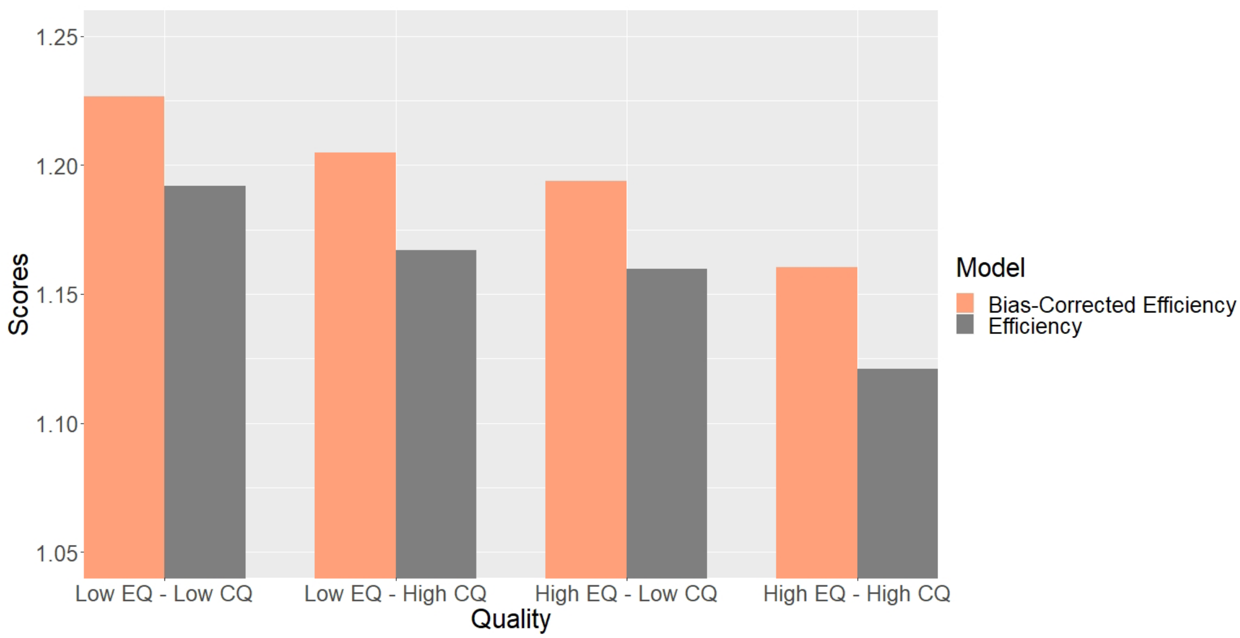

Figure 2: Efficiency Scores of the Quality Quartiles

Previous research does not provide strong evidence regarding the impact of quality on hospital performance. Most researchers attempt to control for quality instead of examining its impact which yields results that are difficult to interpret and unlikely to provide insights when it comes to the value of quality (e.g. Nayar and Ozcan, 2008; Navarro-Espigares and Torres, 2011; Nedelea and Fannin 2013; Fiallos et al., 2017). This study takes a very strong position in that regard. My analyses that involve both a quartile analysis and a regression analysis, provide insightful information and quantifiable results to managers and policymakers which they can work with to make more informed decisions. In addition, my research makes two important contributions to the literature.

First, to the author's knowledge, this is the first study to make use of DEA to investigate the financial viability of hospitals. Technical efficiency of hospitals has been studied extensively, however; my study is a new step in hospital efficiency literature. Second, previous research of DEA applications that dealt with healthcare quality focused on controlling for quality in efficiency calculations rather than exploring how quality affects the efficiency. They used various methods from calculating a quality index (Karagiannis and Velentzas, 2012) to incorporating it into the DEA model (Nedelea and Fannin, 2013). Only a few studies looked into the impact of quality on efficiency and no study has done so by dealing with both dimensions of quality as well as recovery of patients. For instance, Laine et al. (2005) attempt to uncover the association between quality and technical efficiency. However, they only consider clinical quality. Mancuso and Valdmanis (2016) also only include clinical quality in their analysis. Although they find a positive association between quality of care and hospital performance, not considering recovery of patients and experiential quality is a shortcoming of the study. Chowdhury and Zelenyuk (2016), on the other hand, decide to investigate recovery of patients in the regression analysis, yet neither dimension of quality of care is included in their analysis and their results do not demonstrate a significant association. It is also important to note that none of these examples consider experiential quality. Hence, my study that includes both dimensions of quality as well as recovery of patients separates itself from previous attempts by providing insightful results regarding the impact of quality on financial viability.

These results provide insights for both managers and policymakers. They show that it is especially important to focus on healthcare quality for hospitals that have financial concerns. The number of hospitals on the verge of bankruptcy is increasing (Minemyer, 2018; Flanagan, 2018). Given the results of my research, hospital managers that are having financial concerns should make investments to improve their clinical and experiential quality. Moreover, my results demonstrate that even for hospitals that are very efficient, there is still room for improvement which can improve their financial positions. Policymakers can help hospitals by implementing programs and giving incentives to hospitals to improve their quality levels in order to achieve better outcome of care which will prevent hospitals from closing due to improved financial viability. This research also has important implications for academicians. This paper makes the first attempt to use DEA to analyze financial viability of hospitals. Furthermore, this investigation is the first to include both dimensions of quality and recovery of patients in the analysis showing a positive relationship between quality dimensions and financial viability to author's knowledge. Hence this study provides a baseline for academicians to use the dimensions of quality in DEA studies.

Future studies might make use of panel data in the future studies given that CMS data is reported annually. In addition, in light of recent discussions regarding the increasing hospital closures in the U.S., researchers can use this approach to estimate the likelihood of hospital closures by comparing the financial viability of closed hospitals to others.

One limitation of this study was the inconsistency of the data. Although the data set is extensive, it is not consistent over time, which makes it difficult to extend the scope of this research. Another limitation was the measurement dates of each variable. While reports are provided by the CMS annually, the measurement dates for each reported variable are not necessarily consistent with one another. Indeed, I had to exclude certain variables because the measurement dates were not consistent.

Chapter 3

3 The Affordable Care Act and Hospital Closures: A Difference-in-Differences Analysis

3.1 Introduction

In 2005, 14 hospitals across the United States permanently closed[7] their operations. The number of hospital closures increased to 26 in 2018 where approximately 8% of U.S. hospitals were estimated to be facing permanent closure with some pundits predicting that hospitals would continue to close at a 30-a-year pace for the foreseeable future (Flanagan, 2018). However, with the additional challenges brought on by the COVID-19 pandemic, 47 hospitals closed in 2020 (Ellison, 2020). The increasing hospital closure rate is alarming. Some even deem this to be a public health crisis (Carroll, 2019) as it exacerbates existing barriers in accessing health services (Coleman-Lochner and Hill, 2020). For rural areas, hospital closures mean that patients must travel greater distances to access care and this has been linked to increases in patient mortality (Buchmueller et al., 2006; Chou et al., 2014; Kozhimannil et al., 2018). In urban settings, hospital closures decrease competition as well as lower service quality and health outcomes among hospitals operating in the region (Kessler and Geppert 2005; Gaynor et al., 2013).

[7]A closure is defined as the cessation of general hospital services (i.e., no specialization in the treatment of a particular illness or a group of patients) or the conversion to a long-term care facility.

Several studies provide insight into factors directly driving US hospital closures. Kaufman et al. (2016), for example, empirically show that rural hospitals, and hospitals in areas with intense competition, are at an increased risk of closing. This is because such hospitals serve smaller populations and hence, may not attain the requisite patient volumes for sustainable profit margins. Landry and Landry (2009) report that small, independent hospitals are more likely to file for bankruptcy because they struggle to attract patients. Hospitals in catchment areas with older and poorer populations also face elevated risk of closing as certain medical procedures are underutilized and/or undercompensated and thus, profit margins suffer (Kim, 2010; Hsia et al. 2011). Low quality care can also affect a hospital's financial health via the increase in complications, and hence, costs (Flynn et al., 2014). Finally, Kilaru and Mahoney (2020) connect hospital closures to the recent industry-wide focus on bolstering outpatient services as this initiative has reduced demand for inpatient care which has higher margins. As COVID-19 has amplified the strained financial situation of many hospitals, policy makers are under intense public pressure to provide solutions to the looming "closure crisis" (Raffa, 2019; Milmon, 2020).

A number of studies have investigated how structural factors may indirectly but systematically contribute to the increasing rate of hospital closures. In particular, both federal and state-level regulations have been shown to affect hospital financial performance and healthcare outcomes. For instance, McCue and Thompson (2006) report prospective payment systems may lead to lower operating costs and increased profit margins. Propper and Reenen (2010) find that, in their study on the English hospital market, pay regulations are correlated with lower hospital quality. Glance et al. (2021) report that higher scores in the Merit-Based Incentive Payment System are associated with better hospital surgical outcomes as well as a lower mortality and readmission rate. Finally, Holmgren and Bates (2021) find a positive association between the mandated dissemination of quality reports and improvements in quality metrics at U.S. hospitals.

The medical coverage patients have is another important structural factor. Medical coverage directly relates to patient volumes and eligible reimbursements hospitals receive for the services they provide. This paper focuses on analyzing the effect of systematic changes to medical coverage embodied in the passing of the Affordable Care Act (ACA) in 2010 and its association with hospital closures. Specifically, I analyze whether and how compliance with the ACA-mandated Medicaid coverage expansion has affected hospital closure rates.[8]

In theory, compliance with the Medicaid coverage expansion mandate should reduce uncompensated care[9], boost patient volumes (e.g., low-income patients would be more likely to seek out medical services as they would be covered by Medicaid), increase hospital revenues and, thereby, reduce hospital closure risk. Those who disagree with this perspective argue, however, that the mandate exacerbates the financial struggle hospitals face from the under-compensation of care (Turner and Roy 2013)[10], with the revenue shortfall from under-compensation being greater than the revenue increase associated with reducing uncompensated care. A 2015 policy paper authored by the U.S. Senate Republican Committee went as far as to accuse the ACA of being ". . . a major factor causing rural hospitals to shut down . . . [because of] . . . cuts to Medicare providers [and] reduced federal payments to hospitals for the uninsured . . ." (Blunt, 2015).

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[8] The ACA mandated that Medicaid coverage be extended to all adults under the age of 65 with incomes below 138% of the federal poverty level or FPL (NCSL, 2011). Not all US states opted to comply with this mandate.

[9] In the U.S., hospitals are obligated to provide care to patients that require emergency services under the Emergency Medical Treatment and Active Labor Act. If these services are provided to patients with no healthcare insurance or the financial means to pay, they are categorized as "uncompensated care" episodes.

[10] Hospitals are paid a fixed rate that is defined by the Centers for Medicaid and Medicare Services for services provided to Medicaid patients. These fixed rates might be lower than what hospitals can potentially charge to patients with private insurance to cover actual costs of service.

Inconsistent and contradictory empirical evidence has fueled this debate. Although the proportion of uninsured adults aged 18–65 has decreased from 22.3% in 2010 to 13.3% in 2018 because of the ACA (Goodnough et al., 2020), the decline has not necessarily alleviated hospital financial stress. According to Reiter et al. (2015), hospitals in states opting out of the Medicaid coverage expansion mandate appear to be financially more vulnerable due to higher rates of uncompensated care than those in states complying with the mandate. Dranove et al. (2016), for instance, show that uncompensated care decreased in states complying with the mandate. Blavin (2017) finds a positive association between the mandate and larger hospital operating margins; the effect is particularly strong for small, non-metropolitan hospitals. Finally, rural hospitals' likelihood of closure was shown to be higher in states that did not comply with the ACA-mandated Medicaid coverage expansion (Scott, 2020). In contrast, Young et al. (2019) report that hospitals in states complying with the mandate are facing substantial payment shortfalls which are putting them in financial distress. Moghtaderi et al. (2020) also provide evidence demonstrating that relative gains in Medicaid revenue due to the mandate are offset by declines in commercial insurance revenue.

In this paper, I present a causal analysis to determine whether the ACA-mandated Medicaid coverage expansion systematically decreased the risk of hospital closures in the U.S. In particular, my empirical models estimate the effect of Medicaid coverage expansion on the number of hospital closures and also investigate the operational drivers behind this outcome. Estimating the effect of Medicaid coverage expansion on hospital closures determines the extent to which this mandate has affected access to health services. Pinpointing the operational drivers aids policy makers and hospital administrators in devising interventions to potentially neutralize the closure risk.

To facilitate the analysis, I compile a dataset of hospital closures from 2005 to 2018 from the Centers for Medicaid and Medicare Services (CMS) using the manual confirmation process. I complement the dataset by collecting state-level characteristics such as population level, unemployment rate, and GDP from the U.S. Census Bureau, the U.S.

Bureau of Economic Analysis, and the U.S. Bureau of Labor Statistics. The final panel dataset includes 714 observations from 50 U.S. states and the District of Columbia (D.C.) over 14 years. Ithen perform a Poisson regression on the annual number of hospital closures in each state using a Difference-in-Differences (DID) framework with fixed effects (e.g. Mark et al. 2013; Kondo et al. 2015) to account for the temporal nature of the data and to control for time-invariant unobserved effects that might skew the results. The inclusion of state-level characteristics ensures that the estimates are robust to state-level, time variant, socio-economic controls. I also rigorously demonstrate that the assumptions underlying the DID analysis and Poisson regression are well supported and perform several robustness checks to confirm the validity of the results. The analysis reveals that the expected number of hospital closures in states that complied with the ACA-mandated Medicaid coverage expansion versus states that did not comply is statistically lower by 54% (p=0.004). I also find that the decision to comply with the ACA-mandated Medicaid coverage expansion was driven by the political affiliation of the state population.

I then investigate six operational drivers behind closures: hospital size (inpatient beds), resource investment (number of employees); patient volume (number of discharges per year); care quality (experiential quality survey results); and financial health (both operational expenses and patient revenue). Comparing closed hospitals to those that survived, I find that, on average, a closed hospital is significantly smaller (51% of a surviving hospital), has fewer employees (76% of a surviving hospital), experiences lower utilization (65% of a surviving hospital), and has lower revenue (66% of a surviving hospital) despite having slightly lower expenses than surviving hospitals (80% of a surviving hospital) while still being able to deliver a similar level of quality as compared to surviving hospitals (97% of a surviving hospital). Next, I use the DID framework to perform a hospital-level analysis to understand how states' compliance with the ACA-mandated Medicaid coverage expansion affected these six operational factors. I find no evidence that the mandate impacted the number of discharges (p=0.46), the number of employees (p=0.15), and hospital expenditures (p=0.42). However, the analysis does indicate a significant and positive association with the total patient revenue

($p < 0.001$) and experiential quality ($p < 0.001$). Thus, it appears that the mandate generated additional revenues and resulted in, more generally, better care experiences for patients without increasing operational costs or impacting patient volumes.

This work makes two contributions to the extant literature. First, prior research has failed to provide conclusive evidence as to how the ACA-mandated Medicaid coverage expansion affects hospital closures. Allen (2017), for example, uses a multilevel modeling framework to analyze hospital closures between 2010 and 2016 but does not make before-and-after comparisons associated with the implementation of the mandate. Lindrooth et al. (2018) use a DID framework to test the association between compliance with the mandate and hospital closures but do not account for the insurance coverage already offered by the state nor do they control for the temporal differences in when states opted to comply. Further, neither Allen (2017) nor Lindrooth et al. (2018) collected enough data to allow for causal inferences and, most importantly, inconsistent results are reported. While Lindrooth et al. (2018) find that state compliance with the ACA-mandated Medicaid coverage expansion reduced hospital closures, Allen (2017) does not find any association. My empirical specification provides a definitive answer by causally linking compliance with the mandate to a reduction in the number of hospital closures. In addition, I present causally constructed evidence as to *how* the ACA-mandated Medicaid coverage expansion decreases the likelihood of hospital closures. Specifically, I find that hospitals in states complying with the mandate experienced higher revenues without changes to their size, resources utilization, and operational costs. I also find that patient volumes remained unchanged while experiential care quality improved. These results suggest that creating new revenue-generating programs may be the most effective way to combat the hospital closure crisis in the US as compared to the implementation of cost mitigation strategies or enacting austerity measures.

3.2 The History of the Affordable Care Act of 2010

The ACA was signed into law by President Barack Obama on March 23, 2010 and systematically overhauls the U.S. healthcare system. The primary goal of the ACA is to provide high-quality and affordable healthcare to every American citizen via three operational levers: (i) to make affordable health insurance available to everyone; (ii) to support innovative medical methods designed to lower costs, and most importantly; (iii) to expand the Medicaid program by increasing the Medicaid income threshold to at least 138% for all adults under the age of 65. Figure 3 depicts the timeline of the evolution of the ACA and the Medicaid coverage expansion provision.

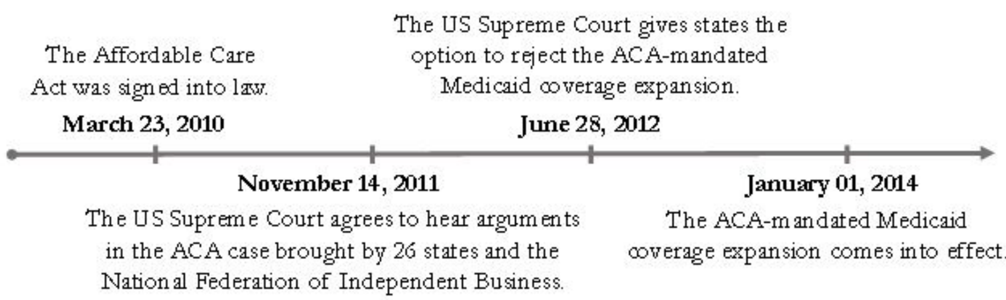

Figure 3: Timeline of the Affordable Care Act of 2010

The Medicaid coverage expansion mandate in the ACA is the most significant change in the bill. Originally, the mandate was planned to affect all 50 states and the District of Columbia without exception starting in January 2014. Following its signing, some states, as well as the District of Columbia, used waivers to adopt the mandate before January 2014. Another 26 states and the National Federation of Independent Business sued the government in federal court challenging the mandate by arguing that the ACA was unconstitutional. The U.S. Supreme Court agreed to hear arguments on November 14, 2011 and on June 28, 2012, they upheld the major provisions of the ACA but ruled that states could not be forced into adopting Medicaid coverage expansion. Thus, the decision gave states the option to not comply with the mandate. Consequently, only 24 states and the District of Columbia decided to comply with the ACA-mandated Medicaid coverage expansion by January 2014. Since then, as of December 2020, an additional 14 states have expanded their Medicaid coverage bringing the total number of states to 38; 12 states have still not adopted it.

For many of the 50 states[11], the adoption of the ACA-mandated Medicaid coverage expansion occurred at different times. Arizona, Connecticut, Delaware, Hawaii, Massachusetts, New York, Vermont, and the District of Columbia had existing insurance coverage equivalent to that of the ACA-mandated Medicaid coverage expansion. Alaska, Louisiana, Indiana, Michigan, Montana, New Hampshire, and Pennsylvania did not expand Medicaid until after January 2014. California, Minnesota, New Jersey, and Washington adopted the mandate during the transition period, i.e., before the ACA became law in 2014 but after its signing in 2010. Thirteen states adopted the ACA-mandated Medicaid coverage expansion in January 2014 when it was originally supposed to come into effect while the remaining 19 states did not adopt the mandate during the study period (i.e., from 2005 to 2018). The special case of Wisconsin should also be noted because it introduced state-level insurance coverage that extended Medicaid benefits to adults under the age of 65 with incomes below 100% of the federal poverty level in 2014 despite opting to not comply with the ACA-mandated Medicaid coverage expansion. Table 7 shows states' adoption choices, the time of adoption in brackets, and the name given to each of the groupings.

[11] Note that data from hospitals in all U.S. territories are excluded (e.g., Guam, Puerto Rico, U.S. Virgin Islands) from this study since Medicaid programs in these regions operates differently (Hall et al., 2019).

Table 7: States' compliance with the ACA-mandated Medicaid expansion

Previous Adopters	Early Adopters	Adopters	Late Adopters	Not Adopted
States that provided comparable state-wide insurance prior to the ACA	States that accepted the Medicaid expansion before January 2014 after it is signed in 2010	States that accepted the Medicaid expansion in January 2014	States that accepted the Medicaid expansion after January 2014	States that have not accepted the Medicaid expansion
Arizona	California [11/10]	Arkansas [1/14]	Alaska [9/15]	Alabama
Connecticut	Minnesota [8/11]	Colorado [1/14]	Louisiana [7/16]	Florida
Delaware	New Jersey [4/11]	Illinois [1/14]	Indiana [2/15]	Georgia
Hawaii	Washington [1/11]	Iowa [1/14]	Michigan [4/14]	Idaho [1/20]
Massachusetts		Kentucky [1/14]	Montana [1/16]	Kansas
New York		Maryland [1/14]	New Hampshire [8/14]	Maine [1/19]
Vermont		Nevada [1/14]	Pennslyvania [1/15]	Mississippi
Washington DC		New Mexico [1/14]		Missouri [7/21]
		North Dakota [1/14]		Nebraska [10/20]
		Ohio [1/14]		North Carolina
		Oregon [1/14]		Oklahoma [7/21]
		Rhode Island [1/14]		South Carolina
		West Virginia [1/14]		South Dakota
				Tennessee
				Texas
				Utah [1/20]
				Virginia [1/19]
				Wisconsin*
				Wyoming

* Wisconsin has started to provide state-wide insurance coverage in January 2014, but has not adopted the Medicaid expansion mandate in the ACA.

3.3 Research Design

3.3.1 Data and Identification of Hospital Closures

The initial data set is a panel containing information about the closures of U.S.-based, acute care (STAC) and critical access (CA) hospitals between 2005 and 2018 for all 50 U.S. states and the District of Columbia. A STAC hospital is a facility that provides inpatient medical care and other related services for surgery, acute medical conditions, or injuries for short-term illnesses or conditions (CMS, 2020). A CA hospital is a designation given by the CMS to rural hospitals exclusively (RHIhub, 2019); hospitals with this designation receive additional reimbursement from the federal government to improve access to healthcare. I identify these hospitals from the Hospital General Information (HGI) files maintained by the Centers for Medicaid and Medicare Services (CMS) and chose 2005 as the start year because it is the inaugural year for the database. The data set is limited to 2005-2018 because the latest available HGI file at the time of this study is for 2019, since the last HGI file for any given year is not available until the start of the next year.

The dependent variable in this study is the number of hospitals that closed in state i in year t. A hospital is considered closed in year t if it ceases to provide general hospital services or is converted into a long-term care facility within that year. To determine this status, the first year the provider ID for a hospital is reported in the HGI files is identified and its presence in subsequent years is checked. The last year for which the unique provider ID is reported in the HGI files is denoted as the closure year. This results in a one-year lag between the last year in the data set and the last available HGI file. Since the last HGI file that can be accessed is for 2019, the last year in which the status of a hospital can be determined is 2018. Hospital closure status is then validated using news media reports, official announcements, and where possible, by direct communication with the health institution. This validation/manual confirmation process is necessary because there are cases where a hospital merges with, or is acquired by, another hospital and starts reporting under a new provider ID. In these cases, the hospital might still provide the same services even though their provider ID is no longer reported. These hospitals are excluded from the data set (both the ones that are merging and the ones that they have merged with) because the provider ID that is associated with these hospitals will include the values for both hospitals which will bias the analysis. Further, it's not clear whether the merger is associated with a negative (e.g., hospital closure) or positive outcome (e.g., synergistic care opportunities). Finally, there are instances where hospitals are given new provider IDs due to a status change and this also requires manual confirmation (e.g., STAC hospitals when they gain CA designation). Such hospitals are included in the data set unless there is a missing year in between their status changes. A summary of the steps used for confirming the operating status of a hospital is presented in Figure 4.

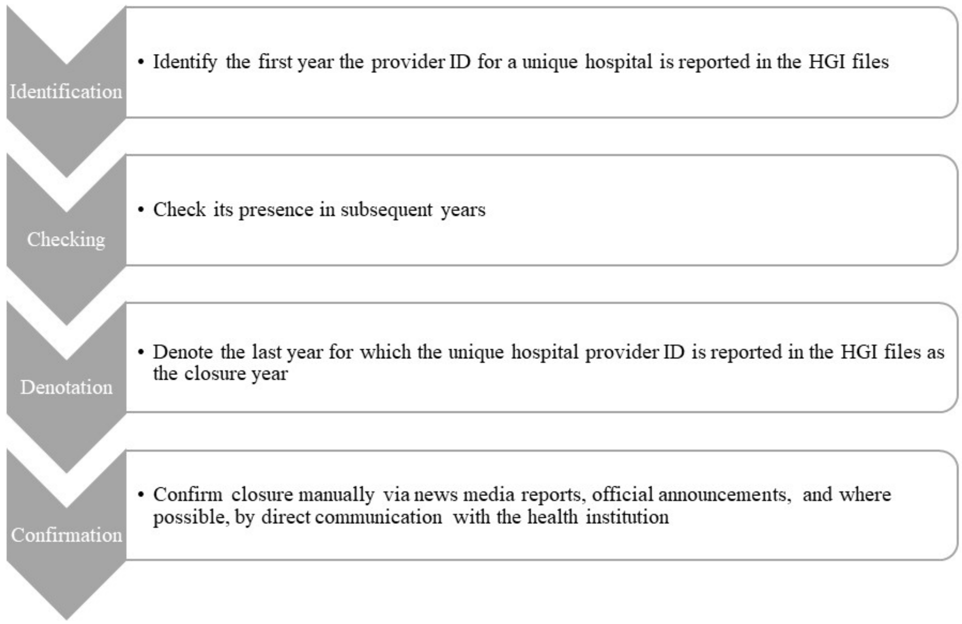

Figure 4: Hospital closure identification steps

I augment the above data set by including variables for each state's population, median income per capita, and total GDP in millions from the U.S. Bureau of Economic Analysis (FRED-a, 2020; FRED-b, 2020)[12]. I take the natural logarithm of these variables for scale and normality concerns. I also obtain the state's unemployment rate reported by the U.S. Bureau of Labor Statistics which can be downloaded from Iowa State University's website (ISU-b, 2020). Descriptive statistics of these variables are found in Table 8. The final panel data set includes 50 states and the District of Columbia over 14 years, yielding 714 state-year observations ($51 \times 14 = 714$). Out of 3,754 hospitals operating in the U.S. over this period, there were 314 closures.

[12] I use the U.S. Census Bureau for years after 2010 (U.S. Census Bureau, 2020) and the U.S. Bureau of Economic Analysis for years before 2010 (ISU-a, 2020).

Table 8: Descriptive Statistics

	Variable	Description	Mean	Median	Std. Deviation
Dependent Variable	Closures	Number of hospital closures in state i, year t	0.45	0	1.03
Independent Variable	POST	Binary variable to represent the Medicaid adoption of state i in year t	0.33	0	0.47
Control Variables	Number of Hospitals	Number of hospitals in state i, year t	82.7	71	64.87
	Income	Natural logarithm of average income per capita in state i, year t	15.12	15.28	1.03
	GDP	Natural logarithm of Gross Domestic Product in state i, year t	12.13	12.16	1.03
	Population	Natural logarithm of total population in state i, year t	10.66	10.65	0.2
	Unemployment	Unemployement rate in state i, year t (%)	5.87	5.4	2.15

To investigate the operational drivers of hospital closures, I focus on six dependent variables: the number of inpatient beds, total yearly discharges, the number of hospital employees, total hospital expenses and revenues, and an aggregate measure of experiential quality. The number of inpatient beds is an important indicator of hospital size (e.g. Sjetne et al., 2007), the number of discharges is a measure of patient volume (e.g. Nimptsch et al., 2018), and the number of employees is a proxy for hospital resources (Ahmed and Amagoh, 2008). Total operating expenses and patient revenues are indicators of financial health. Finally, experiential quality is a measure of the non-technical delivery of health services as perceived by patients during their interactions with the health practitioners (Chandrasekaran et al., 2012). It is associated with how responsive the hospital is to patients' needs and focuses on "how" the service is delivered (Elsaleiby, 2015). I choose experiential quality because it is the only metric for health quality for which the CMS has consistent data on during the study period. Following previous research (Senot et al., 2016), I measure experiential quality as the average of the percentage of patients whose response was "Always" to the first five items and "Yes" to the sixth item in the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) surveys. I then take the logit form of the value.

Specifically, let Q_{itm} be the value of experiential quality question m for hospital i in year t from the HCAHPS survey. Then, aggregate experiential quality for hospital i in year t is $\bar{Q}_{it}$ where

$$\bar{Q}_{it} = \frac{1}{6}\sum_{m=1}^{6} Q_{itm} \qquad (1)$$

I then use the following specification in the regression analysis:

$$EQ_{it} = \log\left(\frac{\bar{Q}_{it}}{1-\bar{Q}_{it}}\right) \tag{2}$$

I also include a wage index to control for the local cost of living (Hsia et al., 2011) and the OPDSH factor to account for hospitals' propensity to treat uninsured and Medicaid patients (Coughlin and Liska, 1998). Resident-to-bed ratio is included to control for the teaching intensity of a hospital which might require more resources and an additional financial burden (Allison et al., 2000). Finally, location (rural vs. urban) is accounted for by the addition of a binary indicator since it has been shown to affect hospital financial viability (Onder et al., 2022). These variables are collected from hospital *Cost Reports* and *CMS Impact Files* in the CMS Hospital Compare database and their associated descriptive statistics are presented in Table 9.

Table 9: Descriptive Statistics 2

Variable	Description	Mean	Median	Std. Deviation
Beds	Number of Beds	172.1	118	176.2
Employees	Number of Employees	1059.7	593.3	1435.3
Discharges	Number of Discharges	8228	4862	9641.1
ExpQuality	Logit form of Experiential Quality	0.916	0.909	0.243
Revenue	Total Patient Revenue (in millions)	693.3	342.3	1029.1
Expense	Total Operating Expense (in millions)	212.81	112.52	303.7
Wage Index	Wage Index	0.98	0.94	0.2
OPDSH	Operating Disproportionate Share Hospital Payment Adjustment Factor	0.09	0.05	0.1
RestoBed	Resident to Bed Ratio	0.06	0	1.6
Location	Binary Urban Identifier	-	-	-

3.3.2 Model Estimation

For the primary analysis, I use a DID model with fixed effects to estimate the effect of Medicaid expansion on hospital closures. This methodology has been widely used in the economics literature to evaluate the impact of policy changes (e.g., Lu and Lu, 2017). In this case, the heterogeneous adoption of the mandate across states allows us to assess how this policy affects hospital closures and serves as a quasi-natural experiment. Thus, states that decide to opt out of this program, or states that have yet to implement the mandate, are used a control group in year t.

Unlike the standard DID approach, the dependent variable is a count variable that follows a Poisson distribution (Mark et al., 2013; Kondo et al., 2015). More specifically, I define Y_{it} as the dependent variable; it represents the number of hospital closures in state i in year t. The variable of interest is $POST_{it}$, a binary variable which equals 1 if state i adopts the Medicaid coverage expansion mandate, or already provides comparable state-level health insurance, in year t and 0 otherwise. The variable is indexed by state and time to account for the heterogeneous adoption of the policy (see, e.g., Lu and Lu, 2017). Let $\boldsymbol{X}_{it}$ be a vector of time-varying state controls that might affect hospital closures. The characteristics that are included are: population level, number of hospitals, income per capita, GDP, and unemployment rate. Population and the number of hospitals are included to account for the size of a state. Naturally, bigger states (i.e., states with more hospitals and more residents) will experience more hospital closures because there are more hospitals available to close. Moreover, the larger the population, the more demand there is, and this may reduce the likelihood of a closure. Income per capita, GDP, and unemployment rate are included to control for the economic health of the state since it is a priori more likely that hospitals will close in economically weaker states. The model includes fixed effects for states ($State_i$) to control for unobserved time-invariant, state-specific properties and year fixed effects ($Year_t$) to control for temporal factors. There are 50 and 13 state and year fixed effects, respectively, with DC and 2005 being used as the references. The mathematical specification is given below:

$$Y_{it} = \beta_0 + \beta_1(POST_{it}) + \boldsymbol{\beta_2 X_{it}} + State_i + Year_t + \varepsilon_{it} \qquad (3)$$

where β_0 is the intercept term, β_1 is the coefficient of interest, $\boldsymbol{\beta_2}$ is the vector of coefficients corresponding to the time-varying state controls, and ε_{it} is the mean zero error term. Due to the DID framework, a value of $\beta_1 < 0$ indicates that the adoption of the ACA-mandated Medicaid coverage expansion causally reduces the number of hospital closures.

3.3.2.1 Model Assumptions

Before presenting the results, I first confirm that the assumptions for the DID analysis are satisfied to ensure that the causal inferences are valid. This is a crucial step to (a) confidently argue that the Medicaid coverage expansion mandate did indeed affect hospital closures; and (b) provide directions for policy makers. Table 10 summarizes the assumptions and the tests I conducted.

Table 10: DID Assumptions

Assumption	**Explanation**	**Test**
Exogeneity	Treatment affects DV only	Visual Support
SUTVA	No interference	Theoretical support
	No variations	Theoretical support
Counterfactual	Parallel Trends	Visual Support
		Theoretical support with a statistical test

First, the treatment event must be exogenous; only the dependent variable should be affected by the treatment. In this case, the treatment is the adoption of the ACA-mandated Medicaid coverage expansion. There is no reason to suspect that state-level characteristics might be impacted by the treatment. In other words, the Medicaid coverage expansion mandate is not expected to affect state characteristics, such as population, GDP, and income levels. Nevertheless, in Figure 5, I provide visual support to confirm this suspicion by plotting the change in state characteristics over time grouped by expansion status. Notice the parallelism between the states that expanded Medicaid coverage and those that did not is unaffected during the study period.

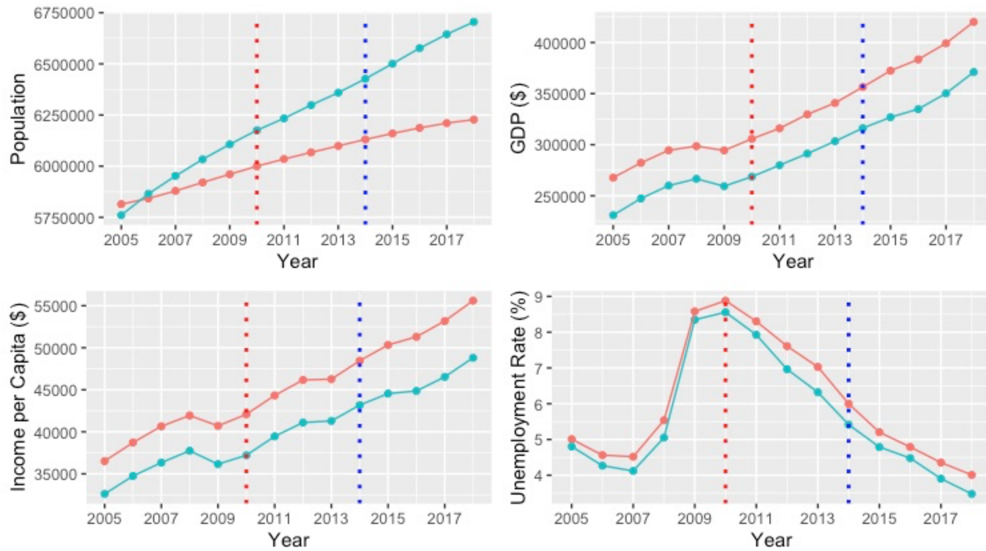

Figure 5: State characteristics by Expansion status over time. The blue line represents states that complied with the ACA-mandated Medicaid coverage expansion while the red line represents states that did not.

Second, the stable unit treatment values assumption (SUTVA) must hold. This specifies that (a) there should be no interference; and (b) there should be no hidden variations of treatment. No interference means that the treatment for any unit should not affect the potential outcomes of other units. For example, if Oregon decides to implement the mandate, it should not impact hospital closures in Texas. Since hospitals are affected by their own states' decisions, there is no reason to suspect that this assumption is violated. No hidden variations of treatment means that there should not be different versions or forms of treatment. In this case, the Medicaid expansion mandate is a federal statute that is equal across states. Hence, this component of SUTVA also holds.

Finally, the key assumption of DID analyses is the counterfactual or parallel trends assumption. It specifies that both treatment and control groups should continue their pre-intervention trends post intervention had the treatment not been administered (Ryan et al., 2019). The counterfactual assumption cannot be statistically tested since the error terms in the scenario where the ACA-mandated Medicaid expansion does not exist and thus, is not observable (Lechner, 2010). As a consequence, I use one visual and one theoretical argument to analyze whether the counterfactual assumption holds; I also support the theoretical argument with a statistical test.

In Figure 6, I plot hospital closures over time; this allows us to visually determine whether the counterfactual assumption holds (e.g., Jaeger et al., 2018; Scott et al., 2020). I group hospitals into states that complied with the ACA-mandated Medicaid coverage expansion prior to year t and those that did not. Both groups exhibit parallel behavior before the ACA was signed in 2010 and after the ACA-mandated Medicaid expansion came into effect in 2014; the ones experiencing more hospital closures before the signing of the ACA experience fewer closures after its implementation.

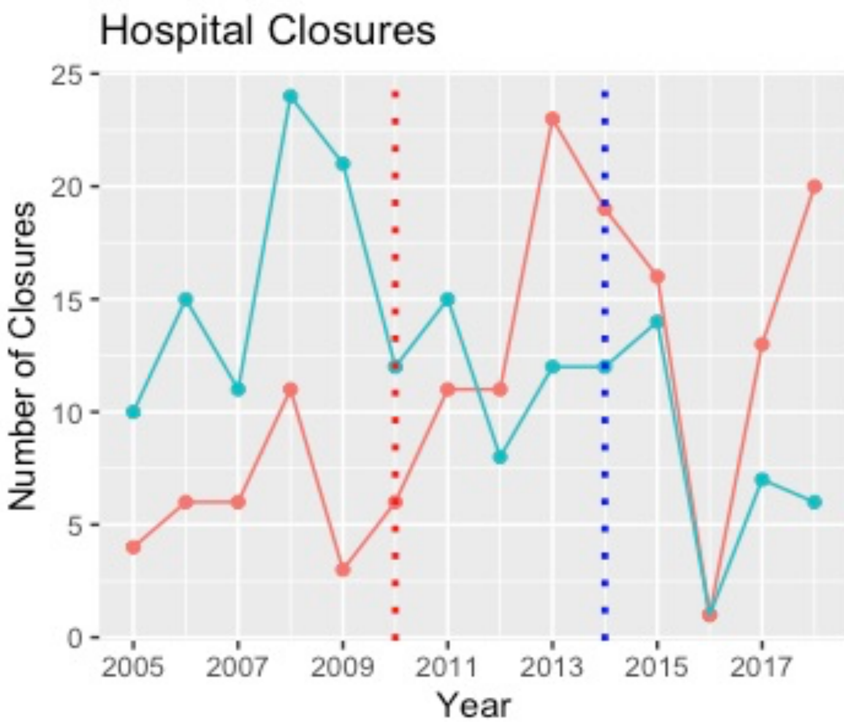

Figure 6: Hospital closures over time per Medicaid expansion. The blue line represents states that complied with the ACA-mandated Medicaid coverage expansion while the red line represents states that did not.

Despite the parallelism observed in Figure 6, one could still be concerned that unobserved confounding might affect the decision to adopt the mandate which might bias the results. For example, states that were a priori more likely to observe fewer hospital closures may also be the ones that decide to comply with the ACA-mandated Medicaid coverage expansion. Alternatively, if states which have high GDP tend to adopt the mandate while those with low GDP do not, one can argue that hospital closures in states with high GDP would improve regardless of its adoption. Theoretically, however, these concerns are unwarranted. Arguments regarding whether a state should adopt the Medicaid coverage expansion mandate focused on issues such as state budgets (Conover, 2017) or individual health insurance (Roy, 2013). Nevertheless, to quantitatively address this concern, I use a logistic regression model to test whether hospital closures are correlated with the decision to comply with the ACA-mandated Medicaid coverage expansion. The purpose here is to demonstrate that there are no issues with how states are grouped that might bias the results (i.e., to show that the counterfactual assumption holds).

For this analysis, I define a binary variable A_i as the dependent variable which takes the value of 1 if the ACA-mandated Medicaid coverage expansion was adopted by state i and 0 otherwise. I include my state-level control variables as independent variables to test if any state-level characteristics affected the decision to expand. States made the decision to expand Medicaid sometime after 2010 and before 2014. I, therefore, take the mean of the independent variables and the dependent variable number of closures over the 3 years between 2010 and 2014. One key feature of states is their political alignment (Sobel, 2014). Thus, I introduce a binary variable $P_i \in \{\text{Democrat}, \text{Republican}\}$ to control for the political affiliation of the state executive branch using outcomes from the 2012 federal election since it best represents the political view of the state when the bill was debated (e.g., Pe'er and Gottschalg, 2011; Glass and Levchak, 2014; Bessett et al., 2015). Finally, I exclude six states[13] that made use of waivers to expand Medicaid before 2014 because they had already made their decision prior to the introduction of the bill. I repeated the analysis using all 50 states and the D.C. and the models yield qualitatively similar results. Formally, I estimate the following model:

$$A_i = \alpha_0 + \alpha_1(Number\ of\ Closures_i) + \boldsymbol{\alpha_2 X_i} + \alpha_3 P_i + \varepsilon_i \qquad (4)$$

where α_0 is the intercept term, α_1 is the coefficient associated with the number of hospital closures in state i between 2010 and 2014, $\boldsymbol{\alpha_2}$ is the vector of coefficients for the

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[13] These six states are California, Connecticut, D.C., Minnesota, New Jersey, and Washington. In Table 7, D.C. and Connecticut are excluded from this list because they already provided health insurance comparable to Medicaid. They are considered one of these states in this analysis because having a comparable health insurance prior to Medicaid expansion does not necessarily mean states complied with the ACA-mandated Medicaid expansion.

time-varying state controls, α_3 is the political affiliation coefficient, and ε_i is the mean zero error term.

The results are reported in Table 11. All variables included in the study, except for political affiliation, are not significant. The analysis suggests that the adoption of the ACA-mandated Medicaid expansion was a political one and not related to any other state-level variables providing support to Sobel (2014) and for the counterfactual assumption. Hence, I can confidently argue that the counterfactual assumption holds in this study and that DID analysis can be used.

Table 11: Adoption of the ACA-mandated Medicaid expansion - Logistic Regression. Model 2 includes the variable of interest: Number of Closures

	Model 1			Model 2		
	Estimate	Pr(>|z|)		Estimate	Pr(>|z|)	
Intercept	- 3.272	0.610		- 3.213	0.616	
Income per Capita	0.000	0.678		0.000	0.698	
GDP	0.000	0.315		0.000	0.309	
Population	- 0.000	0.219		- 0.000	0.212	
Unemployment Rate	0.557	0.141		0.552	0.142	
Red States 2012	- 1.872	0.035	**	- 1.816	0.046	**
Number of Hospitals	0.000	0.993		0.001	0.958	
Number of Closures				- 0.199	0.773	
AIC:	58.892			60.819		
Observations	45			45		

3.4 Results

Table 12 reports the results from estimating (3). In Model 3, I include all state-level, time-varying control variables but exclude the variable of interest, $POST_{it}$. Only the state's population level is positively associated with hospital closures at α=0.01 (p=0.002) with a coefficient of 13.65. In Model 4, I include the variable of interest $POST_{it}$. The results demonstrate that complying with the ACA-mandated Medicaid coverage expansion is significantly and negatively correlated with hospital closures. The expected log count for states complying with the mandate decreases by 0.768 (p=0.004) which is a 54% reduction in number of hospital closures. State population level is, again, the only control variable that is significantly correlated with hospital closures at α=0.01 with a coefficient of 12.58. That is, the expected number of hospital closures increases with the size of a state's population (p=0.005). This is expected as there are more hospitals in higher populated states.

Table 12: DID Results – Poisson regression model. Model 4 includes the variable of interest: $POST_{it}$

	Model 3			Model 4		
	Estimate	Pr(>|z|)		Estimate	Pr(>|z|)	
Intercept	- 151.900	0.949		- 148.500	0.949	
Number of Hospitals	- 0.005	0.613		- 0.009	0.355	
Income per Capita	- 4.928	0.230		- 2.823	0.502	
GDP	0.184	0.947		- 0.887	0.754	
Population	13.650	0.002	***	12.580	0.005	***
Unemployment Rate	- 0.120	0.223		- 0.100	0.316	
POSTit				- 0.768	0.004	***
State fixed effects	Yes			Yes		
Year fixed effects	Yes			Yes		
Number of observations	714			714		
AIC	1,029.20			1,022.60		
Residual Deviance	460.81			452.24		
Degrees of Freedom	645			644		

The model residual deviance can be used to assess the degree to which the predicted values differ from the observed. When a model is true, I can expect the residual deviance to be distributed as a χ^2 random variable with degrees of freedom (df) equal to the model's residual degrees of freedom. Model 4 has a residual deviance of 452.24 with 644 df. The probability of observing a deviance this large if the model fits is essentially 1, indicating that there is significant evidence of fit. I test the difference between Model 3 and Model 4 using a chi-squared test which shows that the inclusion of $POST_{it}$ significantly improves model fit (p<0.001).

Finally, in order to test the validity of the Poisson assumption over other discrete distributions, I check for overdispersion, i.e., I test whether there is more variation in the response than implied by the model. If the response is distributed according to a Poisson random variable, I would expect that the mean and variance be equal. Thus, I estimate (3) using the negative binomial model and compare the log-likelihoods to that of a Poisson model. The results are reported in Table 13. The chi-squared test statistic for over-dispersion yields a value of 0.0277 and the corresponding p-value of 0.434; this fails to reject the null hypothesis of a Poisson distribution.

Table 13: DID Results - Negative binomial regression model

	Model 5		
	Estimate	Pr(>|z|)	
Intercept	-152.200	1.000	
Number of Hospitals	-0.008	0.433	**
Income per Capita	-2.974	0.492	
GDP	-0.838	0.773	*
Population	11.940	0.010	***
Unemployment Rate	-0.105	0.308	
POSTit	-0.772	0.005	***
State fixed effects	Yes		
Year fixed effects	Yes		
Number of observations	714		
AIC	1,024.10		
Residual Deviance	434.36		
Degrees of Freedom	644		

3.4.1 Robustness Tests

I run a total of five robustness checks to confirm the validity of the findings (results are presented in the *Appendix B*). First, I determine whether the results I observe are being driven by the definition of $POST_{it}$. Specifically, in the analysis, $POST_{it}$ equals 1 if state i either complies with the ACA-mandated Medicaid coverage expansion or provides equivalent state-wide health insurance in year t, and 0 otherwise. One can argue, however, that this approach does not test the effect of Medicaid expansion, but rather, the health insurance that is provided as $POST_{it}$ equals 1 both before and after the adoption of the Medicaid expansion for states that had already provided state-wide health insurance. Hence, I redefine $POST_{it}$ to be 1 only when state i complies with the ACA-mandated Medicaid coverage expansion and 0 otherwise. The results are reported in Table 22 and are qualitatively identical. In fact, the newly defined $POST_{it}$ is even more strongly correlated with hospital closures (β_1 =-0.934, p<0.001). This finding suggests that even states that had provided an equivalent level of health insurance coverage as compared to Medicaid benefited from the ACA-mandated expansion. This finding is in agreement with what is reported in Denham and Veazie (2019).

In the second robustness check, I address the issue related to the limited number of hospitals in small states. That is, in some states, there are few hospitals and thus, I would not expect to observe many closures, and this may bias the results. In the data set, the maximum number of closures in any given state-year is 9. Hence, I remove states that have fewer than 9 hospitals during the study period (D.C. and Delaware) and repeat the analysis. The results are reported in Table 23 and are, again, qualitatively similar; $POST_{it}$ is still significantly and negatively correlated with hospital closures at α=0.01 (β_1 =-0.768, p=0.004).

In the third robustness check, I treat Wisconsin as a state that expanded the Medicaid in the ACA (recall, from Section 2, that they provided state-level insurance coverage that extended Medicaid benefits despite not complying with the ACA-mandated Medicaid coverage expansion). The results are reported in Table 24 and are qualitatively similar; $POST_{it}$ is still significantly and negatively correlated with hospital closures at α=0.01 (β_1 =-0.745, p=0.005).

In addition to the analysis described in Section 3.2.1, I further test the parallel trend assumption following recent literature (Wang, 2022). To this end, I include a vector of pretreatment dummies to the model. I include a dummy variable $Expansion_{it}^{k}$ as a control variable which equals 1 if t is k years before state i expanded Medicaid coverage under the ACA and 0 otherwise. Then, I test the significance of the dummy variable $Expansion_{it}^{k}$ for $k = 1$ and 5 where I use $Expansion_{it}^{5}$ as the control variable. A significant coefficient for $Expansion_{it}^{1}$ would indicate that the treatment and control group do not have parallel trends during this period. I chose five years prior to expansion as the control year because this represents the difference between the earliest date that a state expanded Medicaid (California) and the first year in the data set. The results of this test are reported in Table 25, and it appears that the coefficient $Expansion_{it}^{1}$ is not significant at α=0.1 which further supports the validity of the parallel trends assumption. In addition, $POST_{it}$ is still significantly and negatively correlated with hospital closures at α=0.05 (β_1 =-0.728, p=0.011).

In the final robustness check, I conduct a set of hypothetical experiments. I test both the importance of the timing of expansion and any unobserved confounders that might be affecting both the decision to expand and the number of hospital closures. I do this by randomly assigning each treated state a placebo year prior to the enactment of the mandate and designating this period as their expansion year. I then repeat the DID analysis. In this test, I should not observe a significant effect. I sample using 1000 repetitions and observe that 62% of the scenarios were not significant at α=0.1; 72% of the scenarios were not significant at α=0.05; and 87% of the scenarios were not significant at α=0.01. This suggests that the timing of expansion was indeed significant and that the main result is, indeed, robust to unobserved confounders.

3.5 Empirical Extensions

3.5.1 Closed Hospitals vs Survived Hospitals

To better understand why the mandate reduced hospital closures, I now investigate the operational effect that adopting Medicaid expansion had on hospital performance. I compare closed hospitals to those that survived based on six metrics that the extant literature has identified as being relevant: hospital size (inpatient beds), resource investment (number of employees); patient volume (number of discharges per year); care quality (experiential quality survey results); and financial health (both operational expenses and patient revenue). The logit of experiential quality is taken, and rest of the variables are normalized with respect to the number of beds to control for hospital size. Observations are pooled within a state; I then divide the closed hospital value with the value from hospitals that survived. Figure 7 presents the results.

I find that closed hospitals were smaller on average (51% of survived hospitals), experienced less patient volume (65% of survived hospitals), had fewer employees per number of beds (76% of survived hospitals), and generated less revenue per bed (66% of survived hospitals). Although their expenses were lower (80% of survived hospitals), the revenue they generated was significantly lower. Closed hospitals, however, able to provide a perceived quality of care that is on par with hospitals that survived (97% of survived hospitals). This gives us preliminary evidence that hospital closures may not be due to excess costs and changing operational structures.

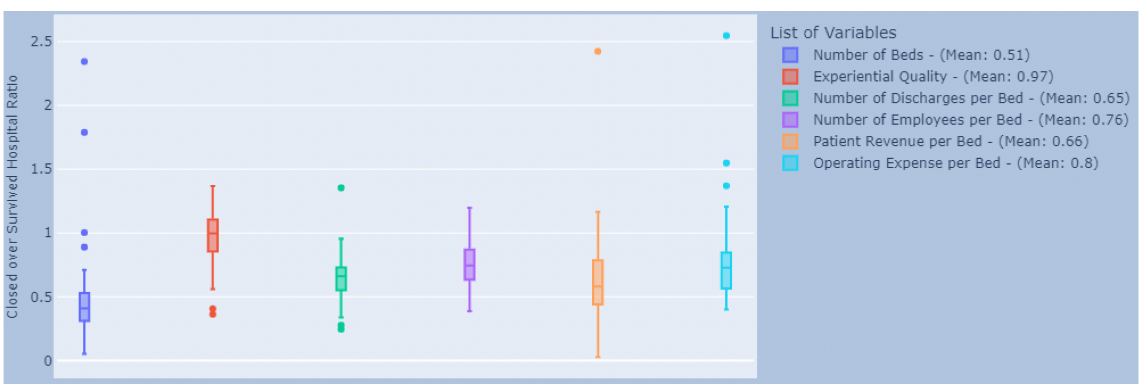

Figure 7: Boxplot of hospital-level operational drivers. Ratio of closed over survived hospitals are plotted using linear quartile method

3.5.2 Hospital-Level Drivers

To further explore the impact of the mandate on operational drivers, I replicate the DID estimation procedure using the six hospital-level operational metrics described in Section 5.1. I note that the exogeneity and SUTVA assumptions remain valid, and I provide visual support for the counterfactual assumption for each of the dependent variables in the *Appendix B (Figures 8-13)*. Observe that parallelism is evident, hence, the DID framework can be confidently applied. For this purpose, I modify (3) by adding subscript j to the model to test the variables of interest at the hospital level. That is, I define Y_{hij} as the dependent variable; it represents a continuous quantity associated with hospital h in state i in year t. I also add a vector of hospital-level, time-varying, control variables $\boldsymbol{Z_{hit}}$ which correspond to the wage index, OPDSH factor, teaching intensity, and location. Formally, the mathematical specification is:

$$Y_{hit} = \beta_0 + \beta_1(POST_{it}) + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\beta_3 Z_{hit}} + State_i + Year_t + \varepsilon_{hit} \qquad (5)$$

where β_0 is the intercept term, β_1 is the coefficient of interest, $\boldsymbol{\beta_2}$ is the vector of coefficients corresponding to the time-varying state controls, $\boldsymbol{\beta_3}$ is the vector of coefficients corresponding to the time-varying hospital-level controls, and ε_{hit} is the mean zero error term. I run six separate regressions (the results are presented in Tables 14-19) that differ only in the dependent variable Y_{hit}, i.e., the number of beds, the number of hospital employees, the number of discharges, total patient revenue (in millions), total operating expense (in millions), and aggregate experiential quality (see Section 3.1). Note that I only include survived hospitals in the analysis, because closed hospitals will have missing years and the impact of the mandate will not be observed.

I find no evidence of an association between the ACA-mandated Medicaid expansion and the number of beds ($\beta_1 = 1.00$; p= 0.46), the number of employees ($\beta_1 = 17.16$; p=0.22), the number of discharges ($\beta_1 = -104$; p=0.14), and hospital expenses ($\beta_1 = 1.33$; p=0.51). These results indicate that, after the implementation of the mandate, hospitals that survived did not hire extra resources (beds, employees) nor did they discharge more patients or incur additional expenses. However, I do find evidence that Medicaid expansion is significantly associated with increases in hospital patient revenue ($\beta_1 = 32.24$; p < 0.001) and increases in experiential quality ($\beta_1 = 0.02$; p < 0.001). Since both patient volumes and hospitals resources did not increase, and expenses were not negatively impacted, it can be deduced that the increase in revenue was most likely driven by a reduction in uncompensated care episodes. Note that all models have high R^2 values (0.89, 0.84, 0.90, 0.92, and 0.81, 0.41) indicating high explanatory power.

Table 14 & 15: Model 10 – DID on Beds & Model 11 - DID on Employees

	Estimate	Pr(>|t|)	
(Intercept)	-406.70	0.22	
POSTit	1.00	0.46	
Discharge	-7.46	0.05	*
WageIndex	0.01	0.00	***
OPDSH	58.18	0.00	***
RestoBed	-0.38	0.90	
Employee	0.02	0.00	***
Location	18.51	0.00	***
Population	54.09	0.01	***
GDP	-25.47	0.12	
Income per Capita	-2.96	0.90	
Unemployment	-0.02	0.98	
State fixed effects	Yes		
Year fixed efffects	Yes		
Number of Observations	33,208		
p-value	0.00		
Rsquared	0.89		

	Estimate	Pr(>|t|)	
(Intercept)	6,240.00	0.07	*
POSTit	17.16	0.22	
Discharge	0.08	0.00	***
WageIndex	-380.30	0.00	***
OPDSH	-917.70	0.00	***
RestoBed	2,452.00	0.00	***
Beds	2.51	0.00	***
Location	-187.70	0.00	***
Population	-688.60	0.00	***
GDP	572.70	0.00	***
Income per Capita	-236.30	0.34	
Unemployment	16.33	0.00	***
State fixed effects	Yes		
Year fixed efffects	Yes		
Number of Observations	33,208		
p-value	0.00		
Rsquared	0.84		

Table 15 & 17: Model 12 - DID on Discharges & Model 13 - DID on Expense

	Estimate	Pr(>|t|)	
(Intercept)	-11,710.00	0.49	
POSTit	-104.00	0.14	
WageIndex	1,716.00	0.00	***
OPDSH	-9.87	0.96	
RestoBed	-4,104.00	0.00	***
Beds	37.04	0.00	***
Employee	2.04	0.00	***
Location	697.60	0.00	***
Population	531.30	0.62	
GDP	-589.30	0.50	
Income per Capita	788.10	0.53	
Unemployment	-57.24	0.04	**
State fixed effects	Yes		
Year fixed efffects	Yes		
Number of Observations	33,208		
p-value	0.00		
Rsquared	0.9		

	Estimate	Pr(>|t|)	
(Intercept)	-875.30	0.08	*
POSTit	1.33	0.51	
Discharge	158.80	0.00	***
WageIndex	-0.01	0.00	***
OPDSH	-131.70	0.00	***
RestoBed	202.70	0.00	***
Beds	0.59	0.00	***
Employee	0.16	0.00	***
Location	-14.75	0.00	***
Population	-24.48	0.43	
GDP	71.20	0.00	***
Income per Capita	26.26	0.47	
Unemployment	0.18	0.82	
State fixed effects	Yes		
Year fixed efffects	Yes		
Number of Observations	33,208		
p-value	0.00		
Rsquared	0.92		

Table 16 & 19: Model 14 - DID on Revenue & Model 15 - DID on Quality

	Estimate	Pr(>|t|)	
(Intercept)	-12,930.00	0.00	***
POSTit	32.24	0.00	***
Discharge	515.10	0.00	***
WageIndex	-0.00	0.20	
OPDSH	-735.10	0.00	***
RestoBed	328.80	0.00	***
Beds	2.73	0.00	***
Employee	0.29	0.00	***
Location	-37.37	0.00	***
Population	1,347.00	0.00	***
GDP	-80.36	0.54	
Income per Capita	-475.00	0.01	**
Unemployment	-11.47	0.01	***
State fixed effects	Yes		
Year fixed efffects	Yes		
Number of Observations	33,208		
p-value	0.00		
Rsquared	0.81		

	Estimate	Pr(>|t|)	
(Intercept)	3.38	0.02	**
POSTit	0.02	0.00	***
Discharge	0.00	0.00	***
WageIndex	-0.14	0.00	***
OPDSH	-0.47	0.00	***
RestoBed	-0.11	0.00	***
Beds	0.00	0.00	***
Employee	0.00	0.00	***
Location	-0.06	0.00	***
Population	-0.19	0.06	*
GDP	0.10	0.21	
Income per Capita	-0.07	0.49	
Unemployment	0.00	0.05	*
State fixed effects	Yes		
Year fixed efffects	Yes		
Number of Observations	23,622		
p-value	0.00		
Rsquared	0.41		

3.6 Conclusion and Discussion

The recent increase in the number of hospital closures in the United States may be an indication that a looming political and social crisis is on the horizon (Raffa, 2019; Milmon, 2020). Although hospital-level drivers that cause hospital closures have been well-studied, few papers investigate the effect of structural factors. Adoption of the ACA-mandated Medicaid expansion was a major policy change that has had far-reaching effect although its impact on hospital closures is still the center of controversy. Using a validated data set of a state-level characteristics, hospital metrics, and a hospital's operating status from 2005-2018, I provide empirical evidence that compliance with the Medicaid expansion in the ACA causally reduced hospital closures in states complying with the mandate by 54%. Moreover, I find no evidence of the expansion's impact on hospitals' patient volume, number of employees/beds, and operating expenses. Nevertheless, I do find support that Medicaid expansion increased total patient revenue and improved experiential quality.

The findings suggest that of the two primary benefits that the mandate was expected to address, i.e., a reduction in uncompensated care and increases to patient volumes, only the former has been realized. That is, I found a statistically significant increase in total revenue which suggests that care under-compensation may be a smaller phenomenon than originally thought and the revenue increase hospitals experienced from reducing uncompensated care is greater. The analysis also suggests that patient volumes have not changed. This contradicts classical studies that suggest Medicaid eligibility is associated with an increase in the demand for health services (Currie and Gruber 1996), and instead, indicates that providing insurance to previously uninsured patients may not necessarily increase overall usage (KC and Kim, 2022). I also found no evidence of cost savings which may provide support for research indicating that systematic changes in the mix of patients seeking health services, such as the diversion of uninsured patients from the emergency room to outpatient settings, did not occur (e.g., Gotanda et al. 2019). Finally, I found that patients experienced a higher quality of care when hospitals adopted the mandate which may signal that it acted as a catalyst to strengthen the relationship between employees and their uninsured patients. This result adds context to the literature that studies the effect of Medicaid expansion on operational attributes such as physician availability and wait times (e.g., Miller and Wherry 2017, Greener et al. 2019, and Wang 2022) as unfavorable changes in these performance metrics do not seem to have negatively affected patient's perception about the quality of care they received.

This investigation offers critical insight for hospital administrators and policy makers alike. I demonstrate that while Medicaid expansion has had a positive effect on hospital survival, the decision to adopt the mandate was political. This suggests that in certain states, political agendas may have negatively affected public health, a result which renews calls for bipartisanship and cross-aisle collaboration (e.g., Toussaint, 2017). In contrast to the literature, I find that the additional revenue associated with adopting the mandate did not increase operating costs. Thus, future policies that attempt to address the issue of hospital closures should exclusively focus on efforts to increase revenue rather than on cost mitigation programs. For instance, the Critical Access Hospital system, introduced in 1997, was designed to reduce the financial vulnerability of rural hospitals by increasing reimbursements. Finally, while the mandate has unambiguously helped uninsured patients gain insurance coverage (e.g., Dresden et al. 2017, Klein et al. 2017, Ladhania et al. 2022) it, surprisingly, did little to affect the operational structure of hospitals, i.e., there is no indication that hospitals systematically altered their capacity (e.g., inpatient beds, employees, operating expenses) to prepare for the changes in the number of patients they expected to treat. This is especially surprising as the literature indicates that Medicaid eligibility increases medical usage (Card et al. 2008). Thus, one would surmise that hospitals would implement programs to ensure a seamless transition. The results suggest that if such programs were, in fact, developed, they were cost neutral and did not affect the availability of human/health resources.

This study is not without limitations. Lack of consistent data limits the investigation of certain hospital-level factors. For example, this study does not include performance metrics on the delivery of care such as clinical quality, readmission rate, and mortality rate. Nevertheless, these variables are indirectly captured by the analysis of operational expenses and patient volumes in that low quality care leads to an increase in adverse outcomes which can affect a hospital's financial health via an increase in patient volumes (re-admissions) and operational costs (e.g., Flynn et al., 2014). Nevertheless, it remains unclear whether hospitals made systematic changes to internal policies in response to Medicaid expansion so as to realize revenue increases without changing capacity or affecting expenditures. Thus, future work should examine the interaction between employees and hospitals in states that expanded Medicaid and how this relationship changed after the adoption of the ACA. This would allow for a richer discussion as to the structure of successful revenue-generating programs and potentially, how they could be adapted to struggling hospitals.

Chapter 4

4 Discussion and Conclusions

4.1 Overview

In this dissertation, I investigate the impact of the U.S. Affordable Care Act on hospital closure rates following the rollout of the ACA beginning in 2010. Hospital survival is a vital issue in the United States, especially because hospitals had been closing at a 30-a-year pace, and characterized as a public crisis (Flanagan, 2018; Coleman-Lochner and Hill, 2020). Policy changes have been shown to contribute to hospital closures. Hence, I focus on the impact of the Affordable Care Act (ACA) on U.S. hospital closure rates. The range of studies on the ACA is an important research topic because the ACA represents the largest overhaul of the U.S. healthcare system since the introduction of the Medicare and Medicaid (healthcare for senior citizens, and for low-income individuals and families, respectively) programs in 1965. Moreover, the ACA remains the center of controversy in the U.S. with politicians aiming to overturn it. To that end, I explore two policy changes related to the ACA and how they affected hospital closures. In each project, I examine one specific policy change that is introduced in the ACA. In the first investigation, I study the impact of the Hospital Readmissions Reduction Program (HRRP) on hospitals' financial viability. For the second investigation, I study the impact of the ACA-mandated Medicaid coverage expansion on hospital closures. Both policy changes have received their fair share of criticism for having caused hospital closures (E.g., Blunt, 2015; Catron 2017).

4.2 Does healthcare quality help the financial viability of U.S. hospitals? A data envelopment analysis approach

The HRRP ties CMS reimbursements that hospitals receive from the U.S. government to their readmission rates to improve healthcare for Americans thus making a hospital's readmission rate important financial and healthcare delivery indicators. Given the hospital closure crisis in the U.S., with approximately 8% of hospitals facing permanent closure (Flanagan, 2018), hospitals' financial health is an important discussion area for both researchers and policy makers. Thus, I first defined a hospital's *financial viability* as a hospital's ability to achieve both lower costs and lower readmission rates based on their resources. Then, I used Simar and Wilson's two-stage data envelopment analysis (DEA) approach to test how two dimensions of quality of care—experiential quality (patients' perceptions of care) and clinical quality (hospitals' compliance with evidence-based care) impact this financial viability. Results indicate that *hospitals that offer better quality care are more efficient in achieving financial viability*. In addition, the results demonstrate that excelling in both dimensions offer additional financial benefits for hospitals.

This investigation fills several gaps both in the DEA literature and the healthcare operations management literature. First, mine is the first DEA study that identifies hospital financial viability based on operating costs and readmission rates. Previous research has treated operating costs and readmission rates as separate outcomes. The literature provided directions on how to lower costs or readmission rates independently. However, existing literature fails to explore the trade-offs hospitals face when lowering costs and readmission rates simultaneously. This is the first study to identify and explore these trade-offs along with costs and readmission rates. Second, the literature lacks DEA studies that provide insights on the impact of the quality of patient care and treatment on hospital performance. Most researchers attempt to control for quality when investigating hospital efficiencies instead of examining its impact, which yields results that are difficult to interpret and unlikely to provide insights on the value of healthcare quality (i.e., evidence-based treatment and patient perceptions). This study fills this gap by providing insights for hospital managers and policy makers regarding the impact of quality of care on hospitals' financial viability.

4.3 The Affordable Care Act and Hospital Closures: A Difference-in-Differences Analysis

The second policy change that I investigate is the ACA-mandated Medicaid coverage expansion. This policy expands Medicaid coverage to all U.S. adults with incomes lower than 138% of the federal poverty level starting in 2014 to provide health insurance to adults who cannot afford health insurance. I examine the impact of the relationship between this policy change and hospital closure rates. I first manually identify each U.S. hospital closure between 2005 and 2018 and then implement a difference-in-differences analysis framework with fixed effects using a Poisson regression. Difference-in-differences analyses require a control group to test the effect of the treatment (i.e., ACA-mandated Medicaid coverage expansion). The U.S. Supreme Court gave states the option to not comply with the ADA Medicare expansion mandate. I used the 12 states that did not comply with the mandate as a control group. Results show that the mandate reduced the number of hospital closures in states that complied with the mandate by 54% as compared to states that did not. Then, I explore the hospital-level operational drivers of the hospital closure crisis. Results demonstrate that the mandate increased patient revenue and perceived quality of care, while no evidence was found that the mandate affected the number of hospital discharges, number of employees, and hospital operating expenses. Furthermore, the results suggest that the Medicaid expansion promoted the revenue increase not by increasing the number of patients, but rather by decreasing the uncompensated care hospitals had been dealing with, that is, caring for indigent patients with no federal, state, or private insurance.

This study provides several insights to both researchers and policy makers. First, the results demonstrate that each state's decision to comply with the ACA-mandated

Medicaid coverage expansion was and is mainly political. Specifically, Republican states chose to opt out of the mandate while Democrat states accepted it. This suggests that the hospital closure crisis could be diminished if the political leaders of states that opted not to comply with the mandate decide over time to comply with the mandate. Second, I uncover the exact mechanism by which the ACA-mandated Medicaid coverage expansion reduces hospital closures. The results show that hospital closures decreased *due to the significant total patient revenue increase from Medicaid-covered patients* while the operating costs did not increase. Thus, future policies that attempt to address the issue of hospital closures should focus on efforts to increase revenue rather than cost mitigation measures. Third, the findings suggest that of the two primary benefits that the mandate was expected to address—a reduction in uncompensated care and increases in patient volumes—only the former has been realized. That is, I found a statistically significant increase in hospitals' total patient revenue but not an increase in patient volume, which suggests that under-compensated care may be a smaller result than originally expected (by some) and that the revenue increase to hospitals from the ACA's impact of reducing uncompensated care is greater than expected (by some). Finally, I found that patients perceived a higher quality of care in hospitals that adopted the mandate, which may signal that it acted as a catalyst to strengthen the relationship between employees and their uninsured patients.

4.4 Concluding Remarks

The findings from the two investigations provide support for the ACA. Both policy changes positively impacted quality of care. The HRRP strongly encourages hospitals to improve their quality of care while the Medicaid expansion causally increases experiential quality. Also, both the HRRP and the Medicaid expansion of the ACA has benefited hospitals financially, according to my findings. The arguments proposed by opponents of the ACA that these policies could cause hospitals to close are unfounded. In fact, the Medicaid expansion aspect of the ACA has been increasing hospital patient revenues without causing any costly investments in additional necessary resources such as employees, equipment, and beds.

Given these research findings, one can confidently say that the ACA effectively helped to curb hospital closures and increase the quality of care in the U.S. hospitals in the 38 states that fully adopted the ACA. Hence, lawmakers should focus on how to improve the provisions of the ACA rather than trying to repeal the ACA, which has been at play since the ACA became law in 2010.

This research is not without limitations. Lack of consistent data on patient safety metrics as well as timely and effective care metrics over the years make it difficult to perform a time series analysis. Another limitation is that although the Supreme Court's decision in 2012 provided states with the option to opt out of the ACA-mandated Medicaid coverage expansion, the other provisions of the ACA were upheld by the court (e.g. HRRP, individual mandate, etc.). Thus, analysis of the ACA-mandated Medicaid coverage expansion was possible since a control group of states that opted out was available. However, this is not the case for other ACA provisions (i.e., HRRP) thus, it might not be possible to establish a causal relationship for them.

This dissertation opens a few research avenues. Researchers can investigate how hospital efficiencies have been affected by the policies introduced by the ACA. Using states that opted not to comply with the Medicaid expansion as the control group, a causal effect between the policy (i.e., Medicaid expansion) and hospital efficiency can be explored. This could further explain the ACA's impact on hospitals. Another underexplored area is how the ACA affected the communication between patients and healthcare workers. Researchers can look into how the ACA affected healthcare workers' workload and whether this impacted quality of care. Another point of study could be how the ACA helped improve quality of care, specifically based on changes hospitals made under the ACA that could have impacted quality of care.

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Appendices

Appendix A

Table 17: Experiential Quality Measurements

Measure ID	Description
H_COMP_1_A_P	Patients who reported that their nurses "Always" communicated well
H_COMP_2_A_P	Patients who reported that their doctors "Always" communicated well
H_COMP_3_A_P	Patients who reported that they "Always" received help as soon as they wanted
H_COMP_4_A_P	Patients who reported that their pain was "Always" well controlled
H_COMP_5_A_P	Patients who reported that staff "Always" explained about medicines before giving it to them
H_COMP_6_A_P	Patients who reported that they were given information about what to do during their recovery at home

Table 18: Clinical Quality Measurements

Condition	Measure ID	Description
Heart Attack or Chest Pain	AMI_2	Aspirin Prescribed at Discharge
	AMI_7a	Fibrinolytic Therapy Received Within 30 Minutes of Hospital Arrival
	AMI_8a	Primary PCI Received Within 90 Minutes of Hospital Arrival
	AMI_10	Statin at Discharge
Heart Failure	HF_1	Discharge instructions
	HF_2	Evaluation of LVS Function
	HF_3	ACEI or ARB for LVSD
Pregnancy and Delivery	PC_01	Percentage of Newborns whose Deliveries were Scheduled Early (1--3 Weeks) when a Scheduled Delivery was not Medically Necessary
Pneumonia	PN_6	Initial Antibiotic Selection for CAP in an Immunocompetent Patient
Surgical Care Improvement Project	SCIP_CARD_2	Surgery Patients on a Beta Blocker Prior to Arrival Who Received a Beta Blocker During the Perioperative Period
	SCIP_INF_1	Prophylactic Antibiotic Received 1 Hour before Surgical Incision
	SCIP_INF_2	Prophylactic Antibiotic Selection for Surgical Patients
	SCIP_INF_3	Prophylactic Antibiotics Discontinued within 24 Hours after Surgery
	SCIP_INF_4	Cardiac Surgery Patients with Controlled 6 a.m. Postoperative Blood
	SCIP_INF_9	Postoperative Urinary Catheter Removal
	SCIP_INF_10	Surgery Patients with Perioperative Temperature Management
	SCIP_VTE_2	Surgery Patients Who Received Appropriate Venous Thromboembolism Prophylaxis from 24 Hours before Surgery to 24 Hours after
Blood Clot Prevention and Treatment	VTE_1	Venous Thromboembolism Prophylaxis
	VTE_2	ICU Venous Thromboembolism Prophylaxis
	VTE_3	Anticoagulation Overlap Therapy
	VTE_4	Unfractionated Heparin with Dosages/Platelet Count Monitoring
	VTE_5	Warfarin Therapy Discharge Instructions
	VTE_6	Incidence of Potentially Preventable VTE
Stroke Care	STK_1	Venous Thromboembolism (VTE) Prophylaxis
	STK_2	Discharged on Antithrombotic Therapy
	STK_3	Anticoagulation Therapy for Atrial Fibrillation/Flutter
	STK_4	Thrombolytic Therapy
	STK_5	Antithrombotic Therapy by the End of Hospital Day 2
	STK_6	Discharged on Statin Medication
	STK_8	Stroke Education
	STK_10	Assessed for Rehabilitation

Appendix B

Table 19: Robustness Check 1 – Alternative POSTit identification for already expanded states where I set POSTit equal 1 only if states expanded Medicaid coverage

	Model 6		
	Estimate	Pr(>|z|)	
Intercept	- 146.700	0.950	
Number of Hospitals	- 0.011	0.238	
Income per Capita	- 2.605	0.532	
GDP	- 0.286	0.919	
Population	11.780	0.010	***
Unemployment Rate	- 0.075	0.458	
POSTit2	- 0.934	0.000	***
State fixed effects	Yes		
Year fixed effects	Yes		
Number of observations	714		
AIC	1,017.20		
Residual Deviance	446.86		
Degrees of Freedom	644		

Table 20: Robustness Check 2: Exclusion of Small States where I exclude states with small number of hospitals from the data set

	Model 7		
	Estimate	Pr(>|z|)	
Intercept	- 148.500	0.949	
Number of Hospitals	- 0.009	0.355	
Income per Capita	- 2.823	0.502	
GDP	- 0.887	0.754	
Population	12.580	0.005	***
Unemployment Rate	- 0.100	0.316	
POSTit	- 0.768	0.004	***
State fixed effects	Yes		
Year fixed effects	Yes		
Number of observations	686		
AIC	1,018.60		
Residual Deviance	452.24		
Degrees of Freedom	618		

Table 21: Robustness Check 3: Test of Wisconsin where I treat Wisconsin as an expanded state

	Model 8		
	Estimate	Pr(>|z|)	
Intercept	- 145.173	0.950	
Number of Hospitals	- 0.008	0.373	
Income per Capita	- 2.995	0.475	
GDP	- 0.778	0.783	
Population	12.378	0.006	***
Unemployment Rate	- 0.102	0.307	
POSTit	- 0.745	0.005	***
State fixed effects	Yes		
Year fixed effects	Yes		
Number of observations	714		
AIC	1,023.00		
Residual Deviance	452.62		
Degrees of Freedom	644		

Table 22: Robustness Check 4: Inclusion of vector of dummies for parallel trend assumption

	Model 9		
	Estimate	Pr(>|z|)	
Intercept	- 153.100	0.948	
5 Years Before Expansion	Control	Control	
1 Year Before Expansion	0.174	0.565	
Number of Hospitals	- 0.008	0.358	
Income per Capita	- 2.974	0.499	
GDP	- 0.838	0.777	
Population	11.940	0.005	***
Unemployment Rate	- 0.105	0.282	
POSTit	- 0.772	0.011	**
State fixed effects	Yes		
Year fixed effects	Yes		
Number of observations	714		
AIC	1,025.90		
Residual Deviance	451.52		
Degrees of Freedom	642		

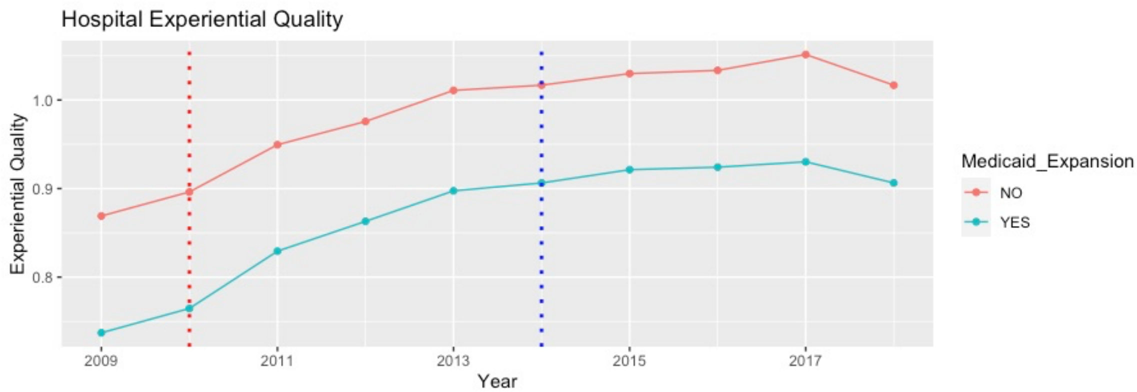

Figure 8: Hospital Experiential Quality - Parallel Trend. The blue line represents states that complied with the ACA-mandated Medicaid coverage expansion while the red line represents states that did not

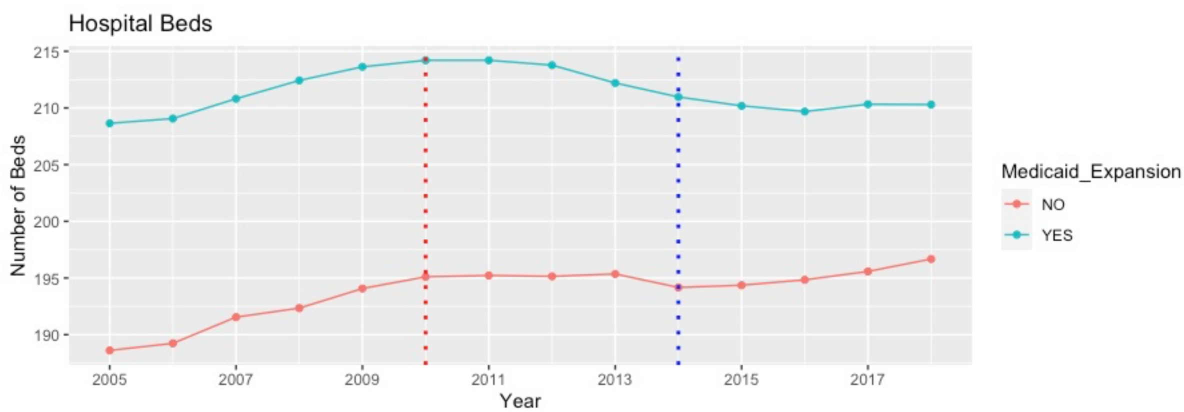

Figure 9: Hospital Beds - Parallel Trend. The blue line represents states that complied with the ACA-mandated Medicaid coverage expansion while the red line represents states that did not

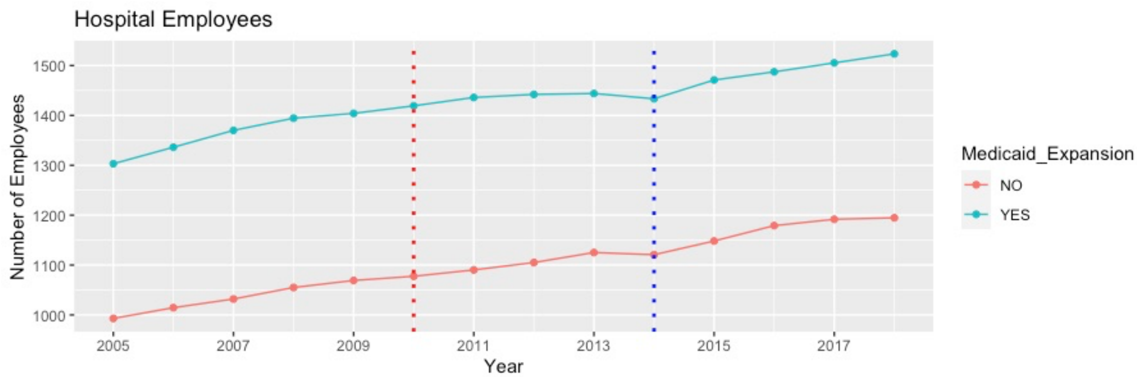

Figure 10: Hospital Employees - Parallel Trend. The blue line represents states that complied with the ACA-mandated Medicaid coverage expansion while the red line represents states that did not

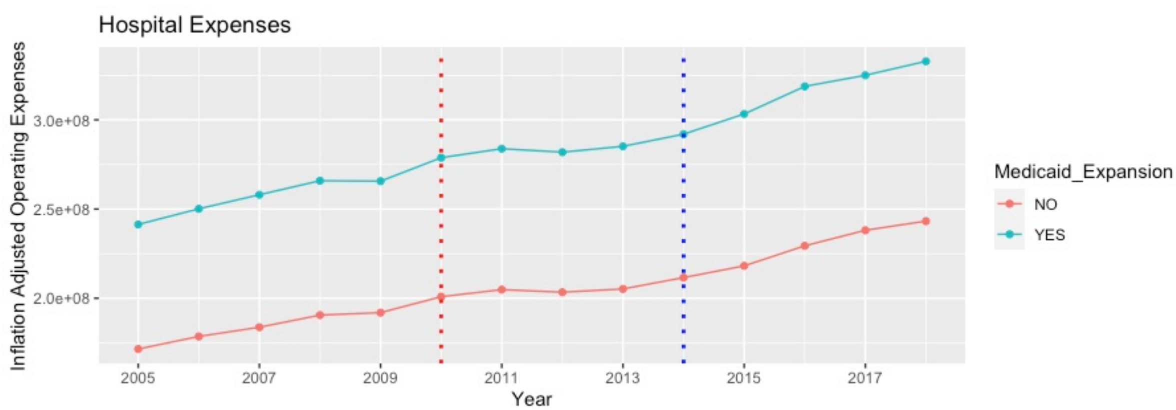

Figure 11: Hospital Expenses - Parallel Trend. The blue line represents states that complied with the ACA-mandated Medicaid coverage expansion while the red line represents states that did not

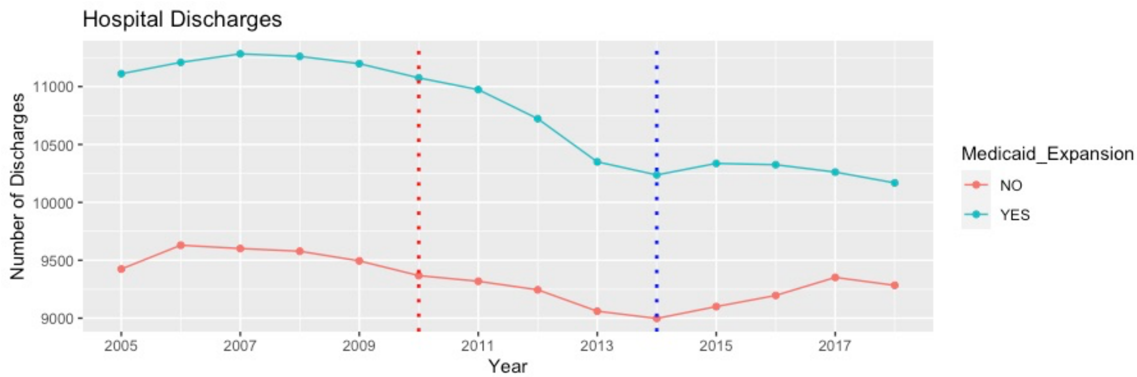

Figure 12: Hospital Discharges - Parallel Trend. The blue line represents states that complied with the ACA-mandated Medicaid coverage expansion while the red line represents states that did not

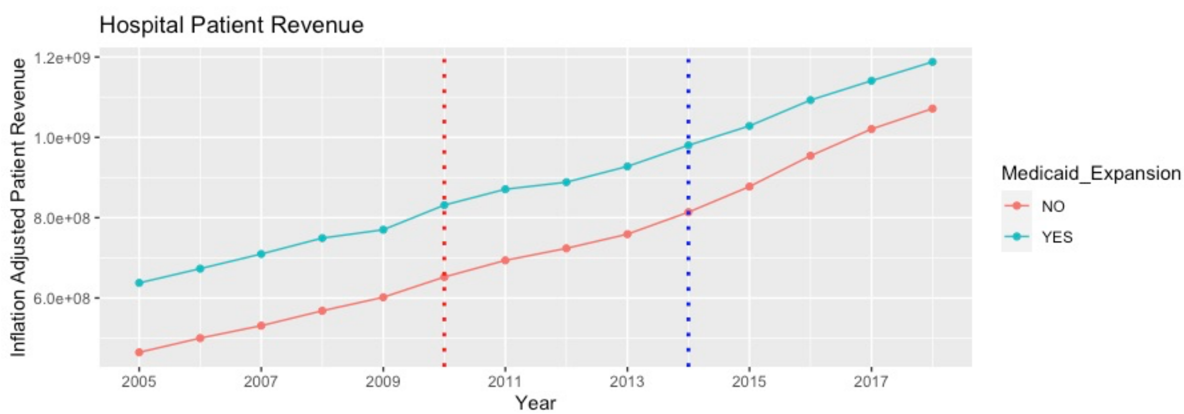

Figure 13: Hospital Patient Revenue - Parallel Trend. The blue line represents states that complied with the ACA-mandated Medicaid coverage expansion while the red line represents states that did not