Impeding Access or Promoting Efficiency? Effects of Rural Hospital Closure on the Cost and Quality of Care

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Abstract

This paper studies the effect of hospital closure on the cost and quality of health care in rural markets. Hospital closure can be welfare improving if it reallocates patients to more efficient facilities but can also lead to treatment delay and worsened health outcomes. I find support for both sides of this debate. Using a difference-in-differences analysis of Medicare claims, I exploit variation in the effects of hospital closure within local markets: I compare enrollees who lost their closest hospital as a result of closure to enrollees who lost their second closest hospital, as a result of the same closure. I show that rural hospital closure led to both a decrease in Medicare spending and an increase in mortality among enrollees with time-sensitive health conditions. I study implications of forestalling hospital closure in the context of the Critical Access Hospital (CAH) program, a large-scale payment reform that increased Medicare revenues for nearly half of all rural hospitals. I show that the CAH program led to a reduction in hospital closures and an improvement in mortality, but the program’s expenditures were substantial relative to these effects.

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1 Introduction

The hospital industry has undergone important structural changes in recent years, driven in large part by declining demand for inpatient care. Nearly 15% of hospitals have closed since 1990 and closure rates have increased over the last decade.\(^1\) While the scale of hospital closure has been substantial, the effects of such closures are uncertain. Hospital closure decreases access to care, raising concerns about treatment delay and adverse health outcomes, but can also reallocate patients to more efficient facilities. In well-functioning markets, exit driven by inefficiency is generally welfare improving, but in hospital markets, it is not clear that competition leads to socially optimal outcomes (Gaynor and Town, 2011).\(^2\)

Uncertainty surrounding hospital closure is reflected in two conflicting policy views. If hospital closure is appropriate, then policies impeding closure may induce higher costs or worse health outcomes. If, on the other hand, hospital closure reflects reductions in appropriate supply, then policy makers should design payments or other regulations that account for the positive effects of keeping hospitals open.

I study the effects of hospital closure on Medicare spending and patient health outcomes in rural markets. The debate surrounding hospital closure is particularly salient in rural markets because the consequences of rural hospital closure are large in terms of both access and efficiency. Rural hospital closure increases travel times (Shen and Hsia, 2012), raising concerns about access to care for residents with acute medical conditions.\(^3\) At the same time, rural hospitals tend to serve small patient populations, suggesting that these hospitals are too small to be working at an efficient scale (Dranove, 1998; Hannan et al., 2003). Taken together, these facts suggest a distance-quality trade-off: rural residents have to travel farther for care after a closure but may be better off if they are treated at higher quality facilities. In addition, recent public policy efforts have devoted substantial resources toward forestalling rural hospital closure. About half of all rural hospitals are exempt from Medicare’s standard, prospective payments, and instead receive higher, cost-based reimbursements under the Critical Access Hospital (CAH) program. These payments amount to approximately $1 billion annually (MedPAC, 2005).


\(^{2}\)Hospital markets have several features that may impede efficient closure. Hospital prices, for example, are set administratively for Medicare and Medicaid patients, and private hospitals often supply public goods (Newhouse, 1970).

\(^{3}\)Mortality in rural areas has been increasing over time, relative to urban mortality, and access to care has been identified as a potential driver of this disparity (Singh and Siahpush, 2014).
I model the impact of hospital closure on health care costs and patient outcomes. Previous work has generally focused on changes in either costs (Deily et al., 2000; Lindrooth et al., 2003; Ciliberto and Lindrooth, 2007) or quality (Buchmueller et al., 2006; Avdic, 2016). However, both are necessary for welfare implications. The primary challenge to studying the impact of hospital closure is that closure may be endogenous to hospital behavior or quality. I address this issue using two complementary empirical strategies.

I begin with a difference-in-differences analysis using Medicare claims, exploiting variation in the effects of hospital closure across enrollees in the same local market. I compare enrollees who lost their closest hospital as a result of closure to enrollees who lost their second closest hospital, as a result of the same closure. I show that hospital closure led to lower spending but worse health outcomes among enrollees who lost their closest facility in the years prior to CAH implementation. I find that hospital closure led to a 5% reduction in Medicare spending, driven entirely by a reduction in inpatient admissions. Hospitals that remained open had somewhat higher prices than those that closed. Examining outcomes, I show that hospital closure led to a 5% increase in mortality among enrollees with time-sensitive health conditions. I find little support for a distance-quality trade-off in the data. While enrollees traveled farther for hospital treatment after a closure, they received care at surviving facilities that were similar to the closed hospitals in terms of quality, namely risk-adjusted mortality rates.

I next study how hospital closure dynamics evolved when Medicare implemented cost-based reimbursement under the CAH program. Using the CAH program as an instrument for hospital closure, I find that the move to cost-based reimbursement reduced the hazard of closing in any year by 25%. Effectively, closure rates fell to essentially zero among hospitals that converted to CAHs during my study period (MedPAC, 2005). My results imply that about 30 hospitals were able to avoid closure in the initial years of the CAH program, relative to approximately 1,300 hospitals that converted to CAHs in the same time period.

I also use the implementation of the CAH program to test if forestalling hospital closure affected patient health outcomes. To do so, I study changes in mortality for a group of enrollees whose closest hospitals converted to CAHs instead of closing. Consistent with the results from my first experiment, I find that enrollees who kept their closest hospital as a CAH had higher spending and lower mortality than enrollees who lost their closest hospital.

There are several welfare and policy implications of my findings, which I take up in a discussion section after the results. First, Medicare savings from hospital closures were

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4Joynt et al. (2015) is a notable exception.
5Time-sensitive care includes emergency admissions with the following presenting conditions: acute myocardial infarction, stroke, heart failure, pneumonia and sepsis, acute respiratory failure and injury.
small relative to the loss of life-years from increased mortality in the years prior to CAH implementation. Social savings from these closures, however, were substantially larger than Medicare savings, given the reductions in fixed costs at closing facilities. In back-of-the-envelope calculations, I find that reductions in fixed costs roughly offset the costs of increased mortality prior to CAH implementation. This result implies that CAH expenditure, to be welfare improving, would have to be well-targeted at hospitals where closure would have especially large mortality effects. I do not find evidence that this was the case. While CAH spending improved enrollee outcomes when targeted at marginal hospitals with a high risk of closure, I find that the vast majority of CAH funds went to inframarginal facilities. Thus, I find that the CAH program was not an efficient policy for forestalling hospital closure.

The remainder of the paper is structured as follows: Section 2 provides background information about hospital closure in rural markets. Section 3 describes the data. Section 4 analyzes the effect of hospital closure on Medicare spending and enrollee health outcomes prior to CAH implementation. Section 5 studies changes in hospital closure patterns under the CAH program. Section 6 examines the policy and welfare implications of hospital closure and Section 7 concludes.

2 Background and Conceptual Framework

2.1 Medicare Hospital Reimbursements

Under the Prospective Payment System (PPS), Medicare reimburses hospitals using prospective, admission-level bundled payments. PPS reimbursements are fixed and do not depend on hospital expenditures. Thus, the PPS system incentivizes productive efficiency by imposing the full marginal cost of services provision on hospitals. PPS payments vary by medical diagnosis, categorized into Diagnosis Related Groups (DRG), and can also vary according to geographic factors such as urban status. Hospital closure increased after the implementation of the PPS (Figure A1), especially among small hospitals. This generated concern that rural hospitals were unable to remain solvent under this payment regime (GAO, 1991; Kaufman et al., 2016).

One reason that small hospitals struggled under the PPS was that low volumes reduced their ability to spread fixed costs across patients. This issue was especially salient in rural

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6Fixed costs savings will not fully accrue to Medicare because (1) Medicare prices are administered and will not adjust to new average hospital costs in the short term and (2) fixed costs savings are shared across payers.

7Hospital payments also depend on whether the facility receives disproportionate share payments or medical education payments.
markets, where there were approximately 1,300 rural hospitals treating fewer than 25 patients per day, with about 200 serving fewer than 5 patients per day (Panel A of Figure 1). These hospitals were highly unprofitable under the PPS, largely because of their high cost structures. In Panel B of Figure 1, I plot average operating revenue and average operating costs per patient day across 25 quantiles of hospital operating margin, restricting the sample to hospitals serving fewer than 25 patients per day. While average revenue per patient day was about $1,700 across margin quantiles, average costs ranged from $1,500 to $3,000 per patient day. Because the least profitable hospitals tended to be very small, fixed costs were spread across fewer patients and semi-fixed costs such as labor were unable to scale down with patient volume (Figure A2).

In response to concerns about rural hospital closure, Medicare created a new program under the Balanced Budget Act of 1997 (BBA97), allowing certain rural facilities to convert to Critical Access Hospitals (CAH) and receive more generous, cost-based reimbursement. Thus, under the CAH program, the marginal costs of service provision shifted from hospitals to the Medicare program, eliminating the efficiency incentives under the PPS. The CAH program has broad participation. There are currently about 1,300 CAHs, about half of all rural hospitals (MedPAC, 2005).

Eligibility for the CAH program is based on hospital location and size. CAHs cannot treat more than 25 patients per day and must be located in a rural area. Rural areas included all rural counties under original program rules and later expanded to include rural areas within urban counties, for example rural census tracts. Federal program rules additionally required that CAHs be 35 miles on primary road/15 miles on secondary road from another provider. However, states were allowed to designate hospitals as Necessary Providers (NP) and exempt them from the distance requirement. State NP criteria were very generous and the majority of CAHs gained eligibility through the NP program. Medicare discontinued NP exemptions in 2006, but allowed all existing CAHs to remain in the program. The Office of the Inspector General (OIG) estimates that only a third of current CAHs would meet the distance requirement if required to re-enroll (OIG, 2013).

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8A hospital cannot, for example, staff fewer than one nurse at a time, regardless of patient count.

9In addition, CAHs must be located in a state with a CMS-approved Rural Health Plan. All but five states had plans approved between 1998 and 2001. CAHs must also maintain an average length of stay (LOS) of 4 days or less. Between 1997 and 2003, CAHs faced a maximum of 15 acute patients per day, and 25 patients total including swing beds. Under the Medicare Modernization Act, this rule was relaxed so that CAHs could treat 25 patients of any type each day.

10Although a goal of the CAH program was to promote access to care, the policy creates offsetting incentives in this area. Because the CAH program combines financial support for hospitals with incentives to downsize, the policy has an ambiguous effect on the overall quantity of care available in rural markets.
2.2 Cost and Quality Implications of Hospital Closure

Hospital closure has uncertain effects on the costs and quality of care. On the one hand, hospital closure can lead to welfare improvements from (1) reallocating patients to more efficient facilities or (2) consolidating patient volume at fewer facilities, reducing fixed costs and allowing surviving firms to benefit from returns to experience. On the other hand, hospital closure can impede access, leading to treatment delay and worsened patient health outcomes. Thus, the overall impact of hospital closure is theoretically ambiguous and is ultimately an empirical question.

Hospital closure can affect health care costs through three basic mechanisms. First, hospital closure has implications for allocative efficiency, which can improve if inefficient hospitals are more likely to close but can worsen if closure affects efficient facilities. Empirical evidence on the effect of hospital closure on allocative efficiency is inconclusive. While some evidence shows that inefficient hospitals are more likely to close (Deily et al., 2000; Lindrooth et al., 2003; Ciliberto and Lindrooth, 2007), other evidence shows that hospital closure is related to low Medicare reimbursements and for-profit status (Bazzoli and Andes, 1995; Succi et al., 1997; Ciliberto and Lindrooth, 2007). This latter evidence suggests that efficient hospitals with poor reimbursement could close and that inefficient non-profits may have suboptimally low closure rates.

Second, hospital closure can impact productive efficiency at surviving firms through the aggregation of volume. These effects stem from two factors. First, given substantial fixed costs required to provide hospital services, aggregation of volume may allow surviving hospitals to better exploit economies of scale. This dynamic is particularly important in rural markets, where hospitals are small and well below output levels where economies of scale are exhausted (Dranove, 1998). Direct empirical evidence addressing the effect of closure on the efficiency of surviving firms is limited to one study, which shows that surviving hospitals are able to provide lower-cost care after a competitor closes, largely because they are able to fill empty beds (Lindrooth et al., 2003).\footnote{A related literature has shown that closing hospitals tend to be smaller than their competitors (Lillie-Blanton et al., 1992; Succi et al., 1997; Ciliberto and Lindrooth, 2007), and are potentially less able to take advantage of economies of scale.} Second, aggregation of volume at surviving hospitals may allow them to benefit from returns to experience (Hannan et al., 2003). To the best of my knowledge, there is no empirical evidence that directly investigates the volume-outcome effect in the specific context of hospital closure, but this relationship has been well-documented in other settings.

While hospital closure thus has implications for efficiency in production, it is not clear how these effects translate into spending by public payers. Even if hospital closure reallocates
patients to lower cost facilities, Medicare spending will only decrease if these facilities are also lower priced, which is not guaranteed under an administered pricing system. Moreover, within-facility efficiency improvements at surviving hospitals, for example through economies of scale, will translate into hospital profits, not Medicare savings, if administered prices do not adjust to the new, lower costs. Despite the importance of efficient Medicare spending, empirical evidence on its relationship with hospital closure is limited. I am aware of only one paper that studies this issue and the sample is limited to 11 hospital closures (Rosenbach and Dayhoff, 1995).

Third, hospital closure can affect costs through its impact on utilization patterns. To the extent that hospital closures increase travel times and the cost of access, utilization is likely to decrease. While reductions in volume lead to decreases in consumer surplus in standard markets, the implications are not clear in health care markets. On the one hand, the presence of moral hazard in hospital markets suggests that reductions in care provision can be welfare improving (Arrow, 1963). On the other hand, consumers are not well-informed about their health care needs and may cut back on both high-value and low-value care when faced with increased costs (Brot-Goldberg et al., 2017). Empirical evidence on changes in utilization in response to hospital closure is limited and has mixed conclusions (Rosenbach and Dayhoff, 1995; Joynt et al., 2015).

In addition to costs, hospital closures can affect patient health outcomes. Arguments in favor of forestalling hospital closure center on decreased access to care for patients with acute medical conditions, where adverse effects of treatment delay have been well-documented (De Luca et al., 2004; Terkelsen et al., 2010; AHA, 2013; Emberson et al., 2014; Jena et al., 2017). In principle, rural residents may face a distance-quality trade-off, where adverse effects of treatment delay are offset by gains from receiving treatment at higher quality facilities. However, I am not aware of any empirical evidence that directly investigates these offsetting effects. Instead, research in this area has generally documented the aggregate effect of hospital closure on patient health outcomes, combining the impact of increased travel with changes driven by quality differentials across hospitals. While some work has documented increases in mortality for patients who have to travel farther after a closure (Buchmueller et al., 2006; Avdic, 2016), other work fails to find any effect (Rosenbach and Dayhoff, 1995; Dayhoff, 1995).

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12 Relatedly, hospital closure can affect private prices at surviving firms by increasing consolidation and market power. To the best of my knowledge, only one study has documented a positive association between hospital closure and prices at surviving firms (Vivian, 2008), but the relationship between consolidation and hospital prices is well-documented in other contexts. See Gaynor and Town (2011) for a review.

13 As with costs, improvements in productive or allocative efficiency can lead to quality gains.

14 Moreover, while a robust literature has shown that closed hospitals tend to be higher cost relative to surviving facilities, I am not aware of any evidence showing that they are lower quality.
3 Data

This paper relies on two primary datasets. First, I use Medicare claims data, specifically the 100% Medicare Provider and Analysis Review (MedPAR) data and Denominator files from 1992-2008. The MedPAR data contain admission-level information on all Medicare fee-for-service (FFS) beneficiaries who access inpatient care. The Denominator files include basic demographic and enrollment information for all FFS enrollees, regardless of whether or not they used inpatient services. The Medicare claims include identifiers for hospitals and enrollees, basic demographic information, and detailed clinical information for each admission such as diagnoses and procedures, spending and survival.

My second data source is the Healthcare Cost Report Information System (HCRIS), which is administrative data that covers the universe of Medicare-certified hospitals and other institutional providers. I use data from between 1990 and 2005. For each hospital record, I observe the hospital identification number, as well as location, size and detailed financial information about operating revenues and costs.

I use the Medicare claims and Cost Reports to create two analytic datasets. The first dataset uses the Cost Reports to track hospital closures and financial health across the implementation of the CAH program. I restrict my sample to hospitals in rural counties that served fewer than 25 patients per day in the pre-CAH period, matching basic eligibility for the CAH program. For each hospital, I use information about Medicare operating revenues and costs to calculate hospitals’ financial health and to simulate counterfactual revenues under the CAH program as if it had been in effect in earlier years.

I use the hospital identification numbers in the Cost Reports to follow hospitals over time and identify potential closures. A well-known problem in the Cost Reports is that hospital identification numbers can change over time — and thus disappear from the data — for reasons other than closure (Joynt et al., 2015). Hospital mergers, for example, can result in new identification numbers (Cooper et al., 2015). To address this problem, I use the Cost Reports to identify suspected closures and then verify each suspected closure using additional data sources, primarily the American Hospital Association (AHA) landscape files and hospital closure reports from the Office of the Inspector General (OIG). Where those sources are insufficient for verification, I use local news articles and other publicly available information.

A related literature has studied emergency department closures and has similarly drawn mixed conclusions (Shen and Hsia, 2012; Hsia et al., 2012).
My second analytic dataset addresses health care use and patient outcomes surrounding hospital closure, linking the Medicare claims with information about hospital closures from the Cost Reports. I restrict my sample to admissions at short-term, acute-care hospitals that occur within 100 miles of enrollees’ home zip-codes. I calculate travel distances as the geodetic distance between zip-code centroids, the most detailed location data available. My main outcome variables are per-capita Medicare spending and admission rates, both at the zip-code level, and enrollee mortality.

I separately study spending and utilization patterns across non-urgent and urgent admissions, where demand for care is likely to vary in its elasticity to increased travel distance. Urgent care includes admissions that originate in the emergency department (ED) and are categorized as urgent or emergency, rather than elective.\textsuperscript{16} Non-urgent admissions include elective admissions as well as any admissions that do not originate in the ED.\textsuperscript{17} I further study 1-year mortality rates among enrollees treated for urgent conditions and for time-sensitive conditions, following the existing literature. Time sensitive conditions include emergency admissions with the following principal diagnoses: acute myocardial infarction, stroke, heart failure, pneumonia and sepsis, acute respiratory failure and injury. To study changes in mortality, I restrict my sample to index hospitalizations in order to avoid confounding driven by changes in readmission rates over time. Index events include hospitalizations among enrollees who have not had another inpatient stay for the same admission type (e.g., urgent) within the last year.

4 Effects of Hospital Closure

In this section, I study the effects of hospital closure prior to the implementation of the CAH program. My empirical strategy exploits variation in the effects of hospital closure across enrollees in the same local market, assessing the impact of hospital closure on Medicare spending and patient outcomes.

4.1 Empirical Strategy

I study the effects of hospital closure using a difference-in-differences (DD), event study analysis of Medicare claims. The treatment group consists of enrollees that lost their closest

\textsuperscript{16} Admissions are elective if the “patient’s condition permitted adequate time to schedule the availability of suitable accommodations,” urgent if the condition “required immediate attention for the care and treatment of a physical or mental disorder,” and emergency if the condition “required immediate medical intervention as a result of severe, life threatening, or potentially disabling conditions” (ResDAC, 2018).

\textsuperscript{17} For transfers, which by definition do not originate in the ED, I assign the urgency level of the initial hospitalization.
hospital as a result of a closure. A large literature has documented patient preferences toward their closest hospital (McClellan et al., 1994; Cutler, 2007) as well as the adverse effects of treatment delay (De Luca et al., 2004; Emberson et al., 2014; Jena et al., 2017), suggesting that changes in the minimum distance to care are relevant. I compare enrollees who lost their closest facility as a result of hospital closure to a control group of enrollees that lost their second closest hospital, as a result of the same closure.

Figure 2 illustrates my empirical approach for an example closure in Lamar County, Alabama. The location of the closed hospital is marked by an X and surviving hospitals are indicated with solid circles. Treatment areas, marked in orange, include the zip-code where the hospital was located and two neighboring zip-codes. Control zip-codes that lost their second closest facility are marked in yellow.

My empirical approach has several advantages. First, the DD approach requires fewer assumptions than a standard event study specification, which would estimate changes before and after hospital closure among all affected enrollees, i.e. all enrollees losing their first closest hospital.18 Second, I do not gain identification from differential distances between enrollees and the closed facility. This differential distance approach has been used in previous studies but raises concerns about endogenous patient-hospital co-location, for example that sicker enrollees choose to live closer to a hospital. In my empirical framework, control zip-codes are not necessarily farther from the closing hospital than treatment zip-codes. Moreover, control enrollees are not necessarily farther from any hospital, even if they are farther from the closed facility.19 Thus, my empirical strategy is valid if enrollees take hospital location into account when choosing where to live, but assumes that enrollees do not internalize differential closure probabilities across facilities when deciding which hospital to live near.

Using the sample of enrollees who lost their first and second closest hospital, I estimate the effect of hospital closure with the following event study specification:

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18 This traditional event study framework would gain identification from variation in the timing of hospital closures across areas. In the context of hospital closures, this empirical approach raises concerns that hospital closure is not random over time, for example if higher quality facilities survive longer than lower quality facilities.

19 In a differential distance estimation, the estimated change in distance to the nearest hospital would be zero for all zip-codes in the control group and also for zip-codes in gray in Figure 2, which are not included in my sample. Variation in the differential distance estimator would thus be driven by changes within the treatment zips.
\[ Y_{izt} = \sum_{k=-5}^{5} \alpha_k \cdot \mathbb{1} (\text{time since close} = k)_{zt} \cdot \mathbb{1} (\text{Lost Closest}) + \sum_{k=-5}^{5} \beta_k \cdot \mathbb{1} (\text{time since close} = k)_{zt} + \delta X_{izt} + \pi_{zt} + \gamma_z + \tau_t + \epsilon_{izt} \]

where \( Y_{izt} \) measures spending, admission rates and health outcomes for enrollee \( i \) in zip-code \( z \) in time \( t \). \( \gamma_z \) are a set of zip-code fixed effects. \( \tau_t \) are calendar time fixed effects, where time is measured in six-month increments. \( X_{izt} \) is a matrix of patient characteristics, including age, gender, race and presenting condition. \( \pi_{zt} \) are time-varying area characteristics including average enrollee age, percent female and percent white. \( \epsilon_{izt} \) is an error term that allows for correlation between observations from the same zip-code. Following Buntin and Zaslavsky (2004), I model Medicare spending using a one part generalized linear model (GLM) with a log link function. I estimate per-capita admission rates and mortality rates using linear probability models.

The coefficients of interest, \( \alpha_k \), measure changes in outcomes among enrollees that lost their closest facility, relative to enrollees that lost their second closest hospital. The six-month period just before the closure serves as the omitted category. I include a full set of event time indicators that apply to all enrollees in the sample (\( \beta_k \)), so that the \( \alpha_k \) coefficients have a traditional, DD interpretation. The key identifying assumption is that there is no unobserved shock that is both contemporaneous with the hospital closure and also correlated with differential patient outcomes across zip-codes.

In the course of my analysis, I estimate two variations of this specification. First, to estimate per-capita Medicare spending and utilization, I collapse the data to the zip-code-time level. Second, for brevity, I estimate the overall, pre-post effect of hospital closure, rather than estimating the effect separately for each time period.\(^{20}\)

A natural concern with my analysis is that distances between zip-code centroids may not be accurate representations of the distance between enrollees and nearby hospitals. This concern arises because geodetic distances differ from driving distances and because enrollee residences are not necessarily near the zip-code centroid. That said, to the extent that treated enrollees are assigned to the control group (and vice versa), my results will understate the true effect of hospital closure.

\[^{20}Y_{izt} = \alpha_k \cdot \text{Post}_{zt} \cdot \mathbb{1} (\text{Lost Closest}) + \beta_k \cdot \text{Post}_{zt} + \delta X_{izt} + \pi_{zt} + \gamma_z + \tau_t + \epsilon_{izt}\]
4.2 Results

4.2.1 Descriptive Statistics

Table 1 summarizes characteristics of enrollees that lost their first and second closest hospitals to closure in the pre-CAH period. Enrollees in the treatment and control groups were similar across demographic characteristics in the pre-closure period and these characteristics remained stable across hospital closure. In both groups, enrollees were 72 years old on average, were 56% female and approximately 90% white. Consistent with past work, I find that enrollees in the treatment group were more likely to receive care at the closed hospital in the pre-closure period (Table A1).

On average, hospital closure led to a 7 mile increase in the distance to the closest hospital among the treatment group, although some distance changes were considerably larger (Figure 3). An increase in travel distances of 7 miles is large in the context of time-sensitive conditions like heart attacks, where treatment delays of even a few minutes are associated with increased mortality (Jena et al., 2017).²¹

4.2.2 Effect of Hospital Closure on Medicare Spending and Utilization

I begin by studying the effect of hospital closure on per-capita Medicare spending (Table 2). I find that hospital closure led to a 5% decrease in total Medicare spending, with the bulk of the spending decrease concentrated among non-urgent admissions. Figure 4 shows how hospital closure affected spending over time, plotting event study regression coefficients (Equation 1) for enrollees who lost their closest facility \((\alpha_k)\) and second closest facility \((\alpha_k + \beta_k)\). After the hospitals closed, spending fell sharply for enrollees who lost their closest hospitals. In contrast, spending changed little among enrollees in the control group. Overall, my results suggest that hospital closure led to an annual Medicare savings of $9 million.²²

Hospital closure can lead to a decrease in spending either through a reduction in utilization or through a shift toward lower priced facilities. To test the effect of hospital closure on utilization, I study changes in per-capita admission rates. In columns 4 through 6 of Table 2, I find that per-capita admission rates decreased by 5% overall after hospital closure, driven by a larger, 9% decrease in non-urgent admissions. Figure 4 shows that these results are driven by decreases in utilization among enrollees who lost their closest facility, relative to stable utilization among the control group. As with the spending analysis, I find no change

²¹The American Heart Association, on the high end, suggests that survival after acute myocardial infarction decreases by 7% for every minute without treatment (AHA, 2013).

²²There are about 225,000 enrollees per year in the treatment group, with an average per-capita spending of $819.
in utilization of urgent care, consistent with inelastic demand.

There is little evidence that Medicare saved money by diverting patients to lower priced facilities after a closure. In fact, DRG-level reimbursements tended to be higher at surviving facilities compared to closed hospitals (Figure A3) because the surviving facilities were more likely to be urban. Taken together, my results challenge the current discourse surrounding hospital closure, which emphasizes the potential for savings from sending patients to more efficient facilities. In contrast, my results suggest that hospital closure can actually increase per-admission Medicare spending, and that savings are more likely to be driven by a reduction in care provision.

Mechanisms Underlying the Utilization Decrease
In Table 3, I explore what is driving the decrease in admission rates. A natural question is whether the reduction in utilization represented an efficient decrease in unnecessary care. One way to test this is to assess changes in readmission patterns. In columns 1 and 2, I show that hospital closure led to statistically insignificant increases in both 7-day and 30-day readmission rates, suggesting little scope for changes in readmission patterns around a hospital closure.

A second question is whether reductions in care are larger for enrollees with potentially high travel costs. In columns 3 through 6, I find evidence to support this hypothesis. First, I compare changes in admission rates for enrollees that experienced increases in travel distance of under and over 15 miles, following the distance-based eligibility criteria of the CAH program. I split the control group according to the increase in distance they would have experienced, had their closest hospital closed. In columns 3 and 4, I find that there was a 17% decrease in admission rates among enrollees with increases in travel distances over 15 miles, and estimate a statistically insignificant decrease in admissions of 3% among enrollees with shorter distance increases. In columns 5 and 6, I further test the importance of travel costs by studying admission rates across enrollees who are younger and older than 80 years of age. I find that utilization decreases are concentrated among older enrollees, consistent with an important role for travel costs.

Finally, I test whether reductions in care were driven by decreased utilization among relatively healthy enrollees. I estimate utilization changes across high and low mortality health conditions, defined relative to the median diagnosis in terms of 1-year mortality. I estimate statistically similar decreases in admission rates across the two subgroups.
4.2.3 Effect of Hospital Closure on Quality and Patient Outcomes

In this section, I examine the effect of hospital closure on mortality rates (Table 4). My empirical work focuses on patients hospitalized for any urgent condition and patients hospitalized for a time-sensitive condition. I restrict the sample to index admissions in both cases. To begin, I show that there was no change in the probability of index admission after a hospital closure, alleviating concerns about differential selection into hospital care over time (columns 1 and 2). In columns 3 and 4, I find that hospital closure had little effect on mortality among enrollees with urgent hospitalizations, but led to a 5% increase in mortality among enrollees treated for time-sensitive conditions, implying that hospital closure led to 70 additional deaths per year. The magnitude of this finding is moderate relative to existing research (Buchmueller et al., 2006; Joynt et al., 2015; Avdic, 2016), but large in the broader context of longevity after an acute clinical episode. Changes in technology and underlying population health have contributed to a decrease in AMI mortality of about 10%, for example (Chandra et al., 2017).

Mechanisms Underlying the Mortality Increase

In the final columns of Table 4, I explore potential mechanisms behind the increase in mortality rates for patients with time-sensitive conditions. With no change in overall volume but a shift in care toward surviving facilities, changes in mortality rates will depend on (1) deleterious effects of treatment delay and (2) the quality differential between closing hospitals and nearby facilities. I assess the importance of treatment delay in columns 5 and 6, testing for differential mortality effects across enrollees that experienced heterogeneous increases in distance to the closest hospital after a closure. To generate these results, I split treatment zip-codes into two groups: areas that experienced increases of under 15 miles and areas with increases of over 15 miles. I split the control group according to the increase in distance that they would have experienced, had they lost their closest hospital. Consistent with adverse effects of treatment delay, I find that the mortality effects are concentrated among enrollees with larger increases in travel distances. I estimate a 10% increase in mortality among enrollees who had to travel over 15 additional miles to their closest facility, and a statistically insignificant increase of 3% among enrollees with increases under 15 miles.

Next, I study the distance-quality trade-off directly. In column 7, I estimate the share of enrollees traveling farther than their minimum pre-closure distance to care. For enrollees in the treatment group, this minimum distance is the distance to the closed hospital. Thus, this analysis effectively tests if enrollees were using their closest facility prior to its closure.

23In my sample of enrollees who lost their closest hospital, there are approximately 4,200 admissions for time-sensitive conditions per year and mortality increases by 1.67 percentage points.
I find that the share of enrollees traveling farther than their minimum pre-closure travel distance increased by 24%, or 0.39 standard deviations. In column 8, I study changes in institutional quality of hospitals where enrollees sought care before and after hospital closure. I measure hospital quality as a 1-year risk-adjusted mortality rate (RAMR) in the pre-closure period. Because RAMR varies at the hospital level, the coefficient in column 8 is driven by a reallocation of enrollees across hospitals that vary in quality. I find no evidence that enrollees receive care at higher quality hospitals after their nearest hospital closed, estimating a statistically insignificant change in quality of 1% or 0.05 standard deviations.

Taken together, my results provide little empirical support for the distance-quality trade-off. I find that enrollees travel farther for care after a hospital closure but do not receive care at higher quality facilities. Further investigation suggests that enrollees do not receive higher quality treatment after a closure because it is not available in the local market. In particular, I find that nearby, surviving facilities are similar in quality to the closed hospital (Figure A4, Table A1).

4.3 Robustness Checks

In this section, I assess the robustness of my results across a variety of specification checks, focusing on per-capita Medicare spending and mortality among time-sensitive conditions. For brevity, the results of these checks are included in the Appendix. First, I test whether my results are sensitive to the modeling choices in my main analysis. In Table A3, I show that my results are robust to allowing separate time trends for each closure area, to alternative functional forms, and to clustering standard errors at the closure-area level, rather than the zip-code level. Estimated spending reductions across the models range from 4% to 5.1% (relative to 4.9% in my base case) and estimated mortality increases range from 5.2% to 6.2% (relative to 5.4% in my base case).

Second, I assess the possibility that my results are affected by endogenous patient moving after a hospital closure. In Table A2, I test whether enrollee population size changed after hospital closure and whether hospital closure led to a change in the composition of enrollees in affected zip-codes: average resident age, percent female and percent white. I find no evidence of changes in the underlying enrollee population after closure. Overall population levels are stable, and I estimate small, statistically insignificant changes in enrollee composition over time.

Third, I investigate whether my spending results could be driven by a shift toward outpatient care after a hospital closure. While I cannot observe outpatient care patterns, I address

24 Regarding functional form, I test the robustness of my spending results to an OLS specification. For the mortality analysis, I re-run my results using a logit model.
this concern by testing for differential changes in admission rates for clinical conditions where inpatient treatment is highly substitutable with outpatient care. First, I estimate admission rates for DRGs that were specifically identified as substitutable with outpatient care during my study period. These DRGs primarily include uncomplicated surgeries such as carpal tunnel release and ocular lens procedures. A full list is available in Carter and Ginsberg (1985). Second, I test for differential changes in rates of surgical admissions of enrollees under 80. There has been a large shift from inpatient to outpatient surgeries over the past several decades (MedPAC, 2013), suggesting that inpatient surgeries in my sample may be generally more substitutable with outpatient care than medical admissions for relatively healthy enrollees. In Table A4, I estimate a small, statistically significant increase in the admission rate for DRGs that are most substitutable with outpatient care. Among surgical conditions more generally, I estimate a 5% decrease in the admission rate, statistically similar to my main estimates. These findings suggest that my results are not driven by shifts toward outpatient care after a closure.

Finally, I test the robustness of my mortality analysis to three alternate mortality measures: inpatient, 30-day and 90-day mortality (Table A5). I estimate positive coefficients in all cases, ranging from 4.6% to 7.6%, although some estimates are not statistically significant given power limitations. In Table A6, I further test whether my mortality results are driven by any particular clinical condition within the time-sensitive classification. I construct six alternate samples, dropping each time-sensitive condition in turn. Estimated mortality changes are positive across all subgroups, ranging from 3.8% to 8.0%, and statistically significant at the 10% level in all but one case.

5 Forestalled Hospital Closure under Cost-based Reimbursement

In this section, I study what happened when Medicare shifted toward a policy of subsidizing rural hospitals through cost-based reimbursement in order to forestall closures. To understand the cost and welfare implications of this payment reform, my empirical investigation focuses on two questions. First, did cost-based reimbursement under the CAH program lead to a reduction in closure rates? And if so, how did keeping these hospitals open affect treatment patterns in local markets?
5.1 Hospital Closure under Cost-based Reimbursement

To begin, I study the effect of the CAH program on hospital closure rates using a simulated revenue approach. The core idea is to use pre-CAH data to simulate the additional revenue that hospitals would have received under the CAH program, had the policy been in effect earlier. Using pre-CAH data isolates the mechanical effect of the policy from hospitals’ endogenous responses to the payment reform. I simulate the reimbursement that hospitals would have received from Medicare had they participated in the CAH program in 1990-91, seven years prior to its actual implementation.\textsuperscript{25} Given that the CAH program employs cost-based reimbursement, simulated CAH revenues are the sum of operating expenses and reimbursable capital expenses, both in the inpatient setting.\textsuperscript{26} The mechanical effect of the policy change is estimated as the difference between simulated CAH revenues and actual PPS revenues in 1990-91:

\[
sim \Delta \text{rev}_h = \frac{\sim \text{rev}_{h,CAH90} - \text{rev}_{h,PPS90}}{\text{rev}_{h,PPS90}}
\]

Figure 5 plots the distribution of \( \sim \Delta \text{rev}_h \) among hospitals meeting basic CAH eligibility criteria: hospitals in rural counties with ADCs at or below 25. The average increase in simulated revenues is 14\% with an interquartile range of -21\% to 42\%. Thus, the simulated impact of the program is large and has considerable dispersion. Increases in simulated revenue indicate that hospital operating costs exceeded operating revenues in 1990-91. Likewise, a decrease in simulated revenues indicates that a hospital’s inpatient service was profitable under the PPS in 1990-91 and that it thus would have lost money by converting to cost-based reimbursement. More information on hospitals included in the sample is available in Table A7.

I estimate the effect of simulated revenue changes on hospital closure with the following estimating equation:

\[
\log h_{i,t} = \alpha + \sum_{k=1992/3}^{2004/5} \beta_k \cdot \mathbb{1}(year = k)_{i,t} \cdot \sim \Delta \text{rev}_h + \delta X_{i,t} + \epsilon_{i,t} \tag{2}
\]

where \( h_{i,t} \) denotes the hazard of closure for hospital \( i \) in year \( t \). \( \beta_k \) are the coefficients of interest and capture the time-varying effect of simulated revenue gains on closure rates related to the year of policy reform.

\textsuperscript{25}I use two years of pre-period data to combat noise in the estimates. Existing work has used similar approaches to isolate the mechanical effect of policy changes in the year immediately preceding the reform (Dafny, 2005). This strategy is not possible in the context of hospital closure, since many firms will not have survived through the pre-period.

\textsuperscript{26}Although the CAH program extended cost-based reimbursement to outpatient care, information on outpatient costs and revenues is not available in the 1990 data.
ative to the baseline years: 1990-91. Because closure is a low probability event, I index \( k \) in two-year increments to minimize noise in the estimates. \( \beta_k < 0 \) indicates that hospitals with more to gain from the CAH program were less likely to close. For years prior to 1998, the estimates in \( \beta_k \) investigate the possibility of differential pre-period trends among hospitals differentially affected by the CAH program. \( X_{i,t} \) is a vector of hospital characteristics including rurality, lagged ADC, lagged share of patients with Medicare, lagged county population and a lagged indicator for whether or not there was another hospital in the same county.

The results of the hazard model (Equation 2) are plotted in Panel A of Figure 6. \( \text{sim} \Delta \text{rev}_h \) is uncorrelated with closure hazards prior to CAH implementation, lending support for my empirical strategy. In contrast, closure rates decreased sharply after CAH implementation among hospitals with the most to gain from the program: hospitals where the CAH program had the largest predicted revenue effect. Given an average \( \text{sim} \Delta \text{rev}_h \) of 14%, a coefficient of -2 implies that the CAH program induced a decrease in closure rates of 25% on average. This new, lower closure rate persisted throughout the post-CAH study period, implying that approximately 30 hospitals were able to avoid closure between 1998 and 2005.\(^{27}\) This decrease in closures is small relative to the scale of the CAH program, which had about 1,300 participants by 2005. Given the scale of the program, even a 100% reduction in the hazard rate would imply a small number of forestalled closures relative to CAH participation.\(^{28}\)

I assess the robustness of my results in Panel B of Figure 6, estimating the placebo effect of CAH revenues in a sample of semi-rural hospitals that were ineligible for the CAH program in 1997. Specifically, the placebo sample includes hospitals located in rural census tracts of urban counties and in outlying urban counties, covering facilities that were initially ineligible for the CAH program despite being rural in character.\(^{29}\) The sample includes years prior to 2002, after which CAH eligibility expanded to include some semi-rural hospitals.\(^{30}\) I find no change in closure rates among ineligible, semi-rural hospitals at the time of CAH program implementation, lending support to the validity of my empirical strategy. Further

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\(^{27}\)A decrease in the log hazard rate of -2, together with the mean \( \text{sim} \Delta \text{rev}_h \) of 14% from Figure 5, yields \( \exp(-2 \times 0.14) = 0.756 \). About 8% of hospitals closed between 1990 and 1997. A 25% reduction in the hazard of closure suggests that 6% of hospitals closed between 1998 and 2005, out of 1,388 hospitals.

\(^{28}\)To further contextualize this result, recent evidence suggests that Medicaid expansion under the Affordable Care Act was associated with a 30% increase in Medicaid/uninsured margins and a decrease in closure rates of 80% (Lindrooth et al., 2018).

\(^{29}\)An alternative strategy would be to run a similar placebo test using a sample of all urban hospitals. However, this would require that I verify every hospital closure in the Cost Reports. Moreover, to the extent that urban and rural hospitals are subject to different closure trends, urban hospitals are not an ideal control group.

\(^{30}\)Hospitals in rural areas of urban counties officially gained eligibility in 2000, but guidance about which specific areas would be eligible was delayed several years.
robustness checks are in the Appendix (Figure A5).

5.2 Changes in Treatment Patterns from Forestalled Closure

The reduction in hospital closures under the CAH program can affect spending and mortality patterns in local markets through two basic mechanisms. First, forestalling closure may reverse the treatment pattern changes associated with closure. In particular, areas with a forestalled closure may see higher spending and improved mortality because enrollees are protected from long travel distances, relative to areas with a realized closure.

Second, CAH conversion can itself influence spending and mortality because of the increase in revenues at converting facilities. A rough forecasting based on pre-conversion, PPS operating revenues among converting hospitals suggests that hospital revenues increased by about 20% after CAH conversion (Figure 7). Importantly, part of this revenue increase was driven by hospitals’ endogenous responses to cost-based reimbursement. CAH conversion shifts the marginal costs of service provision from hospitals to Medicare, and hospitals responded to this incentive by increasing operating costs.

Thus, forestalling closure through CAH conversion can have cost and quality consequences for Medicare outside of the direct effect of forestalled closure. In terms of Medicare spending, there are additional costs of CAH conversion driven by increases in spending per admission or per patient-day. This is distinct from the direct effect of forestalling closure on spending, which operates through utilization changes (Table 2). Moreover, if CAH converters used the additional CAH funds to make quality improvements, then CAH conversion can lead to within-facility improvements in patient health outcomes. Again, this mechanism is distinct from the direct effect of forestalled closure on health, which primarily operate through distance effects (Table 4).

I estimate the effect of CAH conversion by comparing enrollees that lost their closest hospital to closure in the pre-CAH period to enrollees that I predict would have lost their closest hospital to closure in the post-CAH period, if not for the CAH program. I use a coarsened exact matching (CEM) procedure to predict which hospitals would have closed in the post-CAH period, had PPS rules continued to be in effect. I begin by measuring 1990 characteristics of hospitals that closed prior to CAH implementation: operating margin, share of patients insured by Medicare, ADC and whether there was more than one hospital in the county. I then select matches for each closed hospital from the pool of hospitals that survived until 1997 and later converted to CAHs. Thus, I do not compare hospitals that looked similar in 1990 but survived differentially over time; instead, I compare hospitals that closed in the pre-CAH period to hospitals that would have had a high risk of closing in the
post-CAH period, had Medicare not switched to cost-based reimbursement. The results of
the match are in Table A8.

Using the matched sample, I estimate the effect of CAH protection on Medicare enrollees
using a DD, event study approach. I measure event time relative to the index event, which
is closure in the pre-CAH period and CAH conversion in the post-CAH period. A natural
concern with this empirical approach is that variation in hospital closure is not random
over time. This suggests that hospitals that closed in the pre-CAH period may be different
than hospitals that would have closed in the post-CAH period, had the program not been
implemented. A related but distinct concern is that my matching algorithm is selecting
hospitals that would not have closed in the post-CAH period, despite their risk factors.
While I cannot know which hospitals would have closed in the absence of the CAH program,
I note that both of these concerns suggest that my results will overstate the benefits of
CAH conversion by comparing closed facilities to hospitals that are unobservably higher
performers.

In Table 5, I show that Medicare spending increased by approximately 7% among en-
rollees who kept their closest hospital as a CAH, relative to enrollees who lost their closest
hospital to closure. In contrast to my prior analyses, I find that this spending increase was
not driven by increases in admission rates (column 2), which were constrained at convert-
ing facilities by capacity maximums under the CAH program (Figure A6). Instead, CAH
conversion was associated with increases in Medicare spending per patient-day (Figure A7).
Thus, while I find that forestalling closure through CAH conversion reversed the Medicare
savings associated with closure, I find that the spending changes operated through different
mechanisms in the pre- and post-CAH periods.

In column 3 of Table 5, I estimate the impact of CAH protection on 1-year mortality. I
show that CAH protection led to a 3 percentage point or 10% decrease in mortality among
enrollees treated for time-sensitive conditions. Compared to the mortality effect of hospital
closure in the pre-CAH period (1.7 percentage points or 5% in Table 4), this change is large.
However, although the magnitudes of these estimates suggest that keeping hospitals open
as CAHs had effects beyond the direct effect of forestalling closure, the estimates are not
statistically different.

6 Discussion: Welfare and Policy Implications

I find that hospital closure affected both Medicare spending and patient health in the years
prior to CAH implementation. To understand the implications of these results, I can loosely
translate my estimates into implied savings per life-year lost (Cutler et al., 2010; Doyle
et al., 2015). As discussed previously, my results indicate that pre-CAH hospital closure led to approximately 70 deaths per year and to $9 million in annual Medicare savings. Estimates from the clinical literature suggest that life expectancy after time-sensitive hospitalizations is approximately 10 years and that quality of life is less than perfect during these years (Kochar et al., 2016; Tengs and Wallace, 2000). Assuming that these estimates apply to my sample of Medicare enrollees, an additional 70 deaths translates to a loss of approximately 560 quality-adjusted life-years (QALY). Comparing this loss of life-years to the Medicare savings, I estimate that hospital closure led to a Medicare savings of roughly $16,000 per lost-QALY, well below standard valuations: $100,000 - $250,000 (Cutler, 2004; Murphy and Topel, 2006).

Importantly, the implied savings to Medicare are distinct from the welfare effects of hospital closure. From a social welfare perspective, a main benefit of hospital closure is the elimination of fixed costs. Fixed cost savings do not fully accrue to Medicare because hospital prices are administered and will not adjust to new average hospital costs in the short term and because fixed costs savings are shared across payers. Estimates from Table A7 show that operating costs were about $5 million per closed hospital. Assuming that fixed costs represent 50% of total operating costs, I calculate that the closures in my sample led to a fixed cost savings of $120 million per year. Taken together, these results suggest that the savings from eliminating fixed costs approximately offset the costs of increased mortality in the pre-CAH period, with an implied savings per life-year of $215,000.

As a caveat, these results do not serve as a full welfare calculation. There are other components of welfare that I cannot measure in this context, for example the effects of hospital closure on health outside of Medicare mortality or on savings from reallocating patients to more efficient hospitals. In terms of health outcomes, this limitation applies to conditions that are not relevant in the Medicare market, such as maternal health, and also to hospitalizations for time-sensitive conditions among younger patients. Among heart attack and heart failure hospitalizations, for example, Medicare accounts for only 55% and 70% of all admissions, respectively.

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31 Quality of life adjustments for the time-sensitive conditions in my sample range considerably but generally fall between 0.7 to 0.9.
32 Kalman et al. (2015) estimate that overhead costs were about 46% of total operating costs across all acute hospitals in 1996. Other work suggests that fixed costs are considerably higher (Roberts et al., 1999). Estimates of fixed cost savings assume that surviving facilities have sufficient capacity to absorb reallocated patients. The low pre-closure occupancy rate at surviving firms in my sample suggests that this is not a strong assumption.
33 Other factors include welfare effects driven by decreased utilization, effects of closing hospitals that are more or less likely to provide public goods than their competitors, impacts on the local economy and changes in the deadweight loss of taxation to fund Medicare spending.
34 Author’s calculations based on HCUPnet.
Next, I turn to the implications of my results for the CAH program. Given that fixed cost savings roughly offset the cost of increased mortality in the pre-CAH period, my results suggest that CAH expenditure would have to be well-targeted at marginal hospitals to be welfare improving. For example, the program could be welfare improving if it directed funds toward hospitals where the mortality effects of closure would be especially large. I do not find evidence that this was the case. On the one hand, I find that CAH expenditure was highly effective when directed at marginal facilities that I predict would have closed without the additional revenue: CAH protection led to a 7% increase in Medicare spending and a 10% decrease in mortality (Table 5), implying a gain of approximately 530 life-years at a cost of $14 million, or $26,000 per life-year saved. However, there was considerable program expenditure at inframarginal facilities with low risk of closure. At a total cost of $1 billion per year, mortality gains from forestalled closure were far outweighed by total program spending. 

Importantly, there are potential benefits of the CAH program outside of forestalled closure if inframarginal hospitals used additional revenue to make quality improvements. The scope for these quality improvements is large, given the revenue increases associated with CAH conversion (Figure 7). Moreover, the increases in operating costs after conversion raise the possibility that hospitals invested the additional funds into new infrastructure that could be quality improving, for example new technology or additional staff. The impact of additional CAH revenues on the quality of participating facilities is an open empirical question that I leave for future work. However, I note that evidence about whether hospitals alter quality in response to increased revenue is mixed. The effects of the CAH revenues on quality would have to be outside the range of the existing literature to be considered cost-effective at traditional levels, although this work is not specifically focused on changes under cost-based reimbursement. 

My results raise questions about whether the CAH program would have been efficient at keeping hospitals open with more precise targeting of marginal hospitals. Given that I find the strongest mortality effects among enrollees with large increases in travel times, distance requirements have the potential to be effective. In Figure A8, I plot cumulative, annual CAH expenditure according to the distance of each CAH to its next closest facility. I find CAH program expenditures would decrease by about $400 million per year if eligibility were restricted to hospitals at least 15 miles from their nearest facility —the original program

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35There are about 3,600 time-sensitive admissions per year among enrollees whose closest hospital converted to a CAH, implying 110 avoided deaths or 880 additional quality-adjusted life-years. These figures are based on the full sample of pre-CAH closures, which includes 48 hospitals. I scale the cost and life-year estimates to account for the fact that I predict that the CAH program led to 30 fewer closures.

36At the high end, Baicker and Staiger (2005) estimate that every $9 million in spending under the Disproportionate Share Hospital program led to one life saved, based on an analysis of AMI mortality among patients over 65.
Comparing these results to my mortality estimates is difficult, since distances between hospitals will not generally equal changes in enrollee travel distances after a closure. With that caveat, the results are suggestive. Even if all mortality effects were related to closures of hospitals more than 15 miles from another facility, the CAH program would not be cost-effective at traditional levels.

7 Conclusion

In this paper, I study the effect of hospital closure in rural markets. I find that hospital closure under the PPS system led to decreases in Medicare spending and increases in mortality among enrollees hospitalized for time-sensitive conditions. I further find that Medicare payment policy has an important role in determining hospital closure rates. Implementing cost-based reimbursement under the CAH program decreased closure rates by 25% and led to improvements in enrollee outcomes. However, I find evidence that these benefits were outweighed by substantial program costs.

My results have several implications for efforts to address hospital closure. First, my work suggests that hospital closure matters for both health care costs and patient survival. While hospital closure can improve productive efficiency through the elimination of fixed costs, these gains do not necessarily accrue to public payers. Indeed, I find that Medicare savings were driven by reductions in care provision, rather than improvements in efficiency for a given admission. In terms of patient outcomes, I find that hospital closure has an unambiguously negative impact on enrollee survival. In particular, enrollees experience adverse effects on increased travel distances after a closure, but do not see offsetting gains from receiving care at higher quality facilities, largely because there is not one available. These results suggest that discussions of a distance-quality trade-off may not be appropriate in isolated rural markets, where access concerns are most severe.

Second, my work argues that broad eligibility for cost-based reimbursement is not an effective policy for forestalling hospital closure. In particular, difficulty in targeting the CAH program led to substantial expenditure at hospitals with low risk of closure. Program costs also increased as hospitals increased their operating costs in response to cost-based reimbursement. My results thus raise questions about whether the CAH program could have successfully kept hospitals open at a lower cost by implementing higher DRG payments, instead of cost-based reimbursement. My analysis in this paper does not speak directly to the wisdom of cost-based reimbursement relative to prospective payment for addressing hospital closure, but suggests that a substantial fraction of program costs were driven by hospitals’

37 This estimate is very similar to the results from OIG (2013).
endogenous responses to cost-based reimbursement.

My analysis has several limitations and suggests avenues for future research. First, I study closures of small hospitals in isolated rural markets, and the results may not be applicable to other settings. Second, I study enrollee health on one dimension: Medicare mortality after time-sensitive hospitalizations. Future work could usefully test whether the effects of hospital closure are similar in other contexts. The effect of hospital closure is of particular interest within maternity care, where treatment delay can be harmful and where access to care has been decreasing in recent years. Third, my analysis focuses on the Medicare market, where price effects of closure are muted by the DRG system. It would be useful for future work to explore how hospital closure contributes to consolidation and private prices in rural markets.

Growing concern about hospital closure raises important questions about how public policy should respond. I present evidence that forestalling hospital closure can be valuable in local markets, but highlight challenges in targeting support to high-risk hospitals. Understanding how public policy can be appropriately designed to address rural hospital closure is a natural avenue for future work.
References


Figure 1: Rural Hospital Characteristics Under Prospective Payment

Panel A. Average Daily Census at Rural Hospitals

Panel B. Operating Margin at Rural Hospitals, ADC < 25

Note: These figures show summary statistics of rural hospitals under Medicare’s Prospective Payment System (PPS). Panel A is a histogram of average daily censuses at rural hospitals in 1990. For scaling purposes, I restrict the sample to hospitals treating fewer than 100 patients per day. Panel B is a non-parametric binned scatter plot of hospital operating margin versus underlying costs and revenues. The sample includes hospitals treating fewer than 25 patients per day between 1990 and 1997 when the PPS was in effect. I bin hospital operating margin into 25 equal-sized bins and plot the mean levels of operating revenues and operating costs within each bin. Revenues and costs are in 1997 dollars.
Figure 2: Effect of Example Hospital Closure in Local Market

Note: This figure illustrates the effects of an example hospital closure in Lamar County, Alabama. The location of the closed hospital is marked with an X and the locations of surviving hospitals are marked with solid circles. Zip-codes that lost their closest hospital as a result of the closure are marked in orange and zip-codes that lost their second closest facility are marked in yellow.
Table 1: Summary Statistics of Medicare Enrollees Losing their Closest and Second Closest Hospitals to Closure

<table>
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<tr>
<th></th>
<th>Pre-Closure Lost Closest</th>
<th>Pre-Closure Lost Second Closest</th>
<th>Diff.</th>
<th>Post-Closure Lost Closest</th>
<th>Post-Closure Lost Second Closest</th>
<th>Diff.</th>
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<tr>
<td>Number of Enrollees</td>
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<td>426859</td>
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<td>681964</td>
<td>516143</td>
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<td>Number of Admissions</td>
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<td>69217</td>
<td></td>
<td>111443</td>
<td>85345</td>
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<td><strong>Enrollee Characteristics</strong></td>
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<tr>
<td>Average Age</td>
<td>72.0</td>
<td>72.2</td>
<td>-0.2</td>
<td>71.9</td>
<td>72.0</td>
<td>-0.1</td>
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<td>Percent Female</td>
<td>56.0</td>
<td>56.0</td>
<td>0.0</td>
<td>55.8</td>
<td>55.8</td>
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<td>Percent White</td>
<td>90.0</td>
<td>91.2</td>
<td>-1.2</td>
<td>90.6</td>
<td>91.5</td>
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<td><strong>Admission Characteristics</strong></td>
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<tr>
<td>Average Age</td>
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<td>74.3</td>
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<td>Percent Female</td>
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<td>56.5</td>
<td>56.8</td>
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<td>Percent White</td>
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<td>90.3</td>
<td>91.2</td>
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<td>Observed 1-year Mortality Rate</td>
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<td>17.9</td>
<td>18.0</td>
<td>0.1</td>
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<td>Predicted 1-year Mortality Rate</td>
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<tr>
<td>Distance to Closest Hospital (miles)</td>
<td>4.6</td>
<td>3.7</td>
<td>0.8</td>
<td>10.7</td>
<td>3.7</td>
<td>6.9***</td>
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Note: This table reports summary statistics from Medicare claims of enrollees that lost their closest hospital as a result of a closure, relative to enrollees that lost their second closest facility as a result of the same closure. The sample includes 48 closures that occurred prior to the implementation of the Critical Access Hospital program. Predicted mortality is based on enrollee age, gender, race and presenting diagnosis. + p<0.1; * p<0.05; ** p<0.01; *** p<0.001.
Figure 3: Effect of Hospital Closure on Distance to Nearest Hospital

Panel A: Distance to Closest Hospital Before and After Closure

Panel B: Distribution of Change in Distance to Closest Hospital, Enrollees who Lost Closest Hospital to Closure

Note: These figures plot changes in enrollee travel distances to their closest hospitals before and after a hospital closure. Panel A is an unadjusted event study and plots average distance to the closest available hospital before and after a closure, for enrollees who lost their closest facility (circles) and for enrollees who lost their second closest facility (X’s). Panel B plots the distribution of changes in distance to the nearest facility across enrollees who lost their closest hospital to closure. A hospital can lead to no increase in travel distance if it was located in the same zip-code as a surviving facility.
### Table 2: Effect of Hospital Closure on Medicare Spending and Admissions

<table>
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<th>Ln(Per-Capita Medicare Spending)</th>
<th>Per-Capita Admissions</th>
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<tr>
<td></td>
<td>(1) (2) (3)</td>
<td>(4) (5) (6)</td>
</tr>
<tr>
<td></td>
<td>All Non-urgent Urgent</td>
<td>All Non-urgent Urgent</td>
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<tr>
<td>Post*Lost Closest Hospital</td>
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<td>-0.0791** (0.0297)</td>
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<td></td>
<td>-0.00833* (0.00353)</td>
<td>-0.00814** (0.00293)</td>
</tr>
<tr>
<td>Number of Closures</td>
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<td>48</td>
</tr>
<tr>
<td>Zip-Time Cells</td>
<td>3403</td>
<td>3403</td>
</tr>
<tr>
<td>Mean of Dep. Var.</td>
<td>819</td>
<td>537</td>
</tr>
<tr>
<td>Percent Change</td>
<td>0.16</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Note: This table presents DD estimates of the effect of hospital closure on Medicare spending and inpatient admissions, comparing enrollees who lost their closest hospital as a result of a closure to enrollees who lost their second closest hospital. Columns 1 through 3 estimate changes in per-capita Medicare spending and columns 4 through 6 estimate changes in per-capita admission rates. Urgent care includes admissions that originate in the emergency department and are categorized as urgent or emergency, rather than elective. The unit of analysis is a zip-time cell. Regressions include zip-code and calendar time fixed effects, in addition to controls for average age, percent white, and percent female at the zip-time level. Standard errors are clustered at the zip-code level. Spending is modeled using a one part GLM with a log link and is in 1997 dollars. Admission rates are modeled using OLS. * p<0.1; ** p<0.05; *** p<0.01; **** p<0.001.
Figure 4: Effect of Hospital Closure on Medicare Spending and Admissions

Panel A: Per-Capita Medicare Spending

*All Admissions*  
*Non-Urgent Admissions*

Panel B: Per-Capita Admission Rates

*All Admissions*  
*Non-Urgent Admissions*

Note: These figures plot event studies of per-capita Medicare spending and admission rates before and after hospital closure, comparing enrollees who lost their first and second closest hospitals to closure. The points are regression coefficients from a DD, event-study specification with zip-code and calendar time fixed effects as well as controls for time-varying zip-code characteristics. See Section 4.1 for more detail on the regression specification. Panel A shows the effect of hospital closure on Medicare spending and Panel B shows the effect on admissions. All effects are plotted as percent changes relative to the time period directly preceding the closure. Spending is modeled using a one part GLM with a log link and is in 1997 dollars. Admission rates are modeled using OLS.
<table>
<thead>
<tr>
<th></th>
<th>All-Cause Readmission Rates</th>
<th>Change in Distance</th>
<th>Enrollee Age</th>
<th>Presenting Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td></td>
<td>7-day</td>
<td>30-day</td>
<td>∆dist. &lt; 15</td>
<td>∆dist. ≥ 15</td>
</tr>
<tr>
<td>Post*Lost Closest Hospital</td>
<td>0.00348</td>
<td>0.00639</td>
<td>-0.00401</td>
<td>-0.00432**</td>
</tr>
<tr>
<td>Observations</td>
<td>198129</td>
<td>198129</td>
<td>3401</td>
<td>3401</td>
</tr>
<tr>
<td>Mean of Dep. Var.</td>
<td>0.06</td>
<td>0.16</td>
<td>0.13</td>
<td>0.03</td>
</tr>
<tr>
<td>Percent Change</td>
<td>0.05</td>
<td>0.04</td>
<td>-0.03</td>
<td>-0.17</td>
</tr>
</tbody>
</table>

Note: This table presents DD estimates of the effect of hospital closure on subgroups of inpatient admissions before and after a hospital closure, comparing enrollees who lost their first and second closest hospitals. Columns 1 and 2 estimate changes in all-cause readmission rates in a sample of index hospitalizations. Columns 3 through 8 estimate changes in per-capita admission rates at the zip-time level. Columns 3 and 4 estimate changes among enrollees who experience changes in distance to nearest facility of under 15 miles after a closure and of at least 15 miles. Enrollees who lost their second closest facility are split according to the increase in distance they would have experienced if they had lost their closest hospital. Columns 5 and 6 estimate changes in admission rates for enrollees who are younger and older than 80 years of age. Columns 7 and 8 estimate changes in admission rates for enrollees who present to the hospital with low and high mortality clinical conditions. Regressions include zip-code and calendar time fixed effects and controls for time-varying zip-code characteristics. Standard errors are clustered at the zip-code level. Admission and readmission rates are modeled using OLS. + p<0.1; * p<0.05; ** p<0.01; *** p<0.001.
Table 4: Effect of Hospital Closure on 1-Year Mortality Rates

<table>
<thead>
<tr>
<th></th>
<th>Pr(Admission)</th>
<th>1-Year Mortality</th>
<th>1-Year Mortality (Time-Sensitive)</th>
<th>Distance vs. Quality (Time-Sensitive)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Urgent</td>
<td>0.000521</td>
<td>0.00616</td>
<td>0.00857</td>
<td>0.183***</td>
</tr>
<tr>
<td>Time-Sensitive</td>
<td>(0.00143)</td>
<td>(0.00463)</td>
<td>(0.00884)</td>
<td>(0.0397)</td>
</tr>
<tr>
<td>Post*Lost Closest Hospital</td>
<td>-0.000226</td>
<td>0.0167*</td>
<td>0.0293*</td>
<td>0.00347</td>
</tr>
<tr>
<td></td>
<td>(0.000852)</td>
<td>(0.00744)</td>
<td>(0.0137)</td>
<td>(0.00298)</td>
</tr>
<tr>
<td>Δdist. &lt; 15</td>
<td>0.00857</td>
<td>0.0293*</td>
<td>0.183***</td>
<td>0.00347</td>
</tr>
<tr>
<td>Δdist. ≥ 15</td>
<td>(0.00884)</td>
<td>(0.0137)</td>
<td>(0.0397)</td>
<td>(0.00298)</td>
</tr>
<tr>
<td>Pr(dist. &gt; min.)</td>
<td>0.183***</td>
<td>0.00347</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hospital RAMR</td>
<td>0.00347</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>3902</td>
<td>116630</td>
<td>29749</td>
<td>42186</td>
</tr>
<tr>
<td>Percent Change</td>
<td>0.0122</td>
<td>0.0282</td>
<td>0.0278</td>
<td>0.267</td>
</tr>
<tr>
<td>Std. Dev. From Mean</td>
<td>-0.0153</td>
<td>0.0544</td>
<td>0.0978</td>
<td>0.0112</td>
</tr>
<tr>
<td>Mean of Dep. Var.</td>
<td>0.0426</td>
<td>0.307</td>
<td>0.300</td>
<td>0.311</td>
</tr>
<tr>
<td></td>
<td>(0.0148)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: This table presents DD estimates of the effect of hospital closure on 1-year mortality rates among enrollees with urgent and time-sensitive hospitalizations, comparing enrollees who lost their closest and second closest hospitals to closure. Urgent care includes admissions that originate in the emergency department and are categorized as urgent or emergency, rather than elective. Time-sensitive care includes emergency admissions with the following presenting conditions: acute myocardial infarction, stroke, heart failure, pneumonia and sepsis, acute respiratory failure and injury. Columns 1 and 2 estimate changes in index admission rates to verify that the probability of admission does not change in response to hospital closure. Columns 3 and 4 model 1-year mortality rates after index admissions. Regressions include zip-code and calendar time fixed effects, and controls for enrollee age, gender, race and presenting condition. Standard errors are clustered at the zip-code level. Columns 5 through 8 explore two potential mechanisms underlying the mortality change among time-sensitive admissions. Columns 5 and 6 estimate mortality changes among enrollees who experienced increases in distance to their closest facility of under and over 15 miles, respectively. Enrollees who lost their second closest facility are split according to the increase in distance they would have experienced if they had lost their closest hospital. Column 7 estimates the effect of hospital closure on the probability that enrollees travel farther than their minimum pre-closure travel distance, e.g., the distance to the closed hospital for enrollees who lost their closest facility. Column 8 estimates changes in the average quality of hospitals where enrollees received care, measured as facility-level, risk-adjusted mortality rates. + p<0.1; * p<0.05; ** p<0.01; *** p<0.001.
Figure 5: Distribution of Simulated Revenue Gains Resulting from Cost-Based Reimbursement under the Critical Access Hospital Program

Note: This figure plots the distribution of simulated revenue gains from moving to cost-based reimbursement under the CAH program from PPS reimbursement. Estimates are based off of 1990-91 characteristics of hospitals that met basic CAH eligibility criteria: location in a rural county and an ADC of 25 or less.
Figure 6: Effect of Simulated Revenue Changes on Hospital Closure

Panel A: Eligible Rural Hospitals

Panel B: Placebo Sample of Ineligible Semi-Rural Hospitals

Note: This figure plots the effect of simulated revenue gains under the CAH program on hospital closure rates over time. Panel A estimates changes in closure rates among hospitals that met basic CAH eligibility criteria: rural hospitals treating fewer than 25 patients per day. Estimates of $\beta_k$ from equation 2 are indexed on the left-axis, estimating the change in the log hazard rate from a unit change in $\text{sim}\Delta \text{rev}$ (e.g. moving from an operating margin of -100% to 0%). See Section 5.1 for more detail on the regression specification. The right axis rescales $\beta_k$ to reflect the average change in simulated revenue under the program. Given an average increase in simulated revenue of 14% (Figure 5), a coefficient of -2 implies a decrease in closure of 25%: $\exp(-2\times0.14) - 1$. Panel B estimates the placebo effects of simulated CAH revenue on closure rates in a sample of semi-rural hospitals that were ineligible for the CAH program.
Figure 7: Hospital Operating Revenues and Costs, Before and After CAH Conversion

Note: This figure plots an unadjusted event study of operating revenues and costs among converting hospitals that convert to CAHs, before and after CAH conversion. The solid lines plot average revenues and costs per hospital. The dashed lines show predicted growth in revenues and costs based on pre-period trends under the PPS. Revenues and costs are in 1997 dollars.
Table 5: Effect of CAH Protection on Medicare Spending, Admissions and 1-year Mortality

<table>
<thead>
<tr>
<th></th>
<th>Changes Under CAH Conversion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td></td>
<td>Ln(Per-Capita Spending)</td>
</tr>
<tr>
<td>Post*CAH Protected</td>
<td>0.0701*</td>
</tr>
<tr>
<td></td>
<td>(0.0322)</td>
</tr>
<tr>
<td>Observations</td>
<td>8776</td>
</tr>
<tr>
<td>Percent Change</td>
<td>0.018</td>
</tr>
<tr>
<td>Mean of Dep. Var.</td>
<td>0.167</td>
</tr>
</tbody>
</table>

Note: This table presents DD estimates of the effect of keeping hospitals open through CAH conversion, comparing enrollees whose closest hospital avoided closure by converting to a CAH to enrollees who lost their closest hospital to closure. For analyses of per-capita spending and admissions, the unit of analysis is a zip-time cell. Regressions include zip-code and calendar time fixed effects, in addition to controls for average age, percent white, and percent female at the zip-time level. For mortality analyses, the unit of analysis is an index admission and the regression includes controls for enrollee age, gender, race and presenting condition. + p<0.1; * p<0.05; ** p<0.01; *** p<0.001.
Appendix

A1 Background Information

Figure A1: Number of Hospital Closures Before and After PPS Implementation

Note: This figure shows the number of hospital closures before and after the implementation of the Prospective Payment System (PPS) by Medicare in 1983. Prior to the PPS, Medicare reimbursed hospitals on a cost basis. The data in this figure are approximations based on graphics from the Government Accountability Office (1991).
Figure A2: Association of Hospital Operating Margin with Size and Operating Cost Components

Panel A. Average Daily Census

Panel B. Labor vs. Capital Costs

Note: These figures present non-parametric binned scatter plots of the relationship between hospital operating margin, average daily census and underlying costs. Both figures are based on a sample of rural hospitals treating fewer than 25 patients per day between 1990 and 1997 when PPS reimbursement was in effect. In Panel A, I bin hospital operating margin into 25 equal-sized bins and plot the mean average daily census within each bin. In Panel B, I again bin hospitals according to operating margins and plot full-time equivalents (FTE) per patient day versus bed days per patient day. To facilitate comparison across these measures, they are reported as z-scores.
## A2 Characteristics of Closed and Surviving Hospitals, Pre-CAH Period

Table A1: Summary Statistics for Hospitals by Closure Status

<table>
<thead>
<tr>
<th>Hospital Characteristics</th>
<th>Closed</th>
<th>Open</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Hospitals</td>
<td>48</td>
<td>1075</td>
</tr>
<tr>
<td>Number of Admissions</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>22970</td>
<td>137962</td>
</tr>
<tr>
<td>Lost Closest</td>
<td>20172</td>
<td>60366</td>
</tr>
<tr>
<td>Lost Second Closest</td>
<td>3481</td>
<td>80184</td>
</tr>
<tr>
<td>Demographic Characteristics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Age</td>
<td>76.7</td>
<td>73.9</td>
</tr>
<tr>
<td>Percent Female</td>
<td>60.0</td>
<td>55.5</td>
</tr>
<tr>
<td>Percent White</td>
<td>90.9</td>
<td>90.5</td>
</tr>
<tr>
<td>Admission Characteristics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent Non-Urgent</td>
<td>54.7</td>
<td>56.5</td>
</tr>
<tr>
<td>Percent Urgent</td>
<td>45.2</td>
<td>43.4</td>
</tr>
<tr>
<td>Transferred</td>
<td>7.2</td>
<td>4.5</td>
</tr>
<tr>
<td>Risk Adjusted Mortality Rate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All Admissions</td>
<td>22.4</td>
<td>22.0</td>
</tr>
<tr>
<td>Non-Urgent Admissions</td>
<td>20.2</td>
<td>18.7</td>
</tr>
<tr>
<td>Urgent Admissions</td>
<td>24.2</td>
<td>26.3</td>
</tr>
<tr>
<td>Time-Sensitive Admissions</td>
<td>36.9</td>
<td>36.0</td>
</tr>
</tbody>
</table>

Note: This table reports summary statistics for hospitals that closed and remained open in the pre-CAH period. Hospital characteristics are computed across a sample of enrollees who lost their closest or second closest hospital as a result of closure, in the period before the closure. Urgent care includes admissions that originate in the emergency department and are categorized as urgent or emergency, rather than elective. Time-sensitive admissions are emergency admissions for the following conditions: acute myocardial infarction, stroke, heart failure, pneumonia and sepsis, acute respiratory failure and injury.
Figure A3: DRG Prices at Closed and Surviving Hospitals

Note: This figure plots prices at closed hospitals and those that remain open. Each circle represents a Diagnosis Related Group (DRG), and the size of the circle indicates the number of admissions in that category. In DRG titles, “CC” stands for complicating condition. The sample is restricted to beneficiaries that lost their closest or second closest hospital, and prices measured in the pre-closure period for DRGs with at least 100 admissions at a closed facility in the pre-closure period. The dashed line is the 45 degree line and indicates equivalent prices across closed and surviving facilities.
Figure A4: Enrollee Travel Distances and Facility Quality: Closed vs. Surviving Facilities

Note: This figure plots gradients of enrollee travel distances to nearby hospitals and risk-adjusted mortality rates (RAMR) at the same facilities in the pre-closure period. The X’s plot z-scores of enrollee travel distances to their closest hospital, which closes in the pre-CAH period, and the next four closest hospitals. The circles plot z-scores of RAMR at the same hospitals.
## A3 Robustness Checks: Effects of Hospital Closure

Table A2: Robustness Check: Alternative Modeling Choices

<table>
<thead>
<tr>
<th></th>
<th>Per-Capita Medicare Spending</th>
<th>1-Year Mortality, Time Sensitive</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Main</td>
<td>Area-Time FE</td>
</tr>
<tr>
<td>Post*Lost Closest Hospital</td>
<td>-0.0494*</td>
<td>-0.0509*</td>
</tr>
<tr>
<td></td>
<td>(0.0245)</td>
<td>(0.0232)</td>
</tr>
<tr>
<td>Observations</td>
<td>3403</td>
<td>3403</td>
</tr>
<tr>
<td>Mean of Dep. Var.</td>
<td>819</td>
<td>819</td>
</tr>
<tr>
<td>Percent Change</td>
<td>-0.04</td>
<td>0.054</td>
</tr>
</tbody>
</table>

Note: This table presents DD estimates of the change in Medicare spending and mortality after hospital closure. Columns 1 and 5 repeat the results from the main specification. Columns 3 and 7 estimate changes using alternate functional forms. Columns 4 and 8 cluster standard errors at the level of the closure-area, rather than zip-code.

Table A3: Robustness Check: Enrollee Population Changes Before and After Hospital Closure

<table>
<thead>
<tr>
<th></th>
<th>Underlying Population Change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Enrollee pop.</td>
</tr>
<tr>
<td>Post*Lost Closest Hospital</td>
<td>-3.504</td>
</tr>
<tr>
<td></td>
<td>(5.346)</td>
</tr>
<tr>
<td>Observations</td>
<td>3403</td>
</tr>
<tr>
<td>Mean of Dep. Var.</td>
<td>514.11</td>
</tr>
<tr>
<td>Percent Change</td>
<td>-0.01</td>
</tr>
</tbody>
</table>

Note: This table tests whether underlying enrollee populations change differentially over time after a hospital closure, comparing enrollees that lost their closest and second closest hospital. Column 1 estimates changes in the underlying population size. Columns 2 through 4 estimate changes in the average age of the underlying population, the percent white and the percent female.
Table A4: Effect of Hospital Closure on Admission for Outpatient Substitutable Surgical Care

<table>
<thead>
<tr>
<th></th>
<th>Admission Type</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) All</td>
<td>(2) Outp. Substitute</td>
<td>(3) Surgical, Age &lt; 80</td>
<td></td>
</tr>
<tr>
<td>Post*Lost Closest Hospital</td>
<td>-0.00833* (0.00353)</td>
<td>0.0000797 (0.000508)</td>
<td>-0.00304 (0.00254)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>3401</td>
<td>3401</td>
<td>3401</td>
<td></td>
</tr>
<tr>
<td>Mean of Dep. Var.</td>
<td>0.16</td>
<td>0.01</td>
<td>0.06</td>
<td></td>
</tr>
<tr>
<td>Percent Change</td>
<td>-0.05</td>
<td>0.01</td>
<td>-0.05</td>
<td></td>
</tr>
</tbody>
</table>

Note: This table presents DD estimates of the effect of hospital closure on Medicare admissions, comparing enrollees that lost their closest and second closest hospitals. Column 1 repeats the estimated effect on aggregate admission from Table 2. Columns 2 and 3 estimate changes in surgical admissions that have high substitutability with outpatient care. The unit of analysis is a zip-time cell. Regressions include zip-code and calendar time fixed effects and controls for time-varying zip-code characteristics. Standard errors are clustered at the zip-code level.
Table A5: Effect of Hospital Closure on Short-Term Mortality Rates

<table>
<thead>
<tr>
<th></th>
<th>Main</th>
<th>Alternate Outcomes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Inpatient</td>
</tr>
<tr>
<td>1-year</td>
<td></td>
<td>30-day</td>
</tr>
<tr>
<td>Post*Lost Closest Hospital</td>
<td>0.0167*</td>
<td>0.00529</td>
</tr>
<tr>
<td></td>
<td>(0.00744)</td>
<td>(0.00646)</td>
</tr>
<tr>
<td>Observations</td>
<td>42186</td>
<td>42678</td>
</tr>
<tr>
<td>Percent Change</td>
<td>0.0544</td>
<td>0.0542</td>
</tr>
<tr>
<td>Mean of Dep. Var.</td>
<td>0.308</td>
<td>0.0975</td>
</tr>
</tbody>
</table>

Note: This table presents DD estimates of the effect of hospital closure on mortality among enrollees hospitalized for a time-sensitive condition, comparing enrollees that lost their closest and second closest hospitals. Column 1 repeats the main estimate of changes in 1-year mortality from Table 4. Columns 2 through 4 estimate changes in mortality over shorter time frames. The unit of analysis is an index admission. Regressions include zip-code and calendar time fixed effects, as well as controls for enrollee age, gender, race and presenting condition. Standard errors are clustered at the zip-code level.

Table A6: Effect of Hospital Closure on 1-year Mortality, Subgroups of Time-Sensitive Admissions

<table>
<thead>
<tr>
<th></th>
<th>(1) Main</th>
<th>(2) Drop AMI</th>
<th>(3) Drop Resp.</th>
<th>(4) Drop Stroke</th>
<th>(5) Drop HF</th>
<th>(6) Drop Pneum./Sepsis</th>
<th>(7) Drop Injury</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post*Lost Closest Hospital</td>
<td>0.0167*</td>
<td>0.0160*</td>
<td>0.0124</td>
<td>0.0248**</td>
<td>0.0143*</td>
<td>0.0160*</td>
<td>0.0154*</td>
</tr>
<tr>
<td></td>
<td>(0.00744)</td>
<td>(0.00765)</td>
<td>(0.00778)</td>
<td>(0.00798)</td>
<td>(0.00836)</td>
<td>(0.00937)</td>
<td>(0.00740)</td>
</tr>
<tr>
<td>Observations</td>
<td>42186</td>
<td>37768</td>
<td>36029</td>
<td>37612</td>
<td>35855</td>
<td>28545</td>
<td>41807</td>
</tr>
<tr>
<td>Percent Change</td>
<td>0.0544</td>
<td>0.0515</td>
<td>0.0381</td>
<td>0.0811</td>
<td>0.0456</td>
<td>0.0542</td>
<td>0.0491</td>
</tr>
<tr>
<td>Mean of Dep. Var.</td>
<td>0.308</td>
<td>0.310</td>
<td>0.326</td>
<td>0.306</td>
<td>0.313</td>
<td>0.295</td>
<td>0.313</td>
</tr>
</tbody>
</table>

Note: This table presents DD estimates of the effect of hospital closure on 1-year mortality for subgroups of time-sensitive conditions. Column 1 repeats the main estimate from Table 4. Columns 2 through 7 estimate changes in mortality among alternate samples of time-sensitive admissions, dropping each clinical condition in turn. The unit of analysis is an index admission. Regressions include zip-code and calendar time fixed effects, as well as controls for enrollee age, gender, race and presenting condition. Standard errors are clustered at the zip-code level.
## A4 Characteristics of Hospitals Meeting Basic CAH Criteria

Table A7: Summary Statistics for Rural Hospitals, ADC < 25

<table>
<thead>
<tr>
<th>CAH Eligible Hospitals</th>
<th>Closed</th>
<th>Open</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Hospitals</td>
<td>127</td>
<td>1393</td>
</tr>
<tr>
<td>Simulated CAH Gain</td>
<td></td>
<td></td>
</tr>
<tr>
<td>sim. Δ rev.</td>
<td>0.50</td>
<td>0.06</td>
</tr>
<tr>
<td>PPS Inpatient Revenue per Day</td>
<td>606</td>
<td>679</td>
</tr>
<tr>
<td>Sim. CAH Inpatient Revenue per Day</td>
<td>758</td>
<td>694</td>
</tr>
<tr>
<td>Overall Hospital Margin</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operating Margin</td>
<td>-0.37</td>
<td>-0.11</td>
</tr>
<tr>
<td>Operating Revenue per Patient Day</td>
<td>1322</td>
<td>1239</td>
</tr>
<tr>
<td>Operating Costs per Patient Day</td>
<td>1718</td>
<td>1370</td>
</tr>
<tr>
<td>Size</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Daily Census</td>
<td>8.69</td>
<td>15.42</td>
</tr>
<tr>
<td>Medicare Bite</td>
<td>0.51</td>
<td>0.46</td>
</tr>
<tr>
<td>Bed Count</td>
<td>33.93</td>
<td>49.28</td>
</tr>
<tr>
<td>Market Characteristics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No Urban Commuting (%)</td>
<td>0.26</td>
<td>0.43</td>
</tr>
<tr>
<td>County Population (thousands)</td>
<td>26.86</td>
<td>22.24</td>
</tr>
</tbody>
</table>

Note: This table reports summary statistics for hospitals that met basic CAH eligibility criteria: located in a rural counties and serving 25 patients per day or fewer. Statistics are reported separately for hospitals that closed and remained open between 1990 and 1998. The statistics are computed based on 1990 characteristics. Medicare bite refers to the share of hospital patients with Medicare insurance.
A5 Hospital Closure under Cost-based Reimbursement

One concern regarding my analysis of the CAH program and hospital closure rates is that closure rates decreased after 1997 not because of cost-based reimbursement, but because unprofitable hospitals had already closed prior to the policy change. To address this concern, I plot the distribution of margins among hospitals that survived through 1997 and those that closed during the same period. In Figure A5, I show that hospitals that survived until 1997 were still highly unprofitable, although they were more profitable at baseline than the hospitals that closed in the pre-CAH period. Among hospitals that survived until 1997, I find that 1997 margins were similar to their baseline (1990) margins, suggesting that these hospitals were not able to survive as a result of improving efficiency over time.

Figure A5: Distribution of Hospital Operating Margins by Closure Status

Note: This figure shows the Epanechnikov kernel densities of hospital operating margins for hospitals than closed between 1990 and 1997 and hospitals that survived during the same time period.
A6 Additional Results: Changes in Treatment Patterns from Forestalled Closure

Table A8: Coarsened Exact Match Results Linking Closed Hospitals to CAH Converters

<table>
<thead>
<tr>
<th></th>
<th>Closed Pre-CAH</th>
<th>CAH Converter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>Unmatched</td>
</tr>
<tr>
<td>Baseline Margin</td>
<td>-0.20</td>
<td>-0.09</td>
</tr>
<tr>
<td>Baseline ADC</td>
<td>10.28</td>
<td>9.48</td>
</tr>
<tr>
<td>Baseline Medicare Bite</td>
<td>0.50</td>
<td>0.40</td>
</tr>
<tr>
<td>Other hospital in county</td>
<td>0.63</td>
<td>0.38</td>
</tr>
</tbody>
</table>

Note: This table presents results of a coarsened exact matching algorithm that links hospitals that closed in the pre-CAH period to CAH converters in the post-CAH period. I match closed hospitals according to their pre-closure characteristics in 1990 to the 1997 characteristics of hospitals that survived until 1997 and later converted to a CAH. Medicare bite refers to the share of hospital patients with Medicare insurance.
Figure A6: Medicare Admissions Before and After CAH Conversion

Panel A. Non-Urgent Admissions

Panel B. Urgent Admissions

Note: This figure plots an event study of admissions around CAH conversion. The sample is restricted to beneficiaries whose closest hospital converted to a CAH.
Figure A7: Medicare Spending per Patient Day, Before and After CAH Conversion

Note: This figure plots an event study of Medicare spending per patient day around CAH conversion. The sample is restricted to beneficiaries whose closest hospital converted to a CAH.
Figure A8: CAH Program Expenditure by Distance from CAH to Nearest Facility

Note: This figure addresses the scope of the CAH program among eligible rural hospitals. It plots cumulative CAH spending across participating hospitals according to the centile of distance to their nearest facility.