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Lina Song
Harvard University

Soroush Saghafian
Harvard Kennedy School

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Do Hospital Closures Improve the Efficiency and Quality of Other Hospitals?

Lina D. Song[1], Soroush Saghafian[2]
[1]PhD Program in Health Policy, Harvard University, Cambridge, MA 02138
[2]Harvard Kennedy School, Harvard University, Cambridge, MA 02138

The recent trend in the U.S. hospital closures can have important impacts on the healthcare sector by changing the operational efficiency and quality of care of the remaining hospitals. We investigate the impact of hospital closures on the surrounding hospitals' efficiency and quality and shed light on mechanisms through which they can be affected. Using and combining various data sources, we find that when a hospital closes, its nearby hospitals improve their operational efficiency without expanding their resources. However, they do so via a speed-up behavior (i.e., by reducing their service durations) instead of an effort to lower their average bed idle time. Importantly, we find that this speed-up response to the increased demand by nearby hospitals negatively affects some (but not all) aspect of the care, including the 30-day patient mortality. Furthermore, hospital closures induce changes in directions that widen social disparity, as their adverse consequences fall disproportionately among hospitals or patients with limited resources. Our results have implications for both hospital administrators and policymakers who strive to improve the efficiency and quality of the healthcare system.

Key words: Hospital Closures; Healthcare Operations Management; Healthcare Quality; Hospital Efficiency
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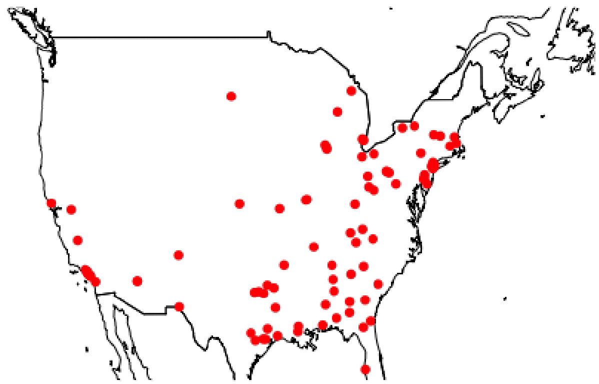
1. Introduction

There has been a substantial number of hospital closures in the U.S. in the past decade (Kaufman et al. 2016, Friedman et al. 2016, MedPAC 2017). Such closures have occurred in various states affecting a large number of people (see, e.g., Figure 1). Given that hospitals in the U.S. are facing an increasing number of challenges, including decreasing demand for inpatient services, elevated reimbursement rate pressures, and unpredictable changes in delivery patterns, the number of hospital closures is expected to rise (Kaufman et al. 2016, Bazzoli et al. 2014, Wertheim and Lynn 1993).

The increasing risk of hospital closures has fueled a debate on the need to implement policies that prevent them. Some argue that hospital closures are advantageous, and hence, should not be

Figure 1: Hospital Closures in the U.S. (2007–2014)



impeded: there are many inefficient or underutilized hospitals in the current system, and closures can improve efficiency by better aligning capacity with demand. Others point out that in many areas of the country, patients still experience difficulties in accessing care, and if not prevented, closures can aggravate this problem. These claims are not mutually exclusive, and both sides are supported by empirical evidence. Hospital closures can be cost-saving to the society by achieving economies of scale (Lindrooth et al. 2003, Capps et al. 2010). At the same time, hospital closures can negatively affect patients by increasing travel distance, reducing access, and potentially harming population health (Hsia et al. 2012, Liu et al. 2014, Buchmueller et al. 2006).

An essential but missing piece of information in this debate that can yield a better understanding of the implications of hospital closures is how they affect the efficiency and/or quality of care of the remaining hospitals in the same market. After hospital closures, patients and payers will have to rely on the remaining hospitals for care delivery, and it is often assumed that the remaining hospitals will not change their care delivery processes. Yet, hospital closures may alter the patient demand and patient mix for the remaining hospitals, and thus, the remaining hospitals may adjust their care delivery processes accordingly. In this paper, we examine the impact of hospital closures on (a) the operational efficiency, and (b) the quality of care delivered in nearby hospitals, and shed light on their implications for society.

Conventional theories from operations management predict a demand pooling effect: when a hospital closure occurs in a market, the nearby hospitals experience greater patient demand, and hence, there will be an improvement in overall utilization of resources such as hospital beds (Kleinrock 1976, Mandelbaum and Reiman 1998). However, the remaining hospitals can also behave strategically in response to the change in demand, and alter their delivery processes. For example, they may expand their capacity instead of serving more patients with their current capacity level. Even if a hospital treats more patients without increasing capacity, it can accommodate the increase in demand with various other mechanisms (e.g., by increasing service or bed utilization rate).

Furthermore, changes in patient demand and delivery patterns after hospital closures can result in changes in the quality of care delivered by the remaining hospitals. Many operations management studies suggest that the operational factors such as service time, waiting time, or efficiency can affect the quality of service (Fleming 1981, Hoot and Aronsky 2008), but the impact of hospital closures on the quality of care provided at the remaining hospital has not been examined. Instead, previous studies that have examined the effect of hospital closures on patient health outcomes focused on patients' limited access to care as a result of hospital closures (Hsia et al. 2012, Liu et al. 2014, Joynt et al. 2015, Buchmueller et al. 2006). Conditional on a patient receiving timely care after hospital closure, s/he can still experience a change in care quality at the remaining hospitals.

In particular, hospital closures may positively impact patient outcomes if the remaining hospitals improve their quality as a result of closures. This mechanism—quality improvement as a result of nearby hospital closures—can occur for at least two reasons. First, the remaining hospitals may improve their quality to prevent themselves from being closed. Second, the increase in demand may allow the remaining hospitals to improve their quality via learning-by-doing and related positive effects of volume on quality known as "volume-outcome effect" or "productivity spillover" (Ramanarayanan 2008, Chandra and Staiger 2007, Birkmeyer et al. 2002)). On the other hand, hospital closures can negatively affect patient outcomes in the remaining hospitals, if they cause them congestions, care delivery delays, or speed-up behaviors (Haas et al. 2018, Chan et al. 2016). Thus, in addition to studying the consequences of closures on the operational efficiency of the surrounding hospitals, we seek to contribute to the literature by providing some evidence and insights into whether and how hospital closures affect patient outcomes.

1.1. Framework

We focus on the U.S. short-term acute-care hospitals that serve patients with acute severe injury or episodes of illness. To investigate the impact of hospital closures on the operational efficiency of the remaining hospitals (our first goal), we define operational efficiency as a measure of how much output is produced per input. Specifically, we consider throughput per bed (i.e., the average number of patients served per bed per unit of time) as our measure of operational efficiency. We focus on beds as hospital resource, given that empty beds are the major contributors to low operational efficiency in hospitals (Keeler and Ying 1996, Gaynor and Anderson 1995). We first examine if hospitals experience an increase in volume following the closure of a nearby hospital. We then examine whether and how hospital closures lead to a change in operational efficiency. To identify the mechanism through which a change in operational efficiency might occur, we investigate changes in capacity, bed utilization, and service duration. Finally, to study the impact of hospital closures on patient outcomes in the remaining hospitals (our second goal), we consider measures such as patient experience, 30-day readmission rates, and 30-day mortality rates, all of which are widely-accepted measures for hospital care quality (Benbassat and Taragin 2000). For both our first and second goals, we also identify the heterogeneous effects of closures on different hospital and patient types and generate insights into variations in the closure effect that might elevate care disparities in the society.

1.2. Data and Empirical Challenges

There are several challenges for estimating the impact of hospital closures on efficiency and patient outcomes. First, there has been limited data on U.S. hospital closures. To our knowledge, no central data keeps track of U.S. hospital closures, although some studies examine rural hospitals closures or closures in specific geographic areas (Kaufman et al. 2016, Lindrooth et al. 2003, Capps et al. 2010). To overcome this limitation, we have independently identified the closed hospitals through own research and validation. As an example, we first identified potentially closed hospitals through Medicare Provider of Service (POS) data and Medicare fee-for-service (FFS) claims data and verified each closure separately through multiple sources including local news, state department documents, or findings from research institutions. Then we used a nationally representative, multi-year patient, hospital, and market level data to improve the generalizability of our findings. Specifically, we used the 20% sample of Medicare FFS claims data to obtain information on each inpatient visit, and then linked this dataset to our hospital (from POS, Hospital Compare, and the Hospital Consumer Assessment of Healthcare Providers and Systems, or HCAPHS) and market[1] (from Area Health Resource Files, or AHRF) data. Our final dataset after combining these data sources (and cleaning them) include 173 closed and 3,517 open hospitals across nine observation years for patient outcomes and 14 observation years for hospital outcomes along with more than 4.9 million inpatient visits (Table 1).

Another challenge in studying the impact of hospital closures is that hospital closure is not exogenous but is correlated with both the market structure and patient characteristics (Succi et al. 1997, Hsia et al. 2011). Such endogeneity among patients, hospitals, and markets can bias the OLS estimate of the hospital closure effect on the outcomes of our interest. To overcome this challenge, we use an extensive set of covariates including patient level data such as utilization patterns and diagnostic history, as well as hospital and area level data such as spending, provider concentration, and the insurance market structure. We also utilize the substantial geographic variation and the timing of U.S. hospital closures along with a multilevel panel data to make use of difference-in-

[1] For our primary analysis, we define a market as the Hospital Referral Regions (HRRs).

Table 1: Overview of Our Final Data

	Number of observations
Hospitals	3,517
Closed hospitals	173
Patients	1,948,833
Inpatient visits	4,906,186
Years (hospital closure)	8
Years (hospital outcomes)	14
Years (patient outcomes)	9
Markets	306

difference (DID) analysis with hospital and market fixed effects as our main empirical strategy. The DID analysis has enabled us to use both cohort and time dimensions, and thereby, adjust for time-invariant unobserved confounders. In addition to our primary analysis, we test for the robustness of our findings through various methods. These include (a) a matched sample that improves the comparability of the comparison groups, and (b) an instrumental variable (IV) analysis that utilizes the state level variation in the decision to expand Medicaid after the Affordable Care Act (ACA) to address potential time-varying unobserved heterogeneity.

1.3. Main Findings

Our results show that when a hospital closes, the nearby hospitals experience an increase in their average number of inpatients served. We find that these hospitals accommodate the increase in demand by improving their operational efficiency (i.e., the number of patients treated per unit of capacity) instead of expanding their resources. Interestingly, this improvement in efficiency is despite the fact that their bed utilization rates remain relatively constant, and is mainly due to a reduction in their average inpatient length of stay. This implies that a speed-up behavior rather than an effort to lower the average bed idle time is the primary mechanism through which nearby hospitals respond to the increase in demand. Furthermore, we find that hospital closures are associated with a substantial increase in patients' 30-day mortality rate of nearby hospitals, which suggests that the speed-up behavior has negative consequences for patients. On the positive side, however, our findings show that hospital closures do not negatively affect other dimensions of quality such as patient experience or 30-day readmission rates. Finally, we find that the effect of hospital closures on both patients and hospitals is heterogeneous, and this heterogeneity is in a direction that can increase social disparities. For example, we observe that sicker or lower-income patients are typically more affected by hospital closures than other patients. Similarly, hospital closures tend to increase the existing efficiency gap between more desirable hospitals (e.g., teaching, urban, non-profit, and large hospitals) and less desirable ones (e.g., non-teaching, rural, for-profit, or small hospitals).

Overall, our results suggest that while hospital closures are effective at improving the operational efficiency of the remaining (and nearby) hospitals, these hospitals do not necessarily improve their efficiency in the most desirable way. In particular, the improvement in operational efficiency—serving more patients per unit of capacity—is not due to more effective use of beds (i.e., reducing idle times), but rather due to spending less time on each patient. Spending less time on each patient may not necessarily be undesirable if it eliminates non-value adding procedures. In fact, the absence of any changes in patient experience and 30-day readmission may indicate that such a change in hospital operations do not have an impact on the immediate or visible aspects of the care delivery or the subjective judgment of the patient. However, our finding—the fact that the reduction in service duration is associated with an increase in 30-day mortality—suggests that some of the value-added procedures might have been eliminated as well.

Put together, our findings indicate that the benefits from the demand pooling effect of closures are negated by the hospitals' response in reducing service durations, which in turn negatively impacts some (but not all) aspects of quality of care. Hospital closures also widen social disparities: the adverse consequences unfortunately fall disproportionately among hospitals or patients with limited resources.

1.4. Main Contributions

The contributions of our study are four-fold. First, it contributes to the literature in health services research and in particular to the evaluation of the impact of provider market changes on the quality of care delivery. Hospital closure is one of the noticeable ongoing changes in the U.S. healthcare system, but evidence on its impact on the quality of care has been limited. Second, our study contributes to the operations management literature on (a) pooling in a queueing system, and (b) the empirical investigation of server behaviors. Specifically, it contributes to the operations management literature on pooling benefits when there are dissimilarities between the pooled activities (see, e.g., Joustra et al. (2010), Saghafian et al. (2012, 2014), Staats and Gino (2012), and the references therein). Furthermore, although there has been attention on understanding the server's behavioral responses to changes in the queue characteristics (see, e.g., Hopp et al. (2007), Song et al. (2015), and the references therein), studies have focused on the micro level behaviors of individuals who behave as servers. In contrast, our study examines behaviors at an organization level. Third, our results have important policy implications for the ongoing debate on the U.S. healthcare delivery system reform. Recently, some policymakers have argued against the payment mechanisms that support inefficient or financially unsustainable hospitals that rely on government subsidies, but the limited evidence on the implications of hospital closures has impeded clear policymaking. By drawing rigorous evidence from nationally representative data, our study provides insights into the impact of hospital closures in a way that can be informative to policymakers. Finally, our results can also have significant managerial implications for hospital administrators. In particular, with increasing pressure on hospitals to achieve greater cost efficiency under tighter budgets, it is exceedingly important for hospital administrators to understand the implications of nearby hospitals' closures, and accordingly revise their management strategies.

2. Conceptual Framework and Hypotheses

2.1. Changes in Efficiency

We first examine if the closure of a hospital in a market results in a redistribution of patient demand to the other open hospitals. Evidence from health economics literature indicates that the demand for medical care can be induced by the supplier (Fuchs 1978, McGuire 2000). In case of hospital closures, patients may stop seeking care instead of choosing an alternative hospital after the closure of their primary hospitals. Even if patients continue to seek care at nearby hospitals, hospitals may strategically limit their care provision. In particular, they may secure different levels of capacity slack to prepare for the stochastic and fluctuating patient demand, and reduce unintended patient delay and turn-aways (Green and Nguyen 2001, Joskow 1980). On the other hand, hospitals that are nearby a closing hospital may experience an increase in demand, given the distance is influential for patients' hospital choice (Hsia et al. 2012, Capps et al. 2010). Thus, we first examine whether or not hospitals in a market experience an increase in overall demand after a nearby hospital's closure. We do so by formally testing the following:

Hypothesis 1. *A hospital closure increases the patient volume of the remaining hospitals in the same market.*

Our results mainly confirm this hypothesis. Hence, we next examine how the hospitals change their operations to meet the increased demand. There are at least two mechanisms through which a hospital can treat more patients per given time (Litvak and Bisognano 2011). First, hospitals may change their resource level such as expanding their number of beds. However, we presume that such a change is unlikely to happen for various reasons, including restrictive regulations imposed on hospital bed supply (e.g., a Certificate of Need, or CON) in most states. To gain a better understanding, we formally test whether or not there are any changes in the capacity level (beds) of nearby hospitals following the closure. Second, instead of increasing capacity, hospitals may increase their operational efficiency to treat more patients with their current level of resources. To gain insights into these issues, we measure the number of patients treated per bed, and test the following:

Hypothesis 2. *A hospital closure does not lead to a change in the number of beds of the remaining hospitals in the same market.*

Hypothesis 3. *A hospital closure increases the operational efficiency of the remaining hospitals in the same market.*

2.2. Mechanisms of Changes in Efficiency

Our first three hypotheses will enable us to test whether the closures have favorable or unfavorable overall impacts on the operational efficiency of the remaining hospitals. However, they will not generate a detailed understanding of possible mechanisms through which remaining hospitals change their operational efficiency following a nearby hospital's closure. There are at least two mechanisms that we shall study to investigate such mechanisms. First, hospitals may increase their bed utilization rate (i.e., accommodate the increased demand by lowering their bed idle times) without making any change in service durations. Second, hospitals may decrease their service durations (e.g., by eliminating non-value added and/or value-added processes during hospitalization). The first mechanism does not require significant investments by a hospital, so it is typically considered a desirable way of improving operational efficiency. However, if the increase in demand is substantial, this mechanism alone might not be sufficient. Thus, it is possible that a hospital uses a combination of these mechanisms.

Conceptualizing a hospital as a general queueing system with s beds that play the role of servers, the throughput per bed λ/s—our measure of efficiency—can be expressed as $\lambda/s = \rho * \mu$, where ρ is the bed utilization, and μ is the service rate. This implies that when s remains constant, an increase in throughput corresponds to a change in one or both of the above-mentioned mechanisms: either (a) an increase in ρ, (b) an increase in μ, or (c) an increase in both ρ and μ.[2] To test these mechanisms empirically, we form two more hypotheses: one with respect to bed utilization and one with respect to service duration. We next discuss each of these separately.

Bed Utilization: Hospitals may increase their bed utilization rate to accommodate a greater number of patients per unit of time per resource. However, hospitals may strategically choose not to raise their bed utilization rate for multiple reasons, including preparation for demand uncertainty (Joskow 1980, Green and Nguyen 2001). To gain insights into the effect of hospital closure on the bed utilization rate, we examine the following:

Hypothesis 4. *A hospital closure changes the bed utilization rate of the remaining hospitals in the same market.*

[2] Of note, an increase in efficiency may indicate a decrease in either ρ or μ while a much increase in the other.

Service Duration: When a hospital faces a need to be more efficient, the providers may face the pressure to perform at a higher efficiency level. Operations management literature suggests that servers can indeed be strategic about the service duration under financial and nonfinancial motivations, and alter their behavior based on the characteristics of the queue (Cachon and Zhang 2007, Debo et al. 2008, Hopp et al. 2007, Jouini et al. 2008, Tan and Netessine 2014, Oliva and Sterman 2001). In particular, the visibility of the queue length or the server occupancy rate can encourage a speed-up behavior by servers (Kc and Terwiesch 2012, Shunko et al. 2017). In our setting, providers do not have full visibility of the entire queue, and hence, it is not clear to what extent the overall average service duration in their hospital changes. To examine whether or not a hospital (as a whole) responds to the increased demand caused by a nearby hospital closure by reducing its service duration, we analyze inpatient length of stay both before and after closure. To this end, we test the following:

Hypothesis 5. *A hospital closure changes the average service duration for the inpatient services of the remaining hospitals in the same market.*

2.3. Hospital Closure and the Care Quality

Changes in volume and operational efficiency can affect the quality of care. Congested hospitals are typically more vulnerable to provider errors and often less able to respond to a patient promptly, resulting in added risk to patient safety (Weissman et al. 2007, Haas et al. 2018). Patient satisfaction may decline as well (Thompson et al. 1996). On the other hand, an increase in patient volume can result in better quality of care. One way this can occur is the well-established "productivity spillover" effect, in which healthcare providers improve quality of care and patient outcomes with increased production experience (Chandra and Staiger 2007). Similarly, an increase in patient volume can provide more opportunities for hospitals to learn and improve their quality (Begg et al. 1998, Birkmeyer et al. 2002, Hillner et al. 2000).

To gain a deeper understanding of the effect of hospital closure on care delivery of other hospitals, we mainly focus on two dimensions of quality: patient experience and patient health outcomes. We examine the first dimension—patient experience—using a national survey of patient experience. For the second dimension—patient health outcomes—we measure readmission rates as well as 30-day mortality rates, the two widely-used outcome measures for inpatient services[3]. Thus, to investigate the effect of hospital closures on quality, we test the following:

[3] The readmission rate is known to be useful for identifying signs of poor inpatient care quality and care coordination (Benbassat and Taragin 2000, Halfon et al. 2006), and the 30-day mortality rate is a well-validated measure of care quality for the type of patients we consider in our study (Tourangeau et al. 2007).

Hypothesis 6. *A hospital closure changes the patient experience of those who received care in the remaining hospitals in the same market.*

Hypothesis 7. *A hospital closure changes the 30-day readmission rate of those who received care in the remaining hospitals in the same market.*

Hypothesis 8. *A hospital closure changes the 30-day mortality rate of those who received care in the remaining hospitals in the same market.*

3. Related Studies

Our work is relevant to the following streams of literature in management science and health economics. First, our work is related to the studies examining how the changes in provider market structure (in particular, the regulation and changes in provider supply) affect the efficiency of the healthcare delivery system. Various studies have found that the amount or structure of provider supply such as the degree of provider density, competition, or regulation can affect the efficiency of the healthcare delivery system (Bates et al. 2006, Rosko and Mutter 2014, Thompson et al. 2012). There are, however, much fewer studies investigating the changes in the supply due to an exit of providers from the market. Early evidence suggests that hospital closure reduces the costs per admission of nearby hospitals through an increase in inpatient admissions, suggesting the existence of economies of scale (Lindrooth et al. 2003, Capps et al. 2010). Yet, another study suggests that hospital closures merely shift high-cost patients to the remaining hospitals instead of improving efficiency (Hodgson et al. 2015). A recent study provides a nuanced perspective by arguing that there are positive or negative economies of scale effect depending on the type of services offered at a hospital (Freeman et al. 2018). Our study is related to this stream of research: we examine the mechanisms through which hospitals' responses to a sudden change in patient demand affect the economies of scale. However, unlike the studies mentioned above, instead of focusing on cost measures, we study the implications on operations and quality.

Second, our study is relevant to the literature on the impact of provider market structure on healthcare quality. Among studies in this vein, our work mainly contributes to those that examine how the reduction in healthcare resources affects the quality of care. A relatively small body of the literature has studied the impact of hospital or emergency department closure on access to care or health outcomes for the patient population in the area (Joynt et al. 2015, Buchmueller et al. 2006, Capps et al. 2010, Hsia et al. 2012, Liu et al. 2014). However, there is limited and mixed evidence on the overall impact of hospital closures on patient outcomes. For example, between two published studies, one shows that hospital closures increase deaths from heart attacks and unintentional injuries (Buchmueller et al. 2006), whereas the other shows that there is no significant difference between the change in mortality or readmission rates (Joynt et al. 2015). In general, measuring the overall impact of closures on the population can result in different findings, as there are multiple channels through which patient health can be affected by hospital closures. Our study contributes to the literature by studying important mechanism through which hospital closures can affect patient health outcomes.

Lastly, our work is related to a growing body of literature on the behavior of servers in queueing systems when queues of customers or servers are pooled in service organizations (see, e.g., Rothkopf and Rech (1987), Boudreau et al. (2003), and the reference therein). Previous studies show that the server's behavioral responses to the queue characteristics can play a crucial role in changing the expected benefits of queue pooling (Cachon and Zhang 2007, Debo et al. 2008, Do et al. 2015). The service behavior can be affected by financial incentives, i.e., how the servers are compensated, or non-financial incentives such as the number of customers and a sense of ownership (Schultz et al. 1998, Debo et al. 2008, Song et al. 2015, Shunko et al. 2017). Because our study views the behavior of a server in a queueing system at a macro level—the hospital as a whole—the existing mechanisms through which behavioral responses appear may not be immediately transferable. The evidence on the collective behavior of an organization (as an aggregated server) in response to the increase in demand has been examined less frequently. Thus, our paper contributes to the literature by examining whether or not the individual level behavioral response matches that of the macro level.

4. Data and Study Sample

4.1. Data

We obtained patient, hospital, and market level information by linking various data sources. Our hospital level information is from Medicare Cost Reports and POS data for years 2004-2017. These data are collected from hospitals that serve Medicare patients and contain information on facility characteristics, healthcare use, and cost. To obtain the patient level information, we used a panel data of FFS Medicare inpatient claims for years 2004-2012. Medicare inpatient claims provide information on all FFS inpatient services use, the types of procedures performed, and diagnosis through International Classification of Diseases (ICD-9) and Healthcare Common Procedure Coding System (HCPCS). We used the Medicare Beneficiary Summary File (BSF) for individual beneficiary's sociodemographic information. We used AHRF for the county level information on health services resources and demographic information, and the Hospital Compare data from the Centers for Medicare & Medicaid Services (CMS) for hospital quality and the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) for patient experience. For our primary analysis, we defined markets based on Hospital Referral Regions (HRRs). We used HRRs instead of other definitions of a healthcare market such as Hospital Service Areas (HSAs) to ensure there are more than one remaining short-term acute care hospitals after closure in each market.

4.2. Identifying Hospital Closures

We defined hospital closure as ceasing to deliver short-term general hospital services. Because we focus on the demand pooling effect, we defined closure based on the continuum of care rather than the changes in the ownership or physical appearance of a hospital. Thus, if a hospital remained in the same physical location but ceased to provide short-term acute care and converted to a different use such as emergency department, rehabilitation facility, or long-term care, we regarded it as closed. However, absent such changes, if a hospital merely changed its name or ownership but stayed in the same physical location, we considered the hospital to be in operation.

To identify potential closures, we first used the Medicare POS data. Specifically, we regarded a hospital as potentially closed if it did not appear in the POS data after a certain year[4]. Next, we calculated the number of claims submitted each year from Medicare inpatient claims. Using these claims, we identified a hospital as potentially closed if its number of hospitalizations has dropped to zero. Among the list of potential closures that met either of our criteria, we then excluded the hospitals that are not short-term acute care hospitals, such as long-term care and psychiatric hospitals[5]. Finally, we systematically searched and validated each hospital's operating status through multiple external sources including local news, state department documents, or a list of rural hospital closures from other research institutions[6]. In a few cases where the evidence was not available or definitive, we called the hospital directly. We were eventually able to confirm the operating status of all hospitals on our list. Figure 2 shows the steps through which we determined hospital closure. In summary, there were 370 potentially closed hospitals, among which we could verify a total of 173 closures[7] across 105 markets between 2007-2014. In general, the closed hospitals had a lower volume, number of beds, efficiency, and bed utilization than the rest (see Table 3 of the Online Appendix). All markets have more than one remaining open hospital after a closure event.

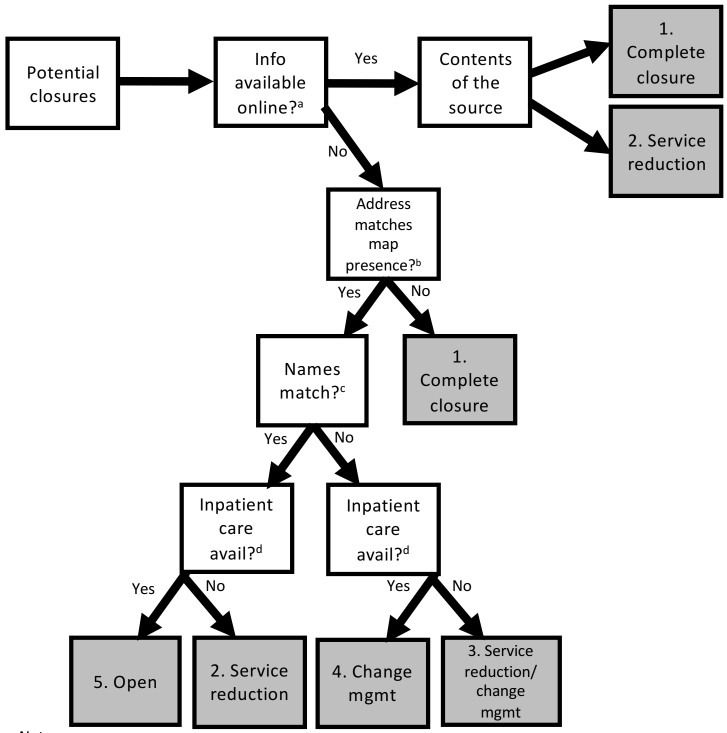
[4] Because virtually all hospitals in the United States, with the exception of military hospitals, participate in the Medicare program, discontinuation of data or claims submission to the CMS suggests it is highly likely that the hospital has experienced changes in operating and/or ownership status.

[5] We excluded these types of hospitals because these hospitals primarily treat chronic patients who have different medical needs and care patterns than the general population.

[6] These sources include a list of rural hospital closures from the University of North Carolina Rural Health Research and Policy Analysis Center and Becker's Hospital Review.

[7] The remaining 197 potentially closed hospitals were confirmed open after the validation process.

Figure 2: The General Procedure for Identifying Hospital Closures.



Notes.

a. Google searched “Name” + “Closure/merger” for information on closures from local news, Yelp, or Wikipedia.
b. Examined the physical presence through google map streetview and the date.
c. Do names of the physical building and the original source match?
d. Checked the hospital’s website to see if inpatient care is available. If the information is not available online, called the hospital.

4.3. Study Sample

Our study sample of hospitals included all the Medicare participating U.S. hospitals that were in operations throughout the study period, which is 2004-2017 for the hospital level outcomes and 2004-2012 for the patient level outcomes. Among our sample, we considered hospitals located in a market that experienced at least one closure during the study period as “treated,” and those that did not experience any closure as “control.” We removed the hospitals in the markets that experienced closures across multiple years, because these hospitals may have concurrently experienced pre- and post-closure effects.

Figure 3 shows the timeline of hospital closures for hospital and patient outcomes, respectively. For each hospital in the treatment group, we defined the index year as the year of a nearby hospital’s closure. We observed the outcomes for three years pre- and post-closure to capture the long-term impact of closures, and excluded the information from the index year to account for the noise during the transition period. Because there were shorter observation years for the Medicare claims data which were used to obtain the patient level outcomes, we were not able to observe the patient level outcomes for the closures in 2012, and the post-observation periods for closures occurred during 2010-2011 were shorter than three years. We addressed this discrepancy in the observation period by performing sensitivity analyses (see Section 6.6). For each hospital in the control group, we included the observation for all years in 2004-2017 for hospital outcomes and in 2004-2012 for patient outcomes.

For our patient level analysis, we considered the study population to be the FFS Medicare beneficiaries who paid at least one visit to the hospitals in our study sample. To improve the comparability, we further restricted the patient population to those who were aged 65 or older, did not have a disability, and were entitled to Medicare due to age[8]. Because patient's treatment status was based on the treatment status of the hospital they visited, a patient was allowed to be counted in both treatment and control groups if s/he made multiple visits to both treatment and control hospitals. We excluded transfers to or from another hospital, admissions for rehabilitation, and emergency department visits that did not result in inpatient admissions from the analysis[9]. There were a total of $1,852,552$ patients in our final sample, and they paid total $4,563,769$ inpatient visits during our study period.

4.4. Dependent Variables

Our dependent variables include four operational measures (volume, beds, efficiency, utilization) and four service or quality measures (service duration, patient experience, readmission, and mortality). Table 2 shows the definition of these variables, source, and their corresponding hypothesis. For utilization, we used the yearly average to address the seasonal and weekly variation in the bed census due to varying patient demand. For service duration[10], we excluded the observations with values greater than 30 days, as our goal is to examine the impact of closures on short-term acute care. For measuring 30-day readmission, we considered inpatient claims that were within 30 days of a previous hospitalization's discharge date. For measuring 30-day mortality, we obtained death information from the Medicare denominator files and calculated the time to death as the number of days between the index discharge date and the date of death. We linked a hospitalization to an incidence of 30-day mortality if death was present within 30 days after discharge.

To study patient experience, we used the HCAHPS survey data collected by CMS. HCAHPS is a national publicly reported survey for patients' perceptions of their hospital experience and is

[8] Although Medicare eligibility age is 65, Medicare also covers a small fraction of people under 65 with disabilities.

[9] Transfer patients were identified as those with the source of inpatient admission code "transfer from a different facility", "transfer from ER", or "transfer from the same facility". Admissions for rehabilitation were identified from the presence of ICD-9 codes indicating care involving the use of rehabilitation procedures: V570, V571, V5721, V573, V5781, V5789, V579, and 462.

[10] We were able to measure the service duration in units of days, but not in units of hours, because the claims data does not provide the exact time of admission and discharge.

Figure 3: Timeline of Hospital Closures for (a) Hospital Outcomes (Top), and (b) Patient Outcomes (Bottom)

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
2007 closure	Pre-closure years			Closure year	Post-closure years			Observations removed						
2008 closure	Obs. removed	Pre-closure years			Closure year	Post-closure years			Observations removed					
2009 to 2012 closure						...								
2013 closure	Observations removed						Pre-closure years			Closure year	Post-closure years			Obs. removed
2014 closure	Observations removed							Pre-closure years			Closure year	Post-closure years		

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012
2007 closure	Pre-closure years			Closure year	Post-closure years			Observations removed	
2008 closure	Obs. removed	Pre-closure years			Closure year	Post-closure years			Obs. removed
2009 closure	Observations removed		Pre-closure years			Closure year	Post-closure years		
2010 closure	Observations removed			Pre-closure years			Closure year	Post-closure years	
2011 closure	Observations removed				Pre-closure years			Closure year	Post-clos. year

Table 2: Definition of Outcome Variables and Data Sources

Outcome variable	Name	Definition	Source	Hypothesis
Volume	VOL_{jt}	Total number of patients discharged from hospital j in year t.	Medicare cost report, POS	1
Inpatient beds	BEDS_{jt}	Total number of inpatient beds for hospital j in year t.	Medicare cost report, POS	2
Efficiency	EFFIC_{jt}	Total number of patients discharged per hospital beds per year, i.e., $\frac{\text{VOL}_{jt}}{\text{BEDS}_{jt}}$.	Medicare cost report, POS	3
Utilization	UTIL_{jt}	Total bed days per available bed days per year, i.e., $\frac{\text{DAYSUSED}_{jt}}{\text{DAYSAVAIL}_{jt}}$, where DAYSUSED_{jt} is the total number of bed days used and DAYSAVAIL_{jt} is $\text{BEDS}_{jt} \times 365$ for hospital.	Medicare cost report, POS	4
Service duration	SERV_{ijt}	Number of days between patient admission and discharge.	Medicare inpatient claims	5
Patient experience	EXPER_{jt}	Proportion of patients who rated the total experience of his/her inpatient visit as high (9 or 10 out of values from 0 to 10) from the HCAHPS survey.	HCAHPS	6
Readmission	READM_{ijt}	A binary variable from the presence of another hospitalization within 30 days after discharge.	Medicare inpatient claims	7
Mortality	MORT_{ijt}	A binary variable for the presence of evidence of death within 30 days after discharge.	Medicare inpatient claims	8

obtained by asking discharged patients questions about their hospital stay (see, e.g., Manary et al. (2013)). We used the overall patient's rating of the experience (1 for lowest and 10 for highest) as a primary outcome measure. Because we do not observe individual level responses, we defined a hospital's overall rating as the total percentage of patients who gave "high" ratings (overall rating of 9 or 10). We also examined the secondary outcomes from each of the 10 core questions about patients' hospital experiences [11]. We excluded the hospitals that received fewer than 100 survey responses in a given year for this part of the analysis. For measuring overall hospital quality, we used Hospital Compare data provided by the CMS (CMS 2018), which provides more comprehensive measures of hospital quality (see Section 4.5).

4.5. Independent Variables

Table 3 shows the definition and sources of the independent variables we used to control for potential confounders and examine effect heterogeneity.

Patient Characteristics: To control for patient heterogeneity, we included demographic characteristics such as age, gender, race, a reason for Medicare eligibility, and the Medicare-Medicaid dual eligibility ("dual-eligible beneficiaries, or duals") which is often used as a proxy for low-income status. We obtained the total number of chronic conditions a beneficiary had in the previous year from the chronic conditions segment of the Medicare BSF. We calculated patient comorbidities using the Charlson Comorbidity Index (Elixhauser Comorbidity classification) from the patient's diagnosis history. The scores range from 0 (lowest severity) to 21 (highest severity) and capture the presence of 30 comorbidities (Elixhauser et al. 1998). Using these scores allows us to control for the variation in patient health. To adjust for the beneficiary's preference for preventive service use, we included whether or not s/he received a pneumococcal vaccination, which is recommended by the Centers for Disease Control and Prevention (CDC) for immunocompetent adults aged 65 years and older. We categorized the admission into three types, i.e., emergent, urgent, and elective, according to the admission type variable on claims. We also divided the admissions into 15 clinical categories based on the primary diagnosis codes[12].

Hospital Characteristics: We obtained relevant hospital characteristics including the size, academic status, ownership, and location[13], and baseline quality. Academic status was identified by whether the hospital received any payment from the Graduate Medical Education (GME) program or Indirect Medical Education (IME) program, which pays hospitals for education and training. We also included an indicator for receiving payment for the Disproportionate Share Hospital (DSH) Payments program, which funds hospitals that treat needy patients. Hospital quality was mea-

[11] These questions include communication with nurses and doctors, the responsiveness of hospital staff, the cleanliness and quietness of the hospital, pain management, communication about medications, discharge information, overall rating of hospital, and whether the patient would recommend the hospital. See Goldstein et al. (2005).

[12] These categories include: infections and parasitic diseases, neoplasms, endocrine, nutritional and metabolic diseases, and immunity disorders, diseases of the blood and blood-forming organs, mental disorders, diseases of the nervous system and sense organs, diseases of the circulatory system, diseases of the respiratory system, diseases of the digestive system, diseases of the genitourinary system, diseases of the skin and subcutaneous tissue, diseases of the musculoskeletal system and connective tissue, congenital anomalies, symptoms, signs, and ill-defined conditions, and injury and poisoning (Centers for Disease Control and Prevention (2013)).

[13] A hospital is rural if its zip-code based Rural-Urban Commuting Area code is greater than 4, or if it was designated as a critical access hospital (CAH), following previous literature (see, e.g., Hart et al. (2005)).

Table 3: Definition of Control Variables and Data Sources

Variable	Description	Data source
Patient characteristics		
Age	Numeric, from 64 and up.	Medicare BSF
Gender	Binary, male or female.	Medicare BSF
Race	Factor, white, black, hispanic, asian, or others.	Medicare BSF
Medicare entitlement	Factor, age, disability, or both.	Medicare BSF
Medicaid eligibility	Binary, dual or non-dual.	Medicare BSF
Comorbidity	Numeric, from 0 (least severe) to 21 (most severe).	Medicare inpatient, outpatient claims
Admission type	Factor, 15 clinically meaningful categories.	Medicare inpatient claims
Hospital characteristics		
Size	Factor, 0-25, 26-100, 101-250, 251+	Medicare cost report, POS
CAH	Binary, CAH or not CAH.	Medicare cost report, POS
Academic status	Binary, teaching or non-teaching hospital.	Medicare cost report, POS
Ownership	Binary, private and public.	Medicare cost report, POS
Location	Binary, rural or urban.	Medicare cost report, POS
DSH	Binary, participate or not participate in DSH program.	Medicare cost report, POS
Quality	Numeric, from 1 (lowest) to 5 (highest).	Hospital Compare data
Market characteristics		
Managed care penetration	Numeric, from 0 (no penetration) to 1 (full penetration).	Medicare BSF
Provider supply	Numeric, number of providers/hospitals per 10,000 persons.	AHRF
Unemployment rate	Numeric, from 0 (full employment) to 1 (full unemployment).	AHRF
Poverty rate	Numeric, from 0 (no poverty) to 1 (full poverty).	AHRF
Population over age 16	Numeric, from 0 (no population above age 16) to 1 (all population above age 16)	AHRF

sured from the publicly available Hospital Compare data provided by the CMS, which draws detailed information on hospital quality from multiple sources, including hospital submitted electronic health records, surveys, and Medicare claims data. The data includes 57 quality measures across seven areas of quality and provides an overall rating as well as quality ratings on different dimensions of care. We used the overall rating which can have values from the lowest one star (5.7% of the total hospitals) to the highest five stars (7.36% of the total hospitals).

Market Characteristics: We included various market level factors that could influence the operations of hospitals. First, health economics literature shows that differences in care delivery and quality may exist between managed care and FFS insurance plan types, and the presence of managed care type plan in an area may have a spillover effect on care delivery into the rest of the non-managed care population (see, e.g., Miller and Luft (1997), Baicker et al. (2013), and the references therein). Thus, we included the yearly county level penetration rate of Medicare managed care plans by calculating the proportion of beneficiaries enrolled in any Medicare Advantage (i.e., Medicare's managed care type plans) out of total Medicare beneficiaries each year. Second, to control for the changes in the degree of market competition, we constructed the Herfindahl-Hirschman indices (HHIs) for hospitals, a standard economic measure of concentration, for each market (i.e., HRR) per year. Third, the level of the provider supply may affect the bed utilization and efficiency. Thus, we adjusted for the area level provider supply such as the total number of primary care physicians, hospital beds, and acute care hospitals per 10,000 persons from AHRF.

Lastly, to adjust for any macro level socio-demographic factors, we controlled for the proportion of population unemployed, in poverty, or aged 16 or older for each county from AHRF.

5. Main Empirical Analysis

5.1. Empirical Strategy Overview

Our main empirical strategy is a DID approach with hospital, market, and year fixed effects to examine the changes in hospital and patient outcomes before and after a hospital closure event. This approach allows for controlling observed and unobserved heterogeneity between the treatment and control group that is constant over time. If the parallel trend assumption is met, DID analysis can provide causal interpretation of the treatment effect. We used a fixed effects model instead of a random effects model because the hospital or market level effects are likely correlated with the observed patient or hospital characteristics. We used hospital level instead of patient level fixed effect since a large proportion of patients had only one hospital visit. Although the treatment status is determined at the market level, we included hospital fixed effects, because patients of different characteristics or conditions may select into different hospitals within the same market. We used a robust standard error clustered by the hospital and the market to account for the within-hospital and within-market correlation of error terms.

We employed the following model for testing hospital level outcomes (hypotheses 1-4 and 6):

$$Y_{jkt} = \alpha \mathbf{X_{jt}} + \beta \text{POSTCLOSURE}_{kt} + \gamma \mathbf{Z_{kt}} + \text{HOSPITAL}_j + \text{MARKET}_k + \text{YEAR}_t + \epsilon_{jkt}. \quad (1)$$

To test patient level outcomes (hypotheses 5,7, and 8), we utilized the following model:

$$Y_{ijkt} = \alpha \mathbf{X_{ijt}} + \beta \text{POSTCLOSURE}_{kt} + \gamma \mathbf{Z_{kt}} + \text{HOSPITAL}_j + \text{MARKET}_k + \text{YEAR}_t + \epsilon_{ijkt}. \quad (2)$$

In both models (1) and (2), Y represents the outcome variables, POSTCLOSURE is a binary variable that indicates that the observation is made post-closure for the treated group, HOSPITAL is the hospital fixed effect, MARKET is the market fixed effect, YEAR is the year fixed effect, $\mathbf{X}$ is the patient characteristics, $\mathbf{Z}$ is the market characteristics, and ϵ is the error term. Indices i, j, k, and t represent a patient, a hospital, a market, and a year, respectively. Bold notation is used to represent vectors.

5.2. Assumptions

The main assumption of our fixed effect models is that conditioned on the unobserved fixed differences by groups, each observation-specific error term is uncorrelated with the explanatory variables in all periods (i.e., strict exogeneity holds). We believe that concerns on this assumption are largely alleviated for multiple reasons. First, the majority of patients pay only one hospital visit during the study period, and thus, a concern on feedback at the individual level is mitigated. Although it is possible that patients choose themselves into hospitals differently based on various hospital and patient characteristics in a way that is not measured by our various covariates, it is likely that the selection process is static and not dynamic. This is especially the case given that the underlying clinical or socio-economic differences for healthcare use do not change dramatically within our study period (see also Fiscella et al. (2000)). Similarly, the unmeasured hospitals' traits such as its practice culture or other inclination for organizational changes are typically (a) slow, and (b) unlikely to be correlated with patient characteristics (Leggat and Dwyer 2005). Thus, with the inclusion of multiple dimensions of patient proxies for health and socio-economic status for each year in our analyses, the strict exogeneity assumption is most likely not violated.

Another critical assumption in our analyses is the parallel trend assumption for the DID approach, which posits that the differences between the treatment and control groups are constant over time. Although this assumption is not formally testable, we examined the trend of various measurable variables stratified by the treatment status to confirm that the pre-closure trends are parallel (Figure 1 of the Online Appendix). Yet, it is still possible that the hospital closure is endogenous to the outcome measures. In particular, nearby hospitals may know the closure in advance and change their behavior strategically in anticipation of such an event. Although some evidence shows that hospital closures are not as easily predictable as it may seem (Wertheim and Lynn 1993), other changes can also occur at the market level (e.g., the way providers consolidate or interact and change their practice patterns) which can, in turn, affect hospital level or patient level outcomes. To address this concern, we adjusted for the market characteristics including the degree of consolidation, managed care insurance penetration, and competition, all of which may be relevant to the care provision in the market. We also examined various washout periods in our sensitivity analysis to mitigate the strategic behavior of nearby hospitals in anticipation of closures (see Section 6.6). Finally, because we cannot completely verify the extent to which these unmeasurable aspects bias our results, we also used an IV approach as part of our robustness checks (see Section 6.5). This IV approach further mitigates the concerns mentioned above and gives us confidence about the validity of our results.

5.3. Matching

We used a matched sample to improve the comparability of our treatment and control groups. Although the regression results from the full and the matched sample turned out to be consistent, we present the results from the matched sample as our main results. This is because the sample population did not fully satisfy the common support assumption, and thus, the matched sample constructs a better comparison group. We first estimated the propensity score of being in the treatment and control groups using a logistic regression model. For the matching process, we used a variation of hospital characteristics (size, star rating, location, DSH payment, academic status, ownership, and location) and patient characteristics (age, gender, race, dual status, and admission type) as our matching criteria. We utilized the nearest-neighbor matching method without replacement. We observed that the samples with fewer matching criteria or hospital characteristics typically resulted in a better balance of observable covariates between the treatment and control groups. The matching criteria for the main sample we adopted were based on hospital characteristics such as size, location, DSH payment, academic status, and ownership. Because of the imbalance between the numbers of hospitals in the treatment and control group, matching resulted in a fewer number of study sample: 1,536 hospitals with 3,234,872 observations among 1,321,530 patients. The summary statistics of the comparison groups after matching can be found in Table 1 of the Online Appendix. We also present the results using full or other matched samples in our sensitivity analyses (see Section 6.6). These variations all provided similar results and verified that our results are fairly robust.

5.4. Instrumental Variable (IV) Analysis

Our fixed effects model does not address the time-varying unobservable confounders that can bias the estimate of the closure effect that we discussed in Section 5.2. Therefore, we incorporated an IV analysis in our DID design (i.e., instrumented difference-in-differences, or DDIV) by identifying an IV that can account for unmeasured confounders (Duflo 2001). Specifically, we made use of the state level variations in the decision to expand Medicaid as an instrument that influences the likelihood of hospital closures but is unlikely to be correlated with our outcome variables. The ACA originally intended to expand Medicaid coverage to low-income adults, but the provision was ruled coercive by the supreme court. Therefore, the states could expand or not expand Medicaid, which created a variation in Medicaid eligibility by state. The expansion may improve the financial health of the hospitals by reducing uncompensated care. Indeed, studies show that Medicaid expansion is associated with improved hospital financial performance and lower likelihood of hospital closure (Lindrooth et al. 2018, Blavin 2016). Using these facts, we estimated our first-stage equation as:

$$\text{CLOSURE}_{jkt} = \beta\text{MEDICAID}_{jt} + \alpha\mathbf{X_{jt}} + \gamma\mathbf{Z_{kt}} + \text{HOSPITAL}_j + \text{MARKET}_k + \text{YEAR}_t + \epsilon_{jkt}, \quad (3)$$

where MEDICAID_{jt} denotes whether hospital j's state expanded Medicaid in year t and CLOSURE_{jkt} indicates whether hospital j's market k had a hospital closure in year t. Our second-stage equation is:

$$Y_{jkt} = \hat{\beta}\text{CLO}\hat{\text{S}}\text{URE}_{jkt} + \alpha\mathbf{X_{jt}} + \gamma\mathbf{Z_{kt}} + \text{HOSPITAL}_j + \text{MARKET}_k + \text{YEAR}_t + \epsilon_{jkt}, \quad (4)$$

where $\text{CLO}\hat{\text{S}}\text{URE}_{jkt}$ is the predicted probability of hospital j being in the treatment group from the first stage, and $\hat{\beta}$ is the impact of hospital closures on outcomes such as volume, bed, efficiency, utilization, and patient experience.

We note that the following assumptions should hold for the estimates from an IV approach to be unbiased: (1) the instrument should not affect the outcome except through treatment (exclusion restriction), and (2) the instrument should be correlated with the treatment variable. We can see from an available study that Medicaid expansion—our IV—is strongly correlated with our treatment variable (see, e.g., Lindrooth et al. (2018)), and hence, condition (2) holds. Our direct tests on the level of correlation between Medicare expansion and our treatment variable further confirms this (see Table 5). Unlike condition (2), however, we cannot directly test condition (1). However, evidence suggests that although Medicaid expansion is associated with the changes in payer mix and financial margins of the hospitals, it does not impact their overall hospitalization rate (Freedman et al. 2017). We also argue that hospitals are unlikely to adjust their operations directly in response to Medicaid expansion: changes in operational metrics due to Medicare expansion typically occurs because Medicare expansion affects hospitals' conditions such as patient mix and financial stability. In addition to the two above-mentioned assumptions required for any for any IV approach, the DDIV approach requires two additional assumptions: (3) the potential changes of both treatment and outcomes should be independent of the instrumental variable, and (4) the effect of the instrument should be monotone. Assumption (4) is well satisfied, since (a) once a market experience hospital closure, it will stay closed throughout the study period, and (b) we excluded the markets that experience multiple closures across multiple years. To verify the parallel trend assumption in (3), we examined the pre-expansion trends of the treatment (being in a market with hospital closure) and the hospital outcomes by expansion status (see Figure 2 of the Online Appendix).

Nevertheless, it should be noted that our IV analysis has some limitations. First, it only applies to the hospital level outcomes due to our data limitation (Medicaid expansion started after 2013, whereas our patient level data is only available up to 2012). Second, the estimate is applicable only to the hospitals whose behaviors are influenced by the IV. Despite these limitations, our IV analysis can help us to validate the findings from our primary analysis and can provide us with an additional robustness check mechanism.

6. Results and Discussions

6.1. Summary Statistics

An average hospital in our data provides 6,454 inpatient care per year and has an average bed utilization of 47% (see Table 2 of the Online Appendix). The average service duration, 30-day readmission rate, and 30-day mortality rate are 4.7 days, 17%, and 6%, respectively, which are consistent with the existing literature (see, e.g., Joynt et al. (2011), Bueno et al. (2010)). In Table

4, we show the baseline characteristics of hospitals and patients in our treatment and control groups. Hospitals in the treatment group are larger, more likely to receive government support, more likely to be a teaching or for-profit hospital, less likely to be rural, and have lower quality ratings. Patients in the treatment group are slightly younger, more likely to be male and White race, less likely to be low-income, and healthier. We adjust these differences in hospital and patient characteristics in our regression model.

6.2. Average Effect

Figure 4 shows the regression results of our primary model for both our hospital and patient level outcomes. These results indicate that hospitals experience a significant increase in patient volume after the closure of nearby hospitals. As one might expect, hospitals respond to the rise in demand neither by increasing their number of beds nor by increasing their bed utilization rate. Nevertheless, our results show that hospitals improve their operational efficiency after the closure of a nearby hospital. Furthermore, we find that the service duration in the remaining hospitals marginally decreases (p-value < 0.1) following a hospital closure. However, we do not observe any statistically significant change in any categories of patient experience after hospital closures when we run regressions for the overall rating and each separate patient experience question (see Table 4 of the Online Appendix). Finally, although our results indicate that the 30-day readmission rate does not change, we observe that the 30-day mortality rate increases by an additional 1.6 person per 1,000 patients (p-value< 0.05), which is about 3% of the current average rate.

Overall, our results indicate that hospitals experience greater demand while maintaining fixed resources after a nearby hospital closure. Furthermore, we find evidence of efficiency improvement following a closure event as measured by the number of patients served per bed per unit of time. However, such an improvement is not due to an increase in bed utilization (lower bed idle times): a reduction in service duration—a speed-up behavior—is the main reason behind the efficiency improvement in the remaining hospitals. Although patients do not report any measurable changes in their care experience, the reduction in service duration has important negative consequences on other aspects of care. In particular, we find that it is associated with a significant increase in the 30-day mortality rate. This suggests that the speed-up respond by the remaining hospitals is likely to include an elimination of some value-added care steps as opposed to removing only the non-value added ones.

6.3. Heterogeneous Effect by Hospital Characteristics

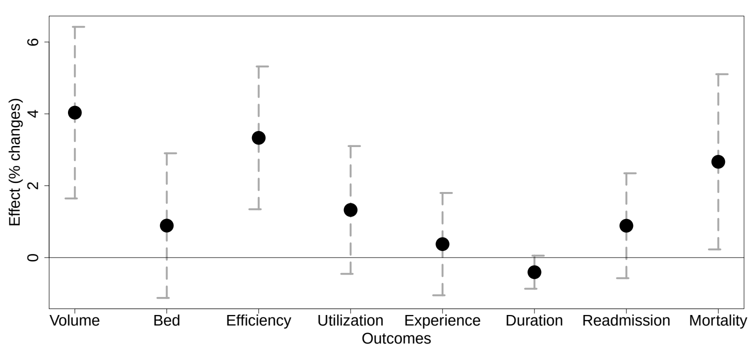
To generate further insights into the consequences of hospital closures, we examined the heterogeneous effect of hospital closures by applying our main models to various subsamples of our data. We stratified hospitals based on academic status, location, ownership, size, and quality (see Table

Table 4: Summary of Hospital and Patient Characteristics in the Treatment and Control Groups

Hospital characteristics	Treatment	Control
Total (n)	1,167	2,350
Avg. num. beds (mean)	154.6	127.6
CAH (%)	23.9	36.0
DSH (%)	63.7	52.6
Teaching hospitals (%)	66.4	55.0
Ownership – nonprofit (%)	56.8	62.7
Ownership – private (%)	19.3	13.6
Ownership – public (%)	23.9	23.7
Location – rural (%)	38.9	44.7
Star rating (mean)	3.0	3.2
Patient characteristic	**Treatment**	**Control**
Total (event-person-year)	3,826,751	1,079,435
Total (persons)	1,479,826	469,007
Age (mean)	78.89	79.28
Age – 65-75 (%)	36.40	34.41
Age – 76-85 (%)	40.91	41.42
Age – 86+ (%)	22.70	24.17
Sex – Male (%)	41.71	40.69
Race – White (%)	90.53	85.09
Race – Black (%)	6.38	10.62
Race – Asian (%)	0.60	1.22
Race – Hispanic (%)	1.45	1.51
Dual (%)	15.56	17.14
Received pneumovax (%)	78.49	77.92
Chronic conditions (mean)	23.17	23.24
Comorbidity score (mean)	3.00	3.23
Admission type – circulatory (%)	18.79	18.99
Admission type – digestive (%)	5.56	5.59
Admission type – endocrine (%)	2.37	2.75
Admission type – ill-defined (%)	3.41	3.63
Admission type – infectious (%)	46.61	47.36
Admission type – injury (%)	6.52	6.24
Admission type – musculoskeletal (%)	7.79	6.18
Admission type – respiratory (%)	5.43	5.67

Note: All differences in covariates between the treatment and control group were statistically significant.

Figure 4: Regression Results: Average Effect of Hospital Closure



Note: Dashed lines depict the 95% confidence intervals around the coefficient of the DID variable. Each model includes the fixed effects for hospital, market, and year. The DID coefficients (SE) for each outcome is 4.03 (1.22), 0.89 (1.03), 3.33 (1.01), 1.33 (0.91), 0.38 (0.73), −0.41 (0.23), 0.89 (0.74), and 2.67 (1.24). Standard errors are robust and two-way clustered at the hospital and year levels.

5 of the Online Appendix). Our results are presented in Figure 5 and show that, after a nearby hospital closes, teaching or urban hospitals experience a significant increase in volume and efficiency, a significant reduction in service duration, and a significant increase in mortality. In contrast, non-teaching or rural hospitals do not experience any significant changes. Overall, we find that the hospitals that are generally perceived as more desirable (such as teaching, urban, non-profit, and large hospitals) experience a significant increase in volume and efficiency, whereas non-teaching, rural, for-profit, or small hospitals are not affected as much. One exception to this is that the efficiency gains are greater among low-quality hospitals than the high-quality ones.

Our results also show that only hospitals that experience both an increase in efficiency and a reduction in service duration are negatively affected in quality of care. Quality of care can be affected through various different pathways such as greater congestion, increase in waiting time, and/or an increase in heterogeneity of the patient mix (Haas et al. 2018, Chan et al. 2016). Yet, the fact that only hospitals with both gains in efficiency and reductions in service duration experience adverse quality outcomes supports our main finding: hospitals that accommodate the increased demand following a nearby hospital closure by improving their efficiency do so through a speed-up behavior, which involves elimination of some value-added care delivery procedures.

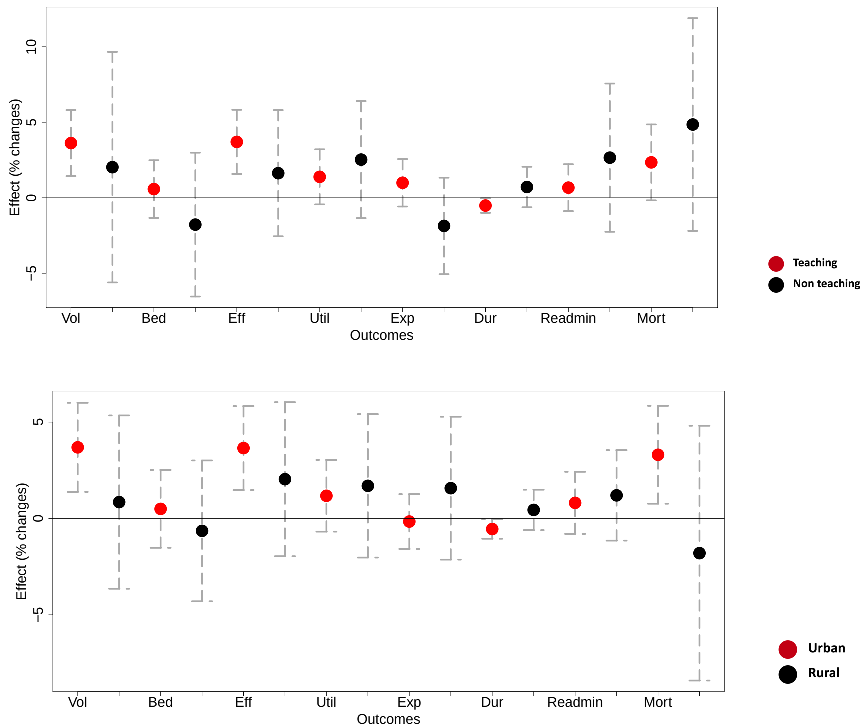
6.4. Heterogeneous Effect by Patient Characteristics

We next discuss our result on the impact of hospital closures on patient outcomes differentiated by patient characteristics such as socio-economic status measured as Medicare-Medicaid dual eligibility and health measured as chronic conditions and comorbidity. Our results presented in Figure 6 show that low-income patients or those with chronic conditions experience a greater reduction in service duration than the rest. Similarly, patients with comorbidities experience a greater increase in 30-day readmission rate, and patients with chronic conditions experience a greater increase in 30-day mortality. However, we find that hospital closures are not associated with additional differences in patient outcomes by admission diagnosis type. Put together, our results show that lower-income patients or those with worse health conditions are typically more affected by the negative consequences of hospital closures than other patients. This implies that hospital closures have the danger of increasing social disparities among patients.

6.5. IV Analysis

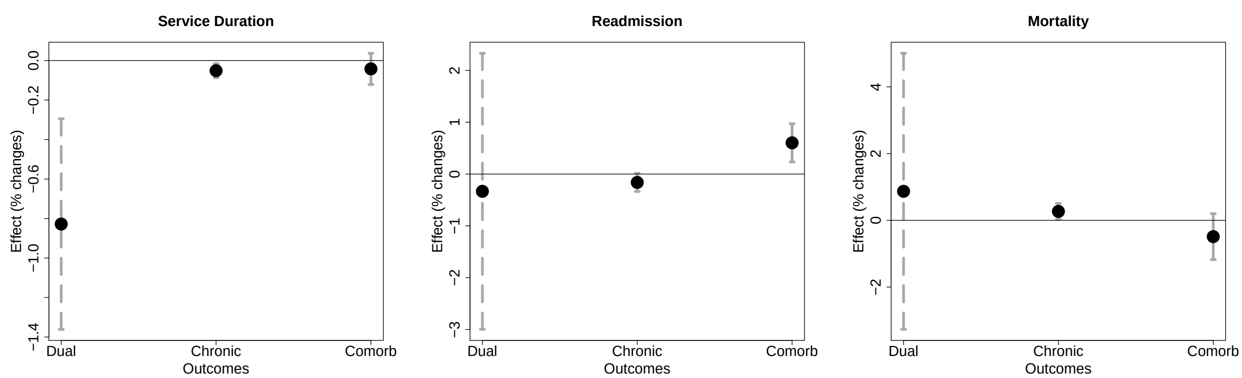
To address the existence of potential time-varying unobserved confounders, we implemented an IV analysis. Table 5 shows the result of the first stage and second stage regression estimates (Equations (3) and (4)). The first column shows that the state's decision to expand Medicaid is a significant predictor of fewer hospital closure in a market. Using the predicted treatment variable from the first stage, we estimated the impact of hospital closures on the nearby hospital's operation measures

Figure 5: Regression Results: Heterogeneous Effect of Hospital Closure by (a) Academic Status (Left), and (b) Location (Right)



Note: Dashed lines depict the 95% confidence intervals around the coefficient of the DID variable. Each model includes the fixed effects for hospital, market, and year. Standard errors are robust and two-way clustered at the hospital and year levels.

Figure 6: Regression Results: Heterogeneous Effect of Hospital Closure by Patient Characteristics on (a) Service Duration, (b) 30-Day Readmission, and (c) 30-Day Mortality



Note: Dashed lines depict the 95% confidence intervals around the coefficient of the interaction terms between DID variable and patient characteristics. Each model includes the fixed effects for hospital, market, and year. The DID coefficients (SE) for each outcome is −0.83 (0.27), −0.051 (0.018), and −0.042 (0.04) for service duration, −0.33 (1.36), −0.16 (0.09), and 0.60 (0.19) for readmission, and 0.87 (2.11), 0.27 (0.12), and −0.49 (0.35) for mortality. Standard errors are robust and two-way clustered at the hospital and year levels.

(the second column). Consistent with our main result, hospitals experience a significant increase in volume and a marginal increase in efficiency and no changes in the number of beds, bed utilization, and patient experience. The fact that the results of our IV analysis and the DID analysis are consistent gives us confidence that our results are fairly robust. Nevertheless, as we discuss in the next section, we also performed various other robustness checks.

6.6. Other Robustness Checks

In addition to the IV analysis, we conducted multiple robustness checks on the sample, model, and variable specification to test the sensitivity of our result.

Matched vs. Full Sample: We examined the impact of using the full sample or matched samples with various matching criteria. Table 6 shows that our main results are typically robust to the matching criteria: the closure effects for all of the outcome variables have the same direction and level of statistical significance as the main results. Notably, the closure effect for the bed utilization marginally increases in some samples, which suggests that a subset of hospitals may have improved their bed utilization. As noted earlier, it is possible to observe both service duration decrease and utilization increase when efficiency increases. Thus, the increase in bed utilization does not negate our conclusion that on average hospitals respond via a speed-up behavior, which is the mechanism behind the operational efficiency improvement.

Model Specification, Study Sample, and Definitions: We examined the sensitivity of our results by varying the study period as well as the definition of our key variables. First, we defined markets as smaller geographic areas for market fixed effects (e.g., HSA as opposed to the originally defined HRR). Second, we removed the markets with a high number of closures (top 10%) to ensure that the main effect did not come from these extreme cases. Third, we examined including the closure year instead of excluding it as in the primary analysis. Fourth, in our primary analysis, hospital closure included both a full closure (i.e., a complete closure of a physical location) and a partial closure (i.e., closure of inpatient wards only). However, patients may still have access to the outpatient or emergency services after partial closures, which may have mitigated the closure effect. We repeated our analysis after limiting the definition of closures to full closures only. Finally, we limited the study period to 2006-2012 for the hospital outcomes so that it matches the observation period for the patient outcome (to ensure that our results are consistent within the same observation period).

All of these changes resulted in observations that are reasonably consistent with our primary analysis (Table 7). For the hospital level outcomes, all the effects and the level of significance are consistent with the main findings. For the patient level outcomes, all the directions of the estimates are consistent with the primary results. However, the closure effects are muted when the markets with a large number of closures or a large number of hospitals are removed from the sample. This can be either due to the reduced sample size or because the markets with a large number of

Table 5: IV Results on Hospital Outcomes

	Medicaid expansion	P-value	Outcome variables	P-value
Hospital closure	-0.16 (0.007)	<0.001		
Vol.			885.7 (452.6)	0.05
Bed			2.7 (7.8)	0.73
Eff.			7.1 (4.0)	0.07
Util.			-0.0026 (0.025)	0.92
Exp.			-2.1 (1.6)	0.2
Hospital FEs	Yes	Yes	Yes	Yes
Area FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes

Note: Standard errors are robust and two-way clustered at the hospital and year levels.

Table 6: Regression Result: Robustness Checks with Various Matching Criteria

	Vol.	P-value	Bed	P-value	Eff.	P-value	Util.	P-value	Exp.	P-value
Original	262.85 (76.8)	$< 10^{-3}$	1.59 (1.33)	0.230	1.34 (0.39)	$< 10^{-3}$	0.01 (0.001)	0.130	0.28 (0.5)	0.570
Match 1	354.3 (109.11)	$< 10^{-3}$	0.13 (1.88)	0.950	1.92 (0.48)	$< 10^{-3}$	0.01 (0.001)	0.090	0.15 (0.5)	0.770
Match 2	348.34 (104.39)	$< 10^{-3}$	0.5 (1.8)	0.780	1.69 (0.48)	$< 10^{-3}$	0.01 (0.001)	0.120	0.29 (0.52)	0.580
Match 3	260.35 (78.63)	$< 10^{-3}$	1.18 (1.36)	0.390	1.31 (0.4)	$< 10^{-3}$	0.01 (0.001)	0.140	0.26 (0.5)	0.610
Match 4	265.45 (77.98)	$< 10^{-3}$	1.32 (1.35)	0.330	1.35 (0.4)	$< 10^{-3}$	0.01 (0.001)	0.090	0.19 (0.5)	0.710

	Dur.	P-value	Readm.	P-value	Mort.	P-value
Original	-0.0054 (0.0035)	0.121	0.0017 (0.0012)	0.152	0.0015 (7e-04)	0.040
Match 1	-0.0063 (0.0037)	0.084	0.0015 (0.0013)	0.234	0.0016 (7e-04)	0.032
Match 2	-0.0059 (0.0036)	0.104	0.0016 (0.0013)	0.220	0.0016 (7e-04)	0.027
Match 3	-0.0058 (0.0035)	0.096	0.0017 (0.0012)	0.174	0.0015 (7e-04)	0.045
Match 4	-0.005 (0.0035)	0.155	0.0019 (0.0012)	0.132	0.0014 (7e-04)	0.046

Note: Each model includes the fixed effects for hospital, market, and year. Standard errors are robust and two-way clustered at the hospital and year levels. Original indicates the sample without matching. Match 1 indicates the matched sample based on limited hospital characteristics (bed, location, DSH, academic status, and ownership). Match 2 indicates the matched sample based on extensive hospital characteristics (bed, location, DSH, academic status, ownership, CAH, star rating, and state). Match 3 indicates the matched sample based on limited hospital characteristics (same criteria as match 1) and patient characteristics (age, gender, race, dual status, and admission type). Match 4 indicates the matched sample based on extensive hospital characteristics (same criteria as match 2) and patient characteristics (age, gender, race, dual status, and admission type).

closures or hospitals experience greater changes from closure. Overall, the results of our various sensitivity analyses indicate that our results are fairly robust: hospital closures increase volume and operational efficiency of nearby hospitals without affecting their resource levels, and this negatively impacts some aspects of quality of care due to a speed-up response by the remaining hospitals.

6.7. Short and Long-Term Effects

We further examined the timing of the closure effect by estimating its short-term and long-term effects separately. In our primary analysis, we defined pre-closure and post-closure periods as three years before and after the year of closure, respectively, which allows capturing the closure effect across multiple years. In order to test the sensitivity of our results to this three-year period assumption, we also examined the effect of closure when the observation period was limited to either one year (short-term) or five years (long-term) post-closure instead of three years (medium-term). Table 8 shows that the long-term effect is mostly similar to the medium-term effect, suggesting that the effect is not transient.

Table 7: Regression Result: Robustness Checks with Various Definitions

	Vol.	P-value	Bed	P-value	Eff.	P-value	Util.	P-value	Exp.	P-value
Market HSA	260.353 (78.626)	0.001	1.182 (1.363)	0.386	1.306 (0.397)	0.001	0.006 (0.004)	0.144	0.258 (0.499)	0.606
Remove closures	276.224 (77.413)	$< 10^{-3}$	1.59 (1.354)	0.240	1.207 (0.413)	0.003	0.007 (0.004)	0.091	0.258 (0.497)	0.604
Remove hospitals	335.259 (106.058)	0.002	1.17 (1.749)	0.503	1.679 (0.502)	0.001	0.005 (0.005)	0.349	0.274 (0.539)	0.611
Include closure year	272.629 (88.763)	0.002	0.736 (1.471)	0.617	1.233 (0.42)	0.003	0.006 (0.004)	0.179	0.227 (0.376)	0.546
Full closure	287.584 (99.461)	0.004	2.033 (1.773)	0.251	1.637 (0.477)	0.001	0.006 (0.005)	0.238	0.786 (0.979)	0.422
2006-2012	259.979 (78.119)	0.001	1.28 (1.277)	0.316	1.185 (0.411)	0.004	0.007 (0.004)	0.102	0.258 (0.499)	0.606

	Dur.	P-value	Readm.	P-value	Mort.	P-value
Market HSA	-0.0049 (0.0035)	0.170	0.0019 (0.0012)	0.123	0.0015 (7e-04)	0.043
Remove closures	-0.0041 (0.0037)	0.269	0.0015 (0.0013)	0.229	0.0012 (8e-04)	0.109
Remove hospitals	-0.0043 (0.0041)	0.288	0.0022 (0.0014)	0.127	0.0012 (8e-04)	0.146
Include closure year	-0.0052 (0.0035)	0.136	0.0019 (0.0012)	0.112	0.0013 (7e-04)	0.062
Full closure	-0.0065 (0.0037)	0.080	0.0021 (0.0013)	0.102	0.0014 (8e-04)	0.075

Note: Each model includes the fixed effects for hospital, market, and year. Standard errors are robust and two-way clustered at the hospital and year levels.

However, we observe that short-term closure effects differ in two main aspects from the medium-term and the long-term effects (Table 9). First, there is a sign of an improvement in bed utilization in addition to a reduction in service duration in short-term, especially among teaching and urban hospitals. Nevertheless, we find that such an increase in bed utilization typically disappears after the first year. Second, rural hospitals show signs of improvement in volume and efficiency in the short-term, although this effect also fades afterward. These suggest that the increase in bed utilization among teaching and urban hospitals or the improvement in efficiency among rural hospitals are feasible but not sustainable, whereas the improvement in efficiency and reduction in service duration are persistent over time.

7. Conclusion

7.1. Summary of Findings

We examined how an exit of a hospital from a market affects the remaining hospitals' operational efficiency and quality. Our results indicate that in response to the increase in patient demand, the remaining hospitals in the market improve their efficiency instead of expanding their resources. However, this improvement in efficiency is not due to better utilization of existing resources in the remaining hospitals but is instead due to a reduction in service duration as a response to the increase in demand. This speed-up behavior allows the remaining hospitals to serve more patients with their current level of resources but has important negative consequences on some aspects of quality of care, especially the 30-day mortality rate. Our results also show that there is extensive heterogeneity in the way the remaining hospitals are affected after a closure, both at the hospital and the patient level. Notably, the fact that only certain types of hospitals (e.g., teaching, urban, non-profit, and large hospitals) experience gains in demand and efficiency suggests that hospital closures may accelerate the closure of other less viable hospitals. Moreover, the negative

Table 8: Five Year Outcomes: Average and Heterogeneity Effect by Academic Status and Location

	Vol.	P-value	Bed	P-value	Eff.	P-value	Util.	P-value	Exp.	P-value
Average effect	326.002 (108.885)	0.003	-0.091 (1.939)	0.962	1.824 (0.49)	$< 10^{-3}$	0.007 (0.005)	0.163	0.241 (0.499)	0.630
Teaching	368.788 (120.767)	0.002	0.704 (2.162)	0.745	1.741 (0.526)	0.001	0.006 (0.005)	0.235	0.525 (0.523)	0.316
non-teaching	50.86 (219.063)	0.816	-5.765 (3.643)	0.114	2.52 (1.384)	0.069	0.013 (0.015)	0.375	-1.303 (1.481)	0.380
Rural	105.293 (80.243)	0.190	0.554 (1.906)	0.771	0.884 (0.949)	0.352	0.005 (0.01)	0.617	1.455 (1.431)	0.310
Urban	388.699 (142.21)	0.006	-0.565 (2.498)	0.821	2.125 (0.568)	$< 10^{-3}$	0.007 (0.006)	0.193	-0.17 (0.48)	0.723
	Dur.	P-value	Readm.	P-value	Mort.	P-value				
Average effect	-0.005 (0.004)	0.166	0.002 (0.001)	0.142	0.002 (0.001)	0.036				
Teaching	-0.006 (0.004)	0.093	0.001 (0.001)	0.330	0.002 (0.001)	0.040				
non-teaching	0.009 (0.008)	0.265	0.004 (0.004)	0.225	0 (0.002)	0.903				
Rural	0.005 (0.007)	0.449	0.001 (0.003)	0.657	-0.001 (0.002)	0.512				
Urban	-0.007 (0.004)	0.083	0.002 (0.001)	0.240	0.002 (0.001)	0.010				

Note: Each model includes the fixed effects for hospital, market, and year. Standard errors are robust and two-way clustered at the hospital and year levels.

Table 9: One Year Outcomes: Average and Heterogeneity Effect by Academic Status and Location

	Vol.	P-value	Bed	P-value	Eff.	P-value	Util.	P-value	Exp.	P-value
Average effect	306.372 (63.661)	$< 10^{-3}$	1.196 (0.91)	0.189	1.626 (0.441)	$< 10^{-3}$	0.009 (0.004)	0.019	0.419 (0.537)	0.435
Teaching	459.706 (98.115)	$< 10^{-3}$	1.484 (1.41)	0.292	2.139 (0.583)	$< 10^{-3}$	0.011 (0.005)	0.018	1.178 (0.569)	0.039
non-teaching	45.306 (36.287)	0.212	-0.172 (0.608)	0.777	0.817 (0.661)	0.217	0.008 (0.007)	0.246	-1.68 (1.21)	0.166
Rural	67.449 (34.592)	0.051	-0.391 (0.648)	0.546	1.421 (0.595)	0.017	0.01 (0.006)	0.123	1.605 (1.225)	0.191
Urban	455.274 (103.254)	$< 10^{-3}$	1.701 (1.461)	0.244	1.808 (0.624)	0.004	0.01 (0.005)	0.066	-0.105 (0.569)	0.853
	Dur.	P-value	Readm.	P-value	Mort.	P-value				
Average effect	-0.005 (0.004)	0.155	0.002 (0.001)	0.132	0.001 (0.001)	0.046				
Teaching	-0.007 (0.004)	0.073	0 (0.002)	0.800	0.001 (0.001)	0.543				
non-teaching	-0.007 (0.011)	0.496	-0.004 (0.005)	0.452	0.003 (0.003)	0.409				
Rural	0.002 (0.009)	0.851	0.002 (0.004)	0.570	-0.004 (0.003)	0.173				
Urban	-0.008 (0.004)	0.028	-0.001 (0.002)	0.484	0.002 (0.001)	0.111				

Note: Each model includes the fixed effects for hospital, market, and year. Standard errors are robust and two-way clustered at the hospital and year levels.

consequences of hospital closures (e.g., an increase in 30-day mortality) disproportionately fall on the more socially vulnerable patients (e.g., sicker patients or those with a lower income). Taken together, our findings suggest that hospital closures can significantly widen the disparity among both providers and patients.

7.2. Limitations

Our study has several limitations. First, there are data limitations. The hospital operation measures we used are from the Medicare cost report and the POS data, which include information on healthcare use for all plan types. However, our health outcome measures are from Medicare FFS claims data. Because the population outside FFS Medicare may have different underlying characteristics and healthcare use, the generalizability of our analysis on the health outcomes can be limited. There is also a difference in the study period between our hospital level and patient level data. Although we performed a sensitivity analysis on overlapping periods and find that the results were consistent, it is possible that there is a difference that is related to the discrepancies in the observation period.

Second, there are limitations in our outcome measures. For measuring patient volume per hospital, we used a yearly average to address the seasonal variability in patient demand. Using the average may limit our ability to capture the variation in demand which may differ by the hospital or patient characteristics. There is also an important limitation to the hospital-reported number of beds that we used. Although hospitals report the total number of certified or licensed beds, which are the beds officially approved by the state, the actual number of beds they use internally (the beds in service) can be fewer than the certified beds (Green 2002). Thus, even if the hospitals did not externally change the number of beds, they could have expanded their number of beds in service when the demand increased. Our analysis only captures what we can observe from our data: the changes in the certified or licensed beds. When a hospital wants to expand its number of certified or licensed beds, they need to go through the CON approval process, which can take some months or even years. We attempted to capture the lengthy regulatory process by including up to three and five post-closure observation years in our main analyses and in our sensitivity analysis, respectively. Nevertheless, the actual process may take even longer.

We also note that our patient experience measures are limited in sample size, as not all patients were able to participate in the survey, which could have contributed to low statistical power in detecting any meaningful changes. For the quality of care measures, it should be noted that although we used most relevant and widely used quality measures for inpatient services, and although we adjusted them using extensive patient level variables, they could have been affected by some external factors that we do not observe in our data. For example, the readmission measure might have been affected by other ongoing changes from the payment reforms such as the hospital readmission reduction program (HRRP)[14], which incentivizes hospitals to pay greater attention to patients and procedures that are more likely to affect their readmission rates.

Finally, as we discussed in Section 5.2, our results are limited by the limitations of the DID method we utilized. We employed several alternative strategies to address such limitations, including an IV approach to examine the time-varying omitted variable bias on the hospital level outcomes. Although the results of the IV analysis on hospital outcomes were consistent with our main results, we were not able to conduct the IV analysis on the patient level outcomes, because our instrument (Medicaid expansion) is only applicable after the years our patient level data were available. For the patient level analysis, we included an extensive set of covariates in our model, performed a variety of robustness checks, and also discussed that the majority of the patients in our sample have a single hospitalization incidence. Overall, our supplementary analyses and vari-

[14] HRRP is a pay-for-performance program established under the ACA that lowers payments to hospitals with too many readmissions.

ous sensitivity tests give us confidence that our results are reasonably robust. Nevertheless, future research is needed to examine the generalizability of our findings.

7.3. Implications for Hospital Administrators and Policymakers

Our results have important implications for both hospital administrators and policymakers. For example, they indicate that hospital administrators should be aware of the short-term and long-term consequences of the operational changes when they respond to the increased demand caused by a nearby hospital closure. In particular, we find that responding to the increased demand through reducing service durations may have dire negative consequences, and maintaining the increased efficiency through improvement in bed utilization requires conscious efforts at the organizational level.

On the policy side, recent healthcare reform has generated an ongoing debate on payment policies (e.g., expanding Medicaid and cutting the Medicaid DSH payment program) for hospitals that treat a greater portion of low-income and vulnerable patients. While these policies help to support safety-net hospitals, they have been controversial since they can directly influence the financial and operating status of existing hospitals that are not viable under market competition forces (Neuhausen et al. 2014, Bazzoli et al. 2014). Our results suggest that although closures of such inefficient hospitals can improve the operational efficiency of the U.S. healthcare system through demand pooling, the increase in efficiency may not correspond to better use of hospital resources. Instead, closures can induce unintended negative consequences on patient outcomes, and may also broaden social disparities. Thus, policymakers may need to implement policies that can either prevent closures or reduce their negative consequences. Future studies can further help policymakers by extending our findings and by addressing some of the limitations of our work.

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Online Appendix

Table 1: Summary of Hospital Characteristics for the Matched Sample

	Hospitals (Closure)	Hospitals (No closure)	P-value
Total (n)	847	1,368	
Beds (Mean)	205.4	199.2	0.12
Disproportionate Share Hospital (%)	85.6	85.4	0.68
Teaching hospitals (%)	89.3	88.8	0.33
Ownership-Nonprofit (%)	61.9	66.1	<0.001
Ownership-Private (%)	21.3	17.9	
Ownership-Public (%)	16.8	16.0	
Rural (%)	26.4	26.1	0.7
Star Rating (Mean)	2.9	3.1	<0.001

Table 2: Summary Statistics of Hospital and Patient Variables

	Mean	SD	Q1	Q3	Cor,vol	Cor,bed	Cor,effc	Cor,util		
Volume	9,488	9,843.77	2,578	13,310	1					
Bed	192.30	328.02	66	255	0.52	1				
Efficiency	46.61	16.45	36.46	56.88	0.42	0.10	1			
Utilization	0.54	0.20	0.40	0.69	0.62	0.25	0.79	1		
	Mean	SD	Q1	Q3	Cor,age	Cor,chron	Cor,comorb	Cor,dur	Cor,readm	Cor,mort
Age	78.97	8.02	73	85	1					
Chronic conditions	23.18	8.82	27	27	0.16	1				
Comorbidity	3.04	2.77	1	5	0.03	0.002	1			
Service duration	4.67	3.97	2	6	0.05	0.001	0.18	1		
Readmission	0.17	0.37	0	0	0.02	0.01	0.18	0.10	1	
Mortality	0.06	0.24	0	0	0.11	0.02	0.07	0.13	0.09	1

Table 3: Characteristics of Closed Hospitals

	Mean	SD	Q1	Q3
Total (N)	173			
Volume	3,073	3,037.88	936.70	4,401
Beds	153.90	160.86	48.70	203
Efficiency	23.75	18.79	13.47	28.11
Utilization	0.30	0.21	0.17	0.36

Table 4: Regression Results: Patient Experience

	DID Coef	SD	P-value
Overall	0.258	0.499	0.606
Doctor communicate	0.057	0.279	0.837
Nurse communicate	0.436	0.332	0.190
Quick help	0.316	0.467	0.499
Staff explain	0.181	0.446	0.685
Pain control	0.083	0.393	0.832
Area quiet	0.377	0.441	0.393
Room clean	0.954	0.504	0.058
Discharge info	0.004	0.319	0.990
Recommend	0.651	0.566	0.250

Table 5: Regression Results: Heterogeneous Effect of Hospital Closure by Hospital Characteristics

	Vol.	Bed	Eff.	Util.	Exp.
Teaching	378.04 (116.49)**	1.19 (2.02)	1.76 (0.52)***	0.01 (0.01)	0.66 (0.54)
Nonteaching	30.06 (57.8)	-0.68 (0.93)	0.47 (0.61)	0.01 (0.01)	-1.37 (1.19)
Rural	14.63 (39.53)	-0.3 (0.88)	0.62 (0.62)	0.01 (0.01)	1.09 (1.31)
Urban	389.61 (124.54)**	1.02 (2.13)	1.72 (0.52)**	0.01 (0.01)	-0.11 (0.5)
Private	35.38 (175.26)	-2.11 (3.53)	0.63 (1.01)	0.01 (0.01)	-1 (1.17)
Public	289.01 (151.39)	3.62 (3.59)	1.21 (0.73)	0.01 (0.01)	1.6 (1.91)
Nonprofit	312.71 (107.98)**	1.01 (1.62)	1.58 (0.53)**	0.01 (0.01)	0.2 (0.5)
Large	408.82 (137.08)**	0.48 (2.35)	1.74 (0.49)***	0.01 (0.01)	0.22 (0.51)
Small	28.3 (26.39)	-0.09 (0.3)	0.48 (0.63)	0 (0.01)	0.21 (1.24)
High quality	225.27 (137.57)	2.63 (2.12)	0.45 (0.67)	0.01 (0.01)	0.78 (0.65)
Low quality	379.71 (185.45)*	-0.67 (3.28)	2.37 (0.82)**	0.01 (0.01)	-0.81 (0.87)
	Dur.	Readm.	Mort.		
Teaching	-0.008 (0.0039)*	0.0011 (0.0013)	0.0014 (0.001)*		
Nonteaching	0.011 (0.0106)	0.0043 (0.0041)	0.0031 (0.0023)		
Rural	0.0068 (0.0082)	0.002 (0.003)	-0.0012 (0.0022)		
Urban	-0.0086 (0.004)*	0.0014 (0.0014)	0.002 (0.001)*		
Private	0.0015 (0.0087)	-9e-04 (0.0037)	0.0027 (0.002)		
Public	-0.0125 (0.0097)	-9e-04 (0.0035)	0.0042 (0.0024)		
Nonprofit	-0.0073 (0.0043)	0.0024 (0.0014)	0.0011 (0.001)		
Large	-0.0072 (0.0058)	0.0017 (0.0019)	9e-04 (0.001)		
Small	-0.0037 (0.0049)	0.0012 (0.0018)	0.0011 (0.0011)		
High quality	-0.0014 (0.0055)	0.0016 (0.0019)	0.0023 (0.0012)		
Low quality	-0.0107 (0.0058)	-0.0013 (0.0019)	0.0015 (0.0011)		

Figure 1: Mean Hospital Outcomes for Treatment and Control Groups

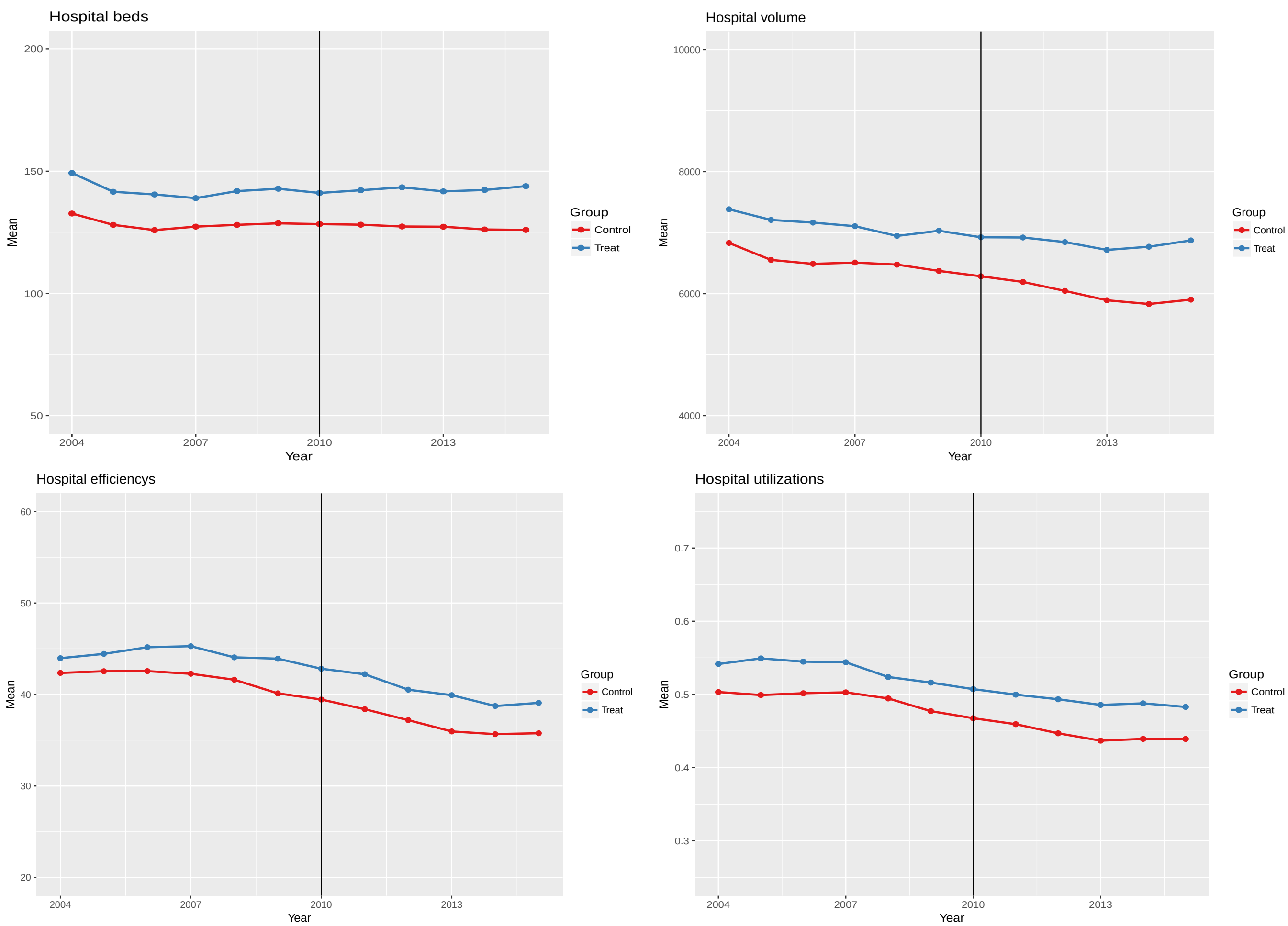

Figure 2: Mean Hospital Outcomes for States with and Without Medicaid Expansion