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IMPACT OF RURAL AND URBAN HOSPITAL CLOSURES ON INPATIENT MORTALITY

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Abstract

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Keywords: hospital closures, rural closures, access to care, California's hospital closures, California's rural hospitals, inpatient mortality, heart attack, stroke, asthma/COPD, sepsis

JEL Codes: I11, I12, I14, I18

1 Introduction

About 15% of U.S. hospitals have closed since 1990 and rates of hospital closure have increased over the last decade (Carroll, 2018). There is sufficient consensus pointing to weakened hospital finances owing to low reimbursement rates and uncompensated care for uninsured patients as the primary cause for hospital (and emergency department (ED)) closures (Lindrooth et al., 2018; Hodgson et al., 2015).[1] These problems are exacerbated in rural areas, especially due to the recent economic downturns and job losses leading to outmigration and shrinking populations, leaving behind populations that are older, sicker, and more reliant on Medicaid and Medicare. Such shifts lead to financially less favorable payer-mixes at hospitals, making hospitals more susceptible to closures. Other factors influencing rural closures include aging facilities, outdated payment

[1] However, there is a lack of consensus regarding the link between Medicaid expansion and hospital (or ED) closures (Lindrooth et al., 2018; Allen, 2017; Friedman et al., 2016; Wishner et al., 2016). As this paper is a state-specific study, explicit discussion of this link between Medicaid expansion and hospital closures is omitted here.

and delivery system models, greater competition from urban hospitals (for patients and for federal resources), and strategic decisions by corporate owners or operators (Kaufman et al., 2016; Wishner et al., 2016; Premkumar et al., 2016).

Hospital closures can severely fracture patient access to care (especially emergency care (Wishner et al., 2016)), leading to treatment delay and adverse health outcomes (Carroll, 2018). At the same time, closures may reallocate patients to more efficient hospitals, improving patient welfare. The net impact of closures, whether rural or urban, on patient outcomes is not well-known, and remains an empirical question.

Rural hospital closures have been of particularly high concern due to increasing rates of rural closures since 2010, and because of the complexities they pose in terms of access and efficiency (Carroll, 2018; Holmes et al., 2017; Kaufman et al., 2016; Wishner et al., 2016; Escarce and Kapur, 2009). From an efficiency standpoint, rural hospitals exiting the market seems inevitable as these hospitals tend to be too small to operate efficiently (Song and Saghafian, 2019; Carroll, 2018; Hannan et al., 2003; Dranove, 1998). However, such exits can have enormous negative implications for patient welfare. Rural closures increase travel times for patients (Troske and Davis, 2019; Hsia and Shen, 2011) and lead to outmigration of health care professionals post-closure (Manlove and Whitacre, 2017; Wishner et al., 2016), severely dismembering patient access to care and exacerbating social disparities in health outcomes (Song and Saghafian, 2019). These concerns have led recent public policy efforts to devote substantial resources towards forestalling rural hospital closure Carroll (2018).

As policymakers grapple to identify instruments capable of addressing the threats hospital closures pose, gaps in understanding must also be closed. Despite the increase in hospital closure rates and prominent media calls to attention (The Takeaway, 2019; Carroll, 2019; Frakt, 2019b; Kaufman et al., 2016), very few studies have analyzed the impact of hospital closures on patient outcomes. Previous studies have instead looked at the financial and economic impact of hospital closures (Manlove and Whitacre, 2017; Hodgson et al., 2015), factors influencing hospital and ED closures (Lindrooth et al., 2018; Wishner et al., 2016; Friedman et al., 2016), and the impact of ED closures on patient outcomes (Hsia et al., 2012). Literature studying the effect of hospital closures, both rural and urban, on patient outcomes is sparse.

Existing studies of the impact of hospital (and ED) closures on patient outcomes yield mixed results and many focus exclusively on Medicare patients (Song and Saghafian, 2019; Carroll, 2018; Joynt et al., 2015; Rosenbach and Dayhoff, 1995). Song and Saghafian (2019) find that hospital closures are associated with an increase in 30-day patient mortality at hospitals, likely due to "speed-up behavior" in which hospitals reduce average length-of-stay, rather than average bed idle time. Carroll (2018) finds that patients losing their closest hospital (compared to those losing their second closest hospital) experience increased mortality. Buchmueller et al. (2006) find that hospital closures increase deaths from heart attacks and unintentional injuries in Los Angeles (LA) county. However, several studies find no impact of hospital (or ED) closures on patient mortality (Joynt et al., 2015; Hsia et al., 2012; Rosenbach and Dayhoff, 1995). Thus, whether it is studies exclusively focusing on Medicare patients (Song and Saghafian, 2019; Carroll, 2018; Joynt et al., 2015; Rosenbach and Dayhoff, 1995), or California-specific studies (Buchmueller et al., 2006; Hsia et al., 2012; Liu et al., 2014), a lack of consensus regarding the impact of hospital (and ED) closures prevails, even when studying similar geographic cohorts and diagnostic conditions in similar time periods. Furthermore, Medicare population as a whole tends to be relatively well-insured, and post-closure barriers to access may be larger for the uninsured and those covered by Medicaid (Rosenbach and Dayhoff, 1995). Nevertheless, these populations have not been sufficiently examined in the hospital closure literature.[2] The lack of relevant studies and uncertainty across the existing ones is crippling from a policy perspective, and could prove detrimental for patients. This warrants further scrutiny of the impact of hospital closures on patient outcomes.

This paper studies the impact of both rural and urban hospital closures in California, 1995-2011, on inpatient mortality. The analysis includes all Medicare and non-Medicare patient admissions diagnosed with sepsis, stroke, asthma/COPD, or acute myocardial infarction (AMI). These diagnostic conditions were chosen because post-closure mechanisms (such as longer travel time or overcrowding at surrounding hospitals) are likely to result in larger adverse impacts for patients with time-sensitive conditions, and these time-sensitive conditions offer more comparability with prior hospital closure studies (Carroll, 2018; Liu et al., 2014; Joynt et al., 2015; Hsia et al., 2012; Buchmueller et al., 2006). The paper is novel in two primary ways; it 1) explicitly differentiates between rural and urban closures as forms of "treatment" expected to affect patients (see motivation for this approach in Section 2.3), and 2) uses a list of California's hospital closures, which attempts to reconcile discrepancies identified in previous lists of California's closures. California is an important state for studying hospital closures, as it had an accelerated rate and the highest number of closures in the year 2000 (Nicholas C Petris Center, 2001; OIG, 2000), and remains a state with one of the highest number of closures in recent years (Troske and Davis, 2019). To our best knowledge, this is the first paper drawing explicit focus to rural closures in California. While the generalizability of state-specific studies can be limited, general insights from a data-rich state, bifurcated by rural and urban closures, can be instrumental in providing impetus for research and policy efforts in relatively more rural states that may be more vulnerable but offer lower data access.

The paper is organized as follows: Section 2 outlines the methodology; Section 2.2 presents the more common methodology estimating the impact of a general hospital closure, whereas Section 2.3 outlines the paper's novel methodology, distinguishing the impact of a rural closure vs. urban closure; Section 3 describes the data, Section 4 presents results, and Section 5 presents conclusions.

2 Methodology

Using a difference-in-difference (DID) approach, two primary specifications were used for examining the impact of hospital closures on inpatient mortality:

- General impact of hospital closures
- Differential impacts of rural and urban closures

Section 2.1 outlines the definition of "affected patients" used for the analysis, while Sections 2.2 and 2.3 detail the two above-mentioned specifications. Separate subgroup analyses were also conducted for each of the time-sensitive conditions: sepsis, stroke, asthma/COPD, and AMI.

2.1 Definition of "Affected Patients"

Several prior studies (Carroll, 2018; Hsia et al., 2012; Buchmueller et al., 2006) use change in geographic distance or driving time post-hospital closure as the primary predictor (or as the basis for

[2] Liu et al. (2014) and Hsia et al. (2012) do study patient outcomes for these populations in the context of ED closures. However, the impact of ED closures can differ from that of hospital closures. As some hospitals may have multiple EDs, ED closures may have a smaller or a different type of disruption of access than a hospital closure does. For instance, the loss of a full hospital is likely to create greater service interruptions than an ED closure would (Buchmueller et al., 2006). The loss of a hospital would also necessitate patients to seek care at a different hospital, whereas patients may end up at the same hospitals post-ED closures.

the primary predictor) affecting patient outcomes. In these studies, affected patients are typically those that experience a change in distance to their nearest hospital as a result of a hospital closure. While distance is an important factor determining patient choice, especially in rural areas, distance sensitivity can vary for different types of procedures (Premkumar et al., 2016) and other factors such as hospital size, technologies available, hospital quality may additionally influence hospital choice (Premkumar et al., 2016; Hodgson et al., 2015; Escarce and Kapur, 2009). Moreover, geodetic distances, driving distances, and driving times may sometimes suffer from measurement inaccuracies (Hsia et al., 2012). Given that prior California-specific studies (two of which use such metrics) (Hsia et al., 2012; Liu et al., 2014; Buchmueller et al., 2006) find differing implications for mortality (albeit due to varying aspects of ED and hospital closures), this paper takes an alternate approach.

Hospital Service Areas (HSAs), which represent local health care markets representing patients' primary care travel pattern, are used for identifying affected patients in this paper, similar to Joynt et al. (2015) and Rosenbach and Dayhoff (1995). A patient is considered affected by a hospital closure if his/her residential zip code was part of an HSA that experienced a hospital closure.

Advantages of such HSA-based identification of affected patients are:

- Implicit inclusion of the distance mechanism while avoiding the assumption that patient hospital choices/travel patterns are based strictly on distance;
- Inclusion of multiple other mechanisms:
  - Immediate detrimental outcomes, as well as lagged outcomes resulting from delayed or foregone care post-closures.
  - Ripple effects, such as overcrowding and overburdening of hospitals, on surrounding communities within the HSA (similar aim as Song and Saghafian (2019); Hodgson et al. (2015); Liu et al. (2014)). Note that overcrowding and overburdening may also lead to negative outcomes at hospitals *outside* the affected HSA. Such spillover effects on patients residing in affected HSAs that travel outside their HSA to seek care post-closure would be measured in the treatment effect. However, spillover effects for patients residing outside the affected HSA would be part of the control group effect. Thus, any adverse treatment effect due to spillovers would be conservatively estimated.
  - Potentially reduced quality at surrounding hospitals due to lower competition when prices are market determined (Frakt, 2019a).
  - Increased efficiency at surrounding hospitals (Gaynor et al., 2015).
  - Effects on patients seeking care both within and outside their residential HSA, and those switching these patterns post-closure. Note that this approach can also overcome a limitation of HSA-based identification of affected *hospitals* rather than of affected patients noted in Liu et al. (2014). That is, if affected patients switch HSAs post-closures, the effect on them, and any effect of overburdening because of them, would be missed if studying affected *hospitals*. This is especially true for rural patients, as they are likely to bypass their residential HSAs post-hospital (or ED) closures in their HSAs.
- Reduction in confounding owing to inadequate control of simultaneous mechanisms. Such confounding can occur when studying only one channel of hospital closure's impact without controlling for others. This type of confounding is mitigated here as all mechanisms are combined into one observed variable.

The primary disadvantage of such HSA-based identification of affected patients is thus the inability to distinguish between various mechanisms of impact, limiting immediate and specific policy implications to emerge. Nonetheless, the paper studies an *overall* impact of hospital closures, in case the adverse effects are sparsely distributed across several channels of impact. Given that scholars are currently split on whether or not hospital closures have any adverse impact on patient outcomes, the paper's approach can reduce this divide to further policy efforts.

2.2 General Impact of Hospital Closures

A general effect of hospital closures is estimated first. In this portion of the analysis, no distinction is made between patients who experience a rural closure vs. those who experience an urban closure in their respective residential HSAs. Variation in timing and reasons of hospital closures throughout California from 1995 to 2011 is exploited using a "staggered" DID or DID with multiple time periods (Stevenson and Wolfers, 2006). This study design is useful when the same policy is implemented in different regions nonconcurrently, or "staggeringly." It measures the effect of a policy, hospital closure in this case, which is constant across time, reasons of closure, and geographical units.

The model is specified as follows:

$$Y_{igt} = \alpha_0 + \alpha_1(Treat_g) + \alpha_2(TreatPost_{gt}) + \alpha_3 X_{igt} + H_i + T_t \tag{1}$$

Y_{igt} is a binary variable indicating whether an admission resulted in death at the hospital. Thus, the following probability is estimated:

$$P(Y = 1|g,t) = F(\alpha_0 + \alpha_1(Treat_g) + \alpha_2(TreatPost_{gt}) + \alpha_3 X_{igt} + H_i + T_t) \tag{2}$$

where F is a logit function and $0 \leq F \leq 1$. $Treat_g$ indicates whether or not the admitted patient's HSA was ever affected in the 1995-2011 period. $TreatPost_{gt}$ indicates whether the admission is from an affected HSA *and* occurs in that HSA's post-closure period. X_{igt} are admission-level and hospital-level covariates that can impact inpatient mortality. H_i are hospital fixed effects and T_t are year fixed effects. α_2 is the parameter of interest.

2.3 Differential Impacts of Rural and Urban Hospital Closures

Previous studies of the impact of hospital closures on mortality treat all hospital closures alike (similar to the approach described in Section 2.2), and do not distinguish between rural and urban closures. However, there are well-documented differences in care-seeking behavior across rural and urban areas. For instance, rural patients typically experience larger travel distances, longer transportation times, and other transportation barriers, compared to urban patients (Lindrooth et al., 2018; Kaufman et al., 2016; Premkumar et al., 2016; Hsia and Shen, 2011). Rural patients are known to bypass nearby rural hospitals for nearby urban hospitals. Rural patients, compared to urban patients, are also much more likely to use hospitals for primary care needs (Premkumar et al., 2016; Wishner et al., 2016). These baseline differences in care-seeking behavior of rural and urban patients can lead to differential effects for hospital closures in rural areas vs. those in urban areas.

Using national data for the years 2011-2014, Troske and Davis (2019) demonstrate that in the aftermath of hospital closures within their zipcodes, rural patients experience a 76% increase in ambulance transportation times, compared to before closure. Although Troske and Davis (2019) find that urban patients experience no change in travel times post-closures occurring within their (urban) zip codes, urban patients residing closer to *rural* closures may nonetheless experience longer ambulance transportation times due to shared resources with rural patients. Such spillover effects from a closure in one zipcode to surrounding zipcodes are relatively under-explored, even though half of the studies that find a negative impact of hospital (or ED) closures on mortality suggest that overcrowding of surrounding hospitals post-closures is a strong contributor towards increased mortality (Song and Saghafian, 2019; Liu et al., 2014).

Additionally, while urban patients seem to shift their usual source of care post-closure from hospitals to physicians' offices or community clinics, which are viewed as more appropriate sources of primary care (Buchmueller et al., 2006), no such favorable substitution is observed for rural patients (Rosenbach and Dayhoff, 1995). Furthermore, there may be a potential decline in physician availability in rural areas due to physicians relocating post-closure (Rosenbach and Dayhoff, 1995), exacerbating rural patients' baseline pattern of seeking primary care at hospitals.

Given that hospital closures negatively impact health care access for rural patients compared to urban patients, and given the existence of strong spillover effects post-closures, spillover effects from rural closures may be larger than those from urban closures. As such, the overall effect of a rural hospital closure, which includes transportation delays and overburdening mechanisms, is hypothesized to be larger than that of an urban closure. Recall that post-closure increases in efficiency leading to quality gains and better outcomes for patients may additionally be at play (Joynt et al., 2015) and may differ depending on whether the closing hospital was rural or urban. Hence, this paper examines the differential impacts of rural and urban closures.

There is an added advantage to this approach. Several prior studies ignore urban closures when measuring the impact of rural closures. Neglecting to account for concurrent urban closures when studying rural closures (or vice versa) confounds estimates. For instance, if urban closures decrease mortality, but are not controlled for when studying the impact of rural closures, the effect of rural closures may be overestimated. If urban closures increase mortality but are not controlled for, the impact of rural closures would be underestimated. This paper limits confounding of this sort by appropriately accounting for both types of closures.

Thus, to allow for potentially different effects of rural vs. urban closures and to control for one type of closure while examining the impact of the other, a staggered DID approach with *two* treatment groups is used: 1) admissions affected due to a rural hospital closure, and 2) admissions affected due to an urban hospital closure.

The model is specified as follows:

$$\begin{aligned} P(Y=1|g,t) =& F(\gamma_0 + \gamma_1(RuralTreat_g) + \gamma_2(RuralTreatPost_{gt}) + \gamma_3(UrbanTreat_g) + \\ & \gamma_4(UrbanTreatPost_{gt}) + \gamma_5 X_{igt} + H_i + T_t) \end{aligned} \tag{3}$$

Note that Equation 3 above is similar to Equation 2, except in its treatment variables. $RuralTreat_g$ indicates whether or not the admitted patient's HSA was ever affected by a rural hospital closure in the 1995-2011 period. $RuralTreatPost_{gt}$ indicates whether the admission is from such an HSA *and* occurs in that HSA's post-rural closure period. $UrbanTreat_g$ indicates whether or not the admitted patient's HSA was ever affected by an urban hospital closure in the 1995-2011 period. $UrbanTreatPost_{gt}$ indicates whether the admission is from such an HSA *and* occurs in that HSA's post-urban closure period. γ_2 and γ_4 are the parameters of interest in this specification.

2.4 Exogeneity of Treatment

Concerns may arise that the impact of hospital closure is endogenous to hospital behavior or hospital quality (Carroll, 2018). That is, hospitals of lower quality or hospitals with worse behavior may be more likely to close. In such cases, HSAs affected by closure may exhibit worse outcomes due to worse hospitals in those areas, and not because of closure. To address such concerns, note firstly that variation in timing of closures makes it highly unlikely that results are due to changes in hospital quality or behavior (unrelated to closures) that coincide with identified closure years of the various hospitals. Additionally, hospital fixed effects are included for controlling any time-invariant hospital effects.[3]

Nevertheless, there may be concerns that hospital closures occur in HSAs where individual patients are relatively older, sicker, poorer, more likely to be racial minorities, and more likely to be uninsured. Thus, to control for disease severity and poverty, patient characteristics such as age, co-morbidities, admission source variables, insurance status and an indicator for whether an admission is from a rural or urban zip code are used.

3 Data

3.1 Closed Hospitals

Although a few recent studies have pointed to the lack of a centralized list of hospital closures and some data issues in identifying closures (Song and Saghafian, 2019; Carroll, 2018), none shed sufficient light on the nature and extent of these issues. This section describes the list of closed hospitals used, and compares it with other reports of California's closures, with the aim of reducing future discrepancies in the hospital closure literature.

OSHPD patient discharge data from 1995 to 2011 is used for identifying hospital closures with a process comparable to that used in Song and Saghafian (2019). A hospital is defined as "closed" if its general acute care admissions dropped to 10 or less in a given year (and remained so in subsequent years) from 1995 to 2011.[4] "Closure year" was defined as the year *prior* to the year in which hospital admissions dropped to 10 or less.[5]

To distinguish appropriately between closed hospitals and hospitals that may exhibit 10 or fewer admissions due to a name/hospital identifier change (owing to a merger or ownership change not resulting in closure), additional sources were consulted for confirming closures. Sources consulted include government reports (OIG, 1995, 1996, 1997, 1998, 1999), closed hospitals list from the LA Times (LA Times Data Desk, 2019), and academic publications and reports (Hodgson et al., 2015; Buchmueller et al., 2006; Nicholas C Petris Center, 2001).[6,7] After the confirmation process, a list of 139 potential closures identified using admissions data was reduced to a list of 99 hospital closures.[8]

[3]Note also that there is no evidence that affected HSAs or closing hospitals provide lower quality of care (even though patients may *perceive* certain rural hospitals to be of poor quality based on anecdotal evidence (Wishner et al., 2016; Escarce and Kapur, 2009)); instead, the bulk of the literature points to differences in financial health and efficiency of treated vs. non-treated facilities (a point also noted by (Carroll, 2018)).

[4]Additional sources mentioned in the next paragraph are used for identifying closures in 2011, as admissions data for 2012 were not available and thus a potential drop in admissions in 2012 cannot be identified.

[5]Alternate analyses using a modified definition of "closure year" were also conducted and are presented in Appendix C. Instead of using the year *prior*, "closure year" was defined as the very year in which a hospital's admissions dropped to 10 or less, and results of this analysis were very similar to the main results presented in the paper.

[6]Closed hospitals data, not used in the primary publication, was also obtained from authors of Hodgson et al. (2015).

[7]Numerous other sources, such as non-profit organization reports (CHCF, 2015; HASC, 2010) and news articles announcing individual hospital closures (or suggesting lack thereof), were also used, but are not all listed here. A complete list of these sources can be provided upon request.

[8]Note that this confirmation process may have resulted in excluding real but under-publicized closures, and thus remains a conservative list of closures. Nevertheless, as will be discussed later in this section, this paper ensures inclusion of the largest number of closures in California, and potential exclusion of a few such hospitals is unlikely to

Seven of the 99 hospitals, which closed and re-opened in the same year and in the same zip code, were excluded from the list of closed hospitals. The resulting 92 hospitals are the confirmed closures used for this analysis.[9]

Next, using 2004 data from United States Department of Agriculture (USDA) Economic Research Service (ERS), hospitals were assigned a rural-urban commuting area (RUCA) code based on the hospital's zip code. RUCA codes were used for classifying hospitals as rural or urban (consistent with (Holmes et al., 2017)). Rural classifications were further confirmed using other sources where hospital closures were reported and using additional internet search.[10] The 92 hospitals were thus classified as follows: 16 rural and 76 urban.

Some discrepancies across other sources of hospital closure lists are worth mentioning here. Hospitals appearing in one data source for a given time period were sometimes entirely excluded from other sources reporting closures in the same period. Additionally, there were some discrepancies regarding the exact year of closure, where the margin of error was typically a year, but in a few cases, this error margin ranged from 3 to 9 years. Because of these discrepancies, the present method for identifying closures has been explicitly outlined, and the resulting list is compared to the primary sources consulted.

Table 1 compares the number of closures in each year with those reported in four of the primary sources consulted. As can be seen, there are discrepancies in number of closures per year across the sources consulted. Nevertheless, the closure list by year is largely consistent with that of the LA times. It also picks up the largest or second largest number of hospital closures in most years. However, as closure year definitions across sources vary slightly, lists by year appear less compatible than comparisons of exact hospitals in each list. Thus, Table 2 compares the actual hospitals in the closure list to each of the four primary sources consulted, disregarding the year of closure for this exercise. 77%-91% of hospital closures reported by other sources are included in this analysis. The remaining 29 excluded hospitals (i.e. 9%-13% of unmatched hospitals implicit in Table 2) are listed in Table 3 alongside the reason for their exclusion.

Direct comparisons of California's closed hospitals, which are part of national studies, were not possible, as California-specific hospital counts or names were not reported in Song and Saghafian (2019); Carroll (2018); Joynt et al. (2015), and the study period does not overlap with that in Troske and Davis (2019). However, the reliance of some of these studies (Carroll, 2018; Joynt et al., 2015) on "Lanscape Change in U.S. hospitals" from American Hospital Association (AHA, 2019) appears problematic as AHA (2019) captures very few closed hospitals from California. For instance, currently available fiscal year reports AHA (2019) indicate zero closures in California from 2006-2011, compared to 13 closures identified from 2006-2011 in the present paper. Additionally, whether a list such as AHA (2019), which includes fewer hospitals, is used during the first step of the closure identification process (Joynt et al., 2015) or only during the verification step (Carroll, 2018) can matter. That is, using such a list with fewer closures as the primary source, or as a first step, implies starting from a narrower list, resulting in an overall smaller list of closures. Whereas, if such a source is one of several sources used for verification, the risk of underestimating the ultimate number of closures is reduced.

Note that the methodology used in this paper for identifying closures through admissions data picks up most missed closures across the various lists, providing a more reconciled and complete list of closures in California from 1995 to 2011. An added advantage of this approach is the reliance on year-to-year comparisons of admissions data vs. on mere year-to-year comparisons

be a problem.

[9] A complete list of these closures is provided in supplemental materials.

[10] Only one hospital, which was classified as urban using RUCA codes, was updated to being "rural" based on other reporting.

of hospital listings (which do not include admissions information). The latter approach may be more susceptible to data reporting issues, as it is easier to wrongly include or exclude one hospital identifier in a given year than it is to wrongly include or exclude several admissions for a given hospital and year.

A few factors contributing to "closure year" discrepancies are also noted here. When a hospital retains its license, but has ceased to admit new general acute care patients, reported closure years may be later than years in which access to care was actually interrupted (also pointed out by Nicholas C Petris Center (2001)). When parts of the hospital remain open (e.g. ambulatory care or EDs), or when hospitals convert to entities providing outpatient or specialty care, official closure years reported may be later or different than years in which general acute care access was interrupted. Definitions of "closure year" should thus be explicitly noted in literature, and appropriate definitions must be adopted depending on the purpose of analysis. The "closure year" definition in this paper is well-aligned with the paper's intention to capture the very first instances of interruptions in general acute care. In cases of closure year discrepancies, closure year in this paper is always earlier than in other reports. Thus, if a hospital stopped providing general acute care services, but was still providing some or other aspects of care, the reduction or interruption in care due to closure, i.e."treatment", would be smaller than if all services were completely shut off. This implies that the paper's estimates are conservative (similar to (Troske and Davis, 2019)).

Table 1: No. of Hospital Closures by Year

Year	No. of Closures	Compare to other sources			
		Petris.org[11]	OIG reports[12]	LA times[13]	Hodgson[14]
1995	6	1	2	-	-
1996	9	3	7	-	-
1997	13	3	6	-	-
1998	10	7	10	14	1
1999	9	3	5	6	0
2000	8	6	7	12	0
2001	1	-	-	4	8
2002	3	-	-	2	6
2003	8	-	-	10	8
2004	9	-	-	6	7
2005	3	-	-	4	4
2006	1	-	-	1	2
2007	5	-	-	2	5
2008	1	-	-	1	6
2009	4	-	-	-	8
2010	2	-	-	-	3
2011	0	-	-	-	2
Total	92	23	37	62	60

The second column from the left indicates the number of closures in our analysis by year. The columns to the right of it indicate the number of closures identified by year in other sources. As neither of the other sources report closures for the entire period between 1995-2011, dashes are used to indicate missing values. Note that in some cases, a closed hospital identified by a source may occur in the following or preceding year for a different source.

[11] Nicholas C Petris Center (2001)
[12] OIG (1995, 1996, 1997, 1998, 1999, 2000)
[13] LA Times Data Desk (2019)
[14] Hodgson et al. (2015)

Table 2: % Closed hospitals matched with other data sources

Other Sources	No. of Closures	No. Matched	% Matched
Petris Center report, 1995-2000	23	21	91%
OIG reports, 1995-2000	37	33	89%
Buchmueller[15] (LA county only), 1997-2003	15	13	87%
LA times, 1998-2008	62	53	85%
Hodgson, 1995-2011	60	46	77%

This table reports the number and percentage of closed hospitals identified by other sources that also occur in our closed hospitals list. Note that the year of closure may differ across the matched hospitals in some cases.

[15] Buchmueller et al. (2006)

Table 3: Closures in other sources that were excluded

	Hospital Name	Year	Source	Reason for exclusion
1	Tustin Hospital	1996	OIG reports	Re-opened within a year under a different name, with same hospital ID.
2	Lakeside Hospital	1996	OIG reports	Name not found in OSHPD data.
3	Watsonville Comm. Hospital	1998	OIG reports	Re-opened within a year.
4	Suncrest Hospital, Orange Co.	1998	Buchmueller	Name not found in OSHPD data & not confirmed in internet search.
5	Los Medanos Comm. Healthcare Dist.	1998	LA times	Name not found in OSHPD data. Possibly closed before 1995.
6	SHC Specialty Hospital	1998	LA times	Name not found in OSHPD data. May exist in closures list under a different name.
7	Kaiser Foundation, Norwalk	1999	Buchmueller	Name not found in OSHPD data & not confirmed in internet search.
8	Saint Louise Mental Health Ctr	1999	LA times	Name not found in OSHPD data & not confirmed in internet search.
9	Kaiser Foundation, El Cajon	2000	Petris.org, LA times	Name not found in OSHPD data. Possibly closed before 1995.
10	Long Beach Community Med. Ctr.	2000	Petris.org, OIG reports	Re-opened within a year under a different name, with same hospital ID.
11	Hoopa Community Hospital	2000	LA times	Name not found in OSHPD data & not confirmed in internet search.
12	Kaiser Permanente, SF French Camp.	2000	LA times	Name not found in OSHPD data & not confirmed in internet search.
13	Anaheim Memorial Medical Ctr.	2001	LA times	Name not found in OSHPD data & not confirmed in internet search.
14	Ukiah Valley Medical Ctr.	2001	Hodgson	No general acute care admissions matched the hospital ID & year not confirmed in internet search.
15	Rehabilitation Institute, Santa Barbara	2001	Hodgson	No general acute care admissions matched the hospital ID & not confirmed in internet search.
16	Fremont Hospital Behavioral Health	2001	Hodgson	No general acute care admissions matched the hospital ID & not confirmed in internet search.
17	Mission Comm. Hospital, San Fernando	2002	Hodgson	Admissions in OSHPD data never dropped to 10 or below.
18	East Valley Pavilion	2002	Hodgson	No general acute care admissions matched the hospital ID & not confirmed in internet search.
19	Lassen Comm. Hospital	2003	LA times	Re-opened within a year in the same zip code.
20	Hazel Hawkins Convalescent Hospital	2003	Hodgson	No general acute care admissions matched the hospital ID & not confirmed in internet search.
21	Mercycare, Mercy General Hospital	2004	Hodgson	No general acute care admissions matched the hospital ID & not confirmed in internet search.
22	Monrovia Community Hospital	2005	LA times	Re-opened within 2 years under a different name, with same hospital ID.
23	Little Co of Mary Transitional Care Ctr	2005	Hodgson	No general acute care admissions matched the hospital ID & not confirmed in internet search.
24	Baywood Court (Eden Medical Ctr.)	2008	Hodgson	No general acute care admissions matched the hospital ID & not confirmed in internet search.
25	Kaiser Fnd Hosp, Carson	2008	Hodgson	No general acute care admissions matched the hospital ID & not confirmed in internet search.
26	Simi Valley Hospital, Heywood	2008	Hodgson	No general acute care admissions matched the hospital ID & not confirmed in internet search.
27	Agnews State Hospital	2009	Hodgson	No general acute care admissions matched the hospital ID & not confirmed in internet search.
28	Palm Drive Nursing & Rehab. Ctr.	2009	Hodgson	No general acute care admissions matched the hospital ID & year not confirmed in internet search.
29	Laurel Grove Hospital	2009	Hodgson	No general acute care admissions matched the hospital ID & year not confirmed in internet search.

This table lists the 29 hospitals considered closed by other sources, which did not meet the criteria of closure for our analysis. The reasons for excluding these hospitals from the closure list are presented in the right-most column.

3.2 Admission-level Analytic File

As depicted in Figure 1 below, the final admission-level analytic file was assembled using publicly available OSHPD patient discharge data, 1995-2011, for admissions with 5-digit residential zip codes,[16] OSHPD Hospital Financials Data, Dartmouth Atlas of Health Care crosswalks, USDA ERS RUCA codes 2004, and closed hospitals list (described in Section 3.1).

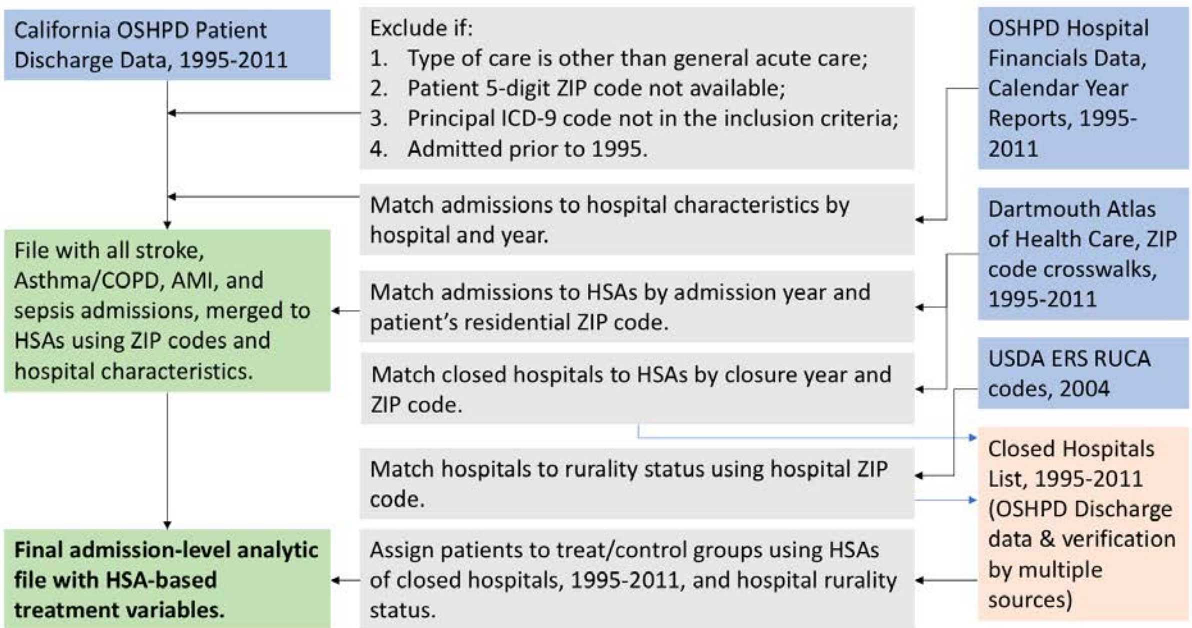


Figure 1: Data flow used to create primary analytic files

As adverse impacts of hospital closures entail mechanisms such as increased distance, increased travel times, and increased overcrowding and overburdening for surrounding communities, patients with time-sensitive conditions are more likely to be impacted negatively. Admissions presenting the following time-sensitive conditions are included in the study: sepsis, stroke, asthma or COPD, and AMI (see Table 4 for ICD-9 diagnostic codes used for identifying these conditions). These time-sensitive conditions, in particular, were chosen to ensure better comparability with prior studies (Carroll, 2018; Liu et al., 2014; Joynt et al., 2015; Hsia et al., 2012; Buchmueller et al., 2006).

[16] Patient admissions whose zip codes were masked or unavailable were dropped (which includes homeless individuals and foreigners). Additionally, admissions at hospitals and zipcodes with fewer than 2000 observations for the entire study period were dropped to ensure convergence of models with hospital fixed effects and zip code-level clustering, described in Sections 2 and 3.3.

Table 4: ICD-9 codes used for patient conditions from the Clinical Classifications Software from Agency for Healthcare Quality and Research (AHRQ) (Hsia et al., 2012)

Sepsis	003.1, 020.2, 022.3, 036.2, 038.0, 038.1, 038.10, 038.11, 038.19, 038.2, 038.3, 038.40, 038.41, 038.42, 038.43, 038.44, 038.49, 038.8,038.9, 054.5, 449, 790.7
Stroke	430, 431, 432.0, 432.1, 432.9, 433.01, 433.11, 433.21, 433.31, 433.81, 433.91, 434.0, 434.00, 434.01, 434.1, 434.10, 434.11, 434.9, 434.90, 434.91, 436
Asthma/COPD	493.00, 493.01, 493.02, 493.10, 493.11, 493.12, 493.20, 493.21, 493.22, 493.81, 493.82, 493.90, 493.91, 493.92, 490, 491.0,491.1, 491.2, 491.20, 491.21, 491.22, 491.8, 491.9, 492.0, 492.8, 494.0, 494, 494.1, 496
AMI	410.0, 410.00, 410.01, 410.02, 410.1, 410.10, 410.11, 410.12, 410.2, 410.20, 410.21, 410.22, 410.3, 410.30, 410.31, 410.32, 410.4, 410.40, 410.41, 410.42, 410.5, 410.50, 410.51, 410.52, 410.6, 410.60, 410.61, 410.62, 410.7, 410.70, 410.71, 410.72, 410.8, 410.80, 410.81, 410.82, 410.9,410.90, 410.91, 410.92

3.3 Variables

The outcome variable, inpatient mortality, is a binary variable, created using the "disposition" variable in the OSHPD discharge data, which includes in-hospital death as one of the values indicating a patient's disposition at the end of a hospital stay. This measure likely underestimates negative outcomes due to hospital closures because it does not capture out-of-hospital mortality. For instance, patients who may have died before generating a hospital admission would not be captured by this measure (similar to (Liu et al., 2014; Hsia et al., 2012)). Additionally, as an indicator of adverse outcomes, mortality captures only the relatively worse effects; smaller effects of closures may be missed. Readmission rates or morbidity may serve as better measures (Hsia et al., 2012), but were not available. As such, the results of this paper using inpatient mortality as an outcome variable would be conservative. Cause-specific mortality (used in Buchmueller et al. (2006)) would have been preferable for strengthening the causal link of the results, but such data was also not available.

Although administrative data can be restrictive in controlling for all clinical confounders, a wide range of factors influencing inpatient mortality are controlled for. These include age category, sex, race, International Classification of Diseases, Ninth Revision (ICD-9) codes, Elixhauser comorbidities (Stagg, 2015; Elixhauser et al., 1998), expected payer category (Medicare, Medi-Cal,[17] private, indigent, self-pay and other), a patient's residential rurality status, and admission source variables. Admission source variables help control for disease severity, as for instance, non-elective admissions may be more urgent or severe than elective admissions (Carroll, 2018; Hsia et al., 2012); patients re-routed from another hospital's ER (and therefore experiencing longer travel time) may be more severe than those not requiring re-route (Hsia et al., 2012).

Hospital-level control variables include hospital control type (city/county, district, investor, non-profit, state), proportion of Medi-Cal days, number of medical staff, and ratio of available bed to licensed beds. Any time-invariant hospital characteristics are controlled for using hospital fixed effects. Year fixed effects were used to control for secular trends.

Additionally, population density per HSA from the year 2000, the number of time sensitive admissions per HSA for each year, Herfindahl-Hirschman Index (HHI) calculated at the HSA-level for hospitals that never closed, and county-level unemployment rates are also included.[18] Summary

[17] Medi-Cal is California's version of Medicaid (Hodgson et al., 2015).

[18] Annual county-level unemployment data was obtained from California Economic Development Department's

statistics for these variables are presented in Appendix A. For the main analysis, standard errors are clustered by zip code to account for any within-zip code correlation, but errors could not be clustered for the subgroup analyses, as models with clustered errors did not converge for subgroup analyses (similar to Hsia et al. (2012)).

4 Results

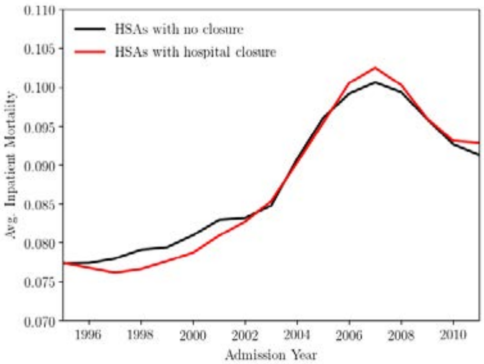
Sections 4.1 and 4.2 present descriptive results, which are followed by estimates of the effects of hospital closure in Sections 4.3 and 4.4. Recall that the impact of hospital closures on inpatient mortality is estimated using two methods; one estimates the general effect of hospital closures, not distinguishing between rural and urban hospitals (described in Section 2.2), and the other estimates differential impacts of rural and urban hospital closures (described in Section 2.3). The latter is the paper's novel contribution to the literature, and is compared with the relatively more common, former approach.

4.1 Common Trends Assumption

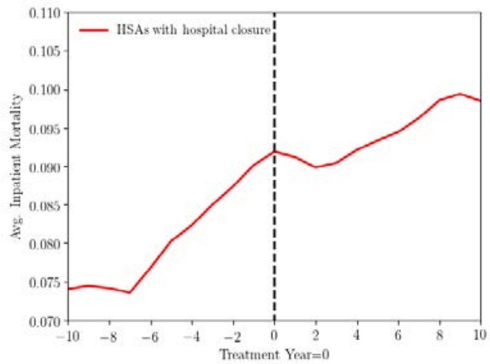
Firstly, treatment and control group trends are presented for HSA-level inpatient mortality (weighted by HSA population density) in the left-column graphs of Figure 2. Figures 2a and 2b correspond to the specification estimating the *general* effect of hospital closures, as described in Section 2.2. Figures 2c through 2f correspond to the specification studying rural and urban closures as differential treatments, as described in Section 2.3. As the validity of the DID approach rests on the assumption that treatment and control groups follow a similar outcome trajectory in the absence of treatment, we note that all three graphs in the left column of Figure 2 exhibit that control and treatment groups roughly follow similar trends, such that the DID approach seems appropriate.

Next, the right-hand side column of Figure 2 presents average HSA-level mortality of the treatment group, before and after treatment, where the treatment year is set to zero. Note that there are no such natural treatment years for control HSAs. Such visual evidence sets expectations of the potential impacts to be discovered (Wing et al., 2018). Figure 2b and 2d suggest potential short-term *decreases* in inpatient mortality due to general hospital closures and urban closures, whereas Figure 2f suggests that rural hospitals potentially increase inpatient mortality. As post-closure effects appear to differ across rural closure and urban closure treatments (compare Figures 2f and 2d), this paper's novel approach, which differentiates between rural and urban closures, appears critical for understanding the patient mortality impact of closures.

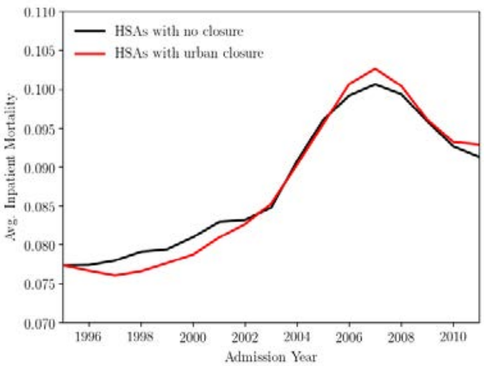
Labor Force Data.



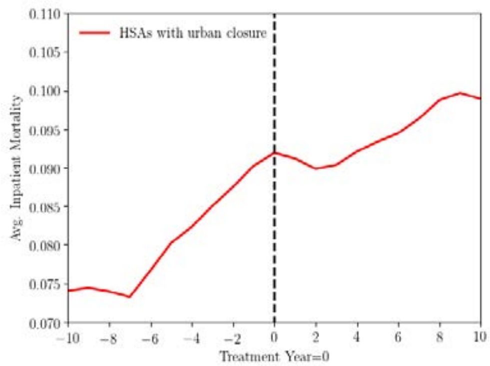
(a) All hospital closures - control vs. treat



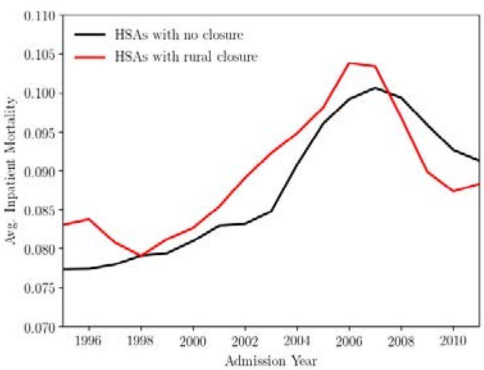
(b) All hospital closures - treatment group



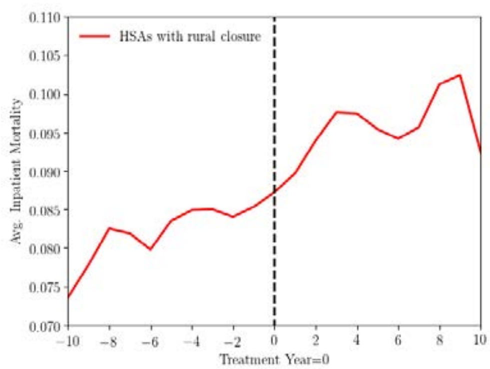
(c) Urban closures - control vs. treat



(d) Urban closures - treatment group



(e) Rural closures - control vs. treat



(f) Rural closures - treatment group

Figure 2: (Left) Average inpatient mortality in HSAs with closure (Treatment) vs. HSAs without closure (Control). (Right) Average inpatient mortality in Treatment HSAs only, with admission year centered at the year of closure or treatment for that HSA. Averages are weighted by zip code-level population density for each HSA from the year 2000.

4.2 Baseline Characteristics in Treatment HSAs vs. Control HSAs

As is typical for DID studies, it is demonstrated that baseline covariates for treatment and control groups, especially with respect to the diagnostic conditions and co-morbidities, are well-balanced. Tables 5, 6, and 7 present proportions (for dichotomous variables), means (for non-dichotomous variables) and standardized differences (calculated using formulas presented in Austin (2011)) between each of the treatment groups and the control group for diagnostic conditions, Elixhauser co-morbidities, and other covariates, respectively.

Table 5: Time-sensitive conditions, Proportions ($\hat{p}$) & Diffs., 1995

	$\hat{p}$, Ctrl	$\hat{p}$, Treat	Std. Diff.	$\hat{p}$, Urban	Std. Diff.	$\hat{p}$, Rural	Std. Diff.
AMI	0.252	0.235	-0.039	0.232	-0.046	0.260	0.018
Stroke	0.252	0.240	-0.027	0.239	-0.030	0.240	-0.027
Asthma/COPD	0.344	0.372	0.058	0.376	0.066	0.350	0.012
Sepsis	0.152	0.152	0.000	0.153	0.002	0.149	-0.008
Observations	74,687	55,925		51,854		6,236	

Asterisks indicate a standardized proportion difference of greater magnitude than 0.1. There are no standardized differences greater than 0.1 for the proportion of time-sensitive admissions in treatment HSAs vs. in control HSAs.

Table 6: Elixhauser Co-morbidities, Proportions ($\hat{p}$) & Diffs., 1995

	$\hat{p}$, Ctrl	$\hat{p}$, Treat	Std. Diff.	$\hat{p}$, Urban	Std. Diff.	$\hat{p}$, Rural	Std. Diff.
Congestive Heart Failure	0.180	0.170	-0.026	0.169	-0.028	0.197	0.043
Cardiac Arrhythmias	0.232	0.216	-0.038	0.217	-0.035	0.217	-0.035
Valvular Disease	0.067	0.059	-0.032	0.06	-0.028	0.063	-0.016
Pulmonary Circulation Disorders	0.021	0.022	0.006	0.022	0.006	0.026	0.033
Peripheral Vascular Disorders	0.044	0.043	-0.004	0.043	-0.004	0.045	0.004
Hypertension, Uncomplicated	0.320	0.32	0.000	0.321	0.002	0.331	0.023
Paralysis	0.124	0.119	-0.015	0.121	-0.009	0.109	-0.046
Other Neurological Disorders	0.097	0.098	0.003	0.099	0.006	0.086	-0.038
Chronic Pulmonary Disease	0.437	0.461	0.048	0.463	0.052	0.46	0.046
Diabetes, Uncomplicated	0.155	0.158	0.008	0.157	0.005	0.165	0.027
Diabetes, Complicated	0.044	0.038	-0.030	0.039	-0.025	0.035	-0.046
Hypothyroidism	0.052	0.050	-0.009	0.050	-0.009	0.061	0.038
Renal Failure	0.041	0.039	-0.010	0.038	-0.015	0.047	0.029
Liver Disease	0.015	0.014	-0.008	0.015	0.000	0.013	-0.017
Peptic Ulcer Disease	0.014	0.012	-0.017	0.012	-0.017	0.013	-0.008
AIDS/HIV	0.002	0.004	0.036	0.004	0.036	0.001	-0.025
Lymphoma	0.006	0.006	0.000	0.006	0.000	0.006	0.000
Metastatic Cancer	0.017	0.017	0.000	0.017	0.000	0.017	0.000
Solid Tumor Without Metastasis	0.026	0.025	-0.006	0.025	-0.006	0.029	0.018
Rheumatoid Arthritis/Collagen Vascular	0.020	0.019	-0.007	0.018	-0.014	0.017	-0.022
Coagulopathy	0.019	0.018	-0.007	0.018	-0.007	0.016	-0.022
Obesity	0.041	0.043	0.009	0.044	0.014	0.036	-0.025
Weight Loss	0.023	0.023	0.000	0.023	0.000	0.020	-0.020
Fluid and Electrolytes Disorders	0.213	0.227	0.033	0.232	0.045	0.204	-0.022
Blood Loss Anemia	0.009	0.008	-0.010	0.008	-0.010	0.004	-0.062
Deficiency Anemia	0.013	0.014	0.008	0.014	0.008	0.013	0.000
Alcohol Abuse	0.028	0.029	0.006	0.029	0.006	0.028	0.000
Drug Abuse	0.014	0.016	0.016	0.016	0.016	0.012	-0.017
Psychoses	0.010	0.011	0.009	0.012	0.019	0.009	-0.010
Depression	0.029	0.029	0.000	0.029	0.000	0.034	0.028
Hypertension, Complicated	0.062	0.065	0.012	0.065	0.012	0.061	-0.004
Observations	74,687	55,925		51,854		6,236	

Asterisks indicate a standardized proportion difference of greater magnitude than 0.1. There are no standardized differences greater than 0.1 for the Elixhauser co-morbidities between treatment and control HSAs.

Table 7: Other Variables, Proportions ($\hat{p}$), Means ($\bar{\mu}$) & Diffs., 1995

	Ctrl	Treat	Std. Diff.	Urban	Std. Diff.	Rural	Std. Diff.
In-hospital death	0.078	0.078	0.000	0.078	0.000	0.084	0.021
Race							
White	0.764	0.703	-0.138*	0.69	-0.166*	0.869	0.273*
Black	0.060	0.108	0.173*	0.114	0.192*	0.035	-0.117*
Native American/Eskimo/Aleut	0.001	0.001	0.000	0.001	0.000	0.000	-0.044
Asian/Pacific Islander	0.043	0.048	0.023	0.051	0.037	0.008	-0.223*
Other	0.041	0.037	-0.020	0.037	-0.020	0.025	-0.089
Missing/Unknown	0.091	0.103	0.040	0.107	0.053	0.061	-0.113*
Admission source of patient							
Home	0.89	0.878	-0.037	0.875	-0.046	0.905	0.049
Residential Care Facility	0.011	0.008	-0.030	0.008	-0.030	0.011	0.000
Ambulatory Surgery	0.003	0.005	0.031	0.006	0.044	0.003	0.000
Skilled Nursing/Intermediate Care	0.034	0.036	0.010	0.038	0.021	0.027	-0.040
Acute/Inpatient Hospital Care	0.053	0.055	0.008	0.056	0.013	0.043	-0.046
Other (Inpatient) Hospital Care	0.005	0.006	0.013	0.006	0.013	0.006	0.013
Prison/Jail	0.000	0.001	0.044	0.001	0.044	0.002	0.063
Other	0.003	0.010	0.087	0.011	0.096	0.001	-0.044
Admission source site							
This Hospital	0.015	0.016	0.008	0.016	0.008	0.017	0.015
Another Hospital	0.059	0.065	0.024	0.066	0.028	0.047	-0.053
Not a Hospital	0.926	0.919	-0.026	0.918	-0.029	0.934	0.031
Admission route							
This Hospital's ER	0.712	0.712	0.000	0.715	0.006	0.689	-0.050
Not an ER or Another Hospital's ER	0.287	0.288	0.002	0.285	-0.004	0.308	0.045
Payer Category							
Medicare	0.545	0.511	-0.068	0.505	-0.080	0.594	0.099
Medi-Cal	0.147	0.163	0.044	0.166	0.052	0.128	-0.055
Private Payer	0.257	0.272	0.034	0.275	0.040	0.232	-0.058
Indigent	0.013	0.02	0.054	0.021	0.061	0.015	0.017
Self-Pay	0.026	0.023	-0.019	0.023	-0.019	0.019	-0.047
Missing/Unknown	0.012	0.010	-0.019	0.01	-0.019	0.013	0.009
Age Category							
Under 1 year	0.019	0.021	0.014	0.021	0.014	0.020	0.007
1-17 years	0.074	0.083	0.033	0.085	0.040	0.061	-0.051
18-34 years	0.037	0.041	0.020	0.042	0.025	0.030	-0.038
35-64 years	0.270	0.285	0.033	0.284	0.031	0.294	0.053
65 years and over	0.600	0.569	-0.062	0.567	-0.066	0.596	-0.008
Sex							
Male	0.484	0.471	-0.026	0.470	-0.028	0.472	-0.024
Female	0.516	0.529	0.026	0.530	0.028	0.528	0.024
Hospital Control Type							
City/County	0.032	0.067	0.161*	0.065	0.154*	0.109	0.304*
District	0.136	0.037	-0.357*	0.039	-0.348*	0.009	-0.505*
Investor	0.119	0.123	0.012	0.128	0.027	0.162	0.123*
Non-Profit	0.713	0.773	0.137*	0.768	0.125*	0.720	0.015
% Medi-Cal days	0.197	0.201	0.023	0.205	0.046	0.177	-0.123*
Medical Staff	304.9	350.5	0.179*	360.3	0.215*	238.8	-0.331*
Available Beds/ Licensed Beds	0.918	0.898	-0.163*	0.895	-0.185*	0.947	0.293*
HSA admissions per year/1000	0.157	0.316	0.968*	0.324	1.010*	0.219	0.485*
Rural admission	0.069	0.021	-0.233*	0.003	-0.361*	0.179	0.338*
Pop. Dens. per sq. mi./1000	0.460	0.741	0.474*	0.785	0.544*	0.224	-0.700*
HHI-HSA for open hospitals	6708.2	3455.7	-1.089*	3457.1	-1.083*	3374.4	-1.242*
County unemp. Rate (%)	7.751	7.698	-0.019	7.343	-0.163*	13.482	1.971*
Observations	74,687	55,925		51,854		6,236	

Asterisks indicate a standardized mean or proportion difference of greater magnitude than 0.1.

Although there is no universally agreed upon criterion regarding what constitutes important imbalance between treatment and control groups, a standardized difference less than 0.1 is considered negligible (Austin, 2011). Tables 5, 6, and 7 report the standardized differences between treatment and control groups, and asterisks indicate standardized differences of 0.1 or higher. As can be seen in Tables 5 and 6, all differences between control and treatment groups with respect to diagnostic conditions and co-mobidities were negligible. Nevertheless, we noted differences of greater magnitude than 0.1 for some variables presented in Table 7. Treatment groups differ from the control group with respect to racial composition, hospital control type, medical staff supply, bed availability, rurality status of patient residence, HSA admissions per year, HSA population density, HSA hospital concentration, and county unemployment rate. General hospital closure and urban closure treatment groups include fewer Whites and more Blacks in treatment vs. control groups. For the rural closure treatment, there were fewer Asians/Pacific Islanders in the treatment group compared to the control. All treatment groups, compared to the control group, consisted of proportion of patient admissions at city/county hospitals and fewer admissions at district hospitals. Treatment groups were also more likely to be in HSAs with lower HHIs than the control group. General hospital closure and urban closure treatment groups were more likely to be at hospitals with higher medical staff, lower bed availability, higher HSA-level population density, compared to the control group, whereas the rural closure treatment group were more likely to be at hospitals with lower supply of medical staff, higher bed availability, and lower population density compared to the control group. While the urban closure treatment group had lower unemployment than the control group, the rural closure treatment group had higher unemployment. There were fewer proportions of rural admissions in the general and urban treatment closure groups, compared to control, whereas there was a greater proportion of rural admissions in the rural treatment group. These differences between control and treatment groups, in the context of hospital closure, have been previously cited in Allen (2017) (hospital ownership) Hsia and Shen (2011)(race), Joynt et al. (2015) (oversupply of medical staff), Rosenbach and Dayhoff (1995) (HSA admissions),Hodgson et al. (2015) (HHI), and Wishner et al. (2016) (unemployment). Note also that the pattern of differences across treatment and control groups can vary depending on whether the closure was rural or urban, emphasizing the need for differentiating between these two treatment groups.

For the DID estimation to be valid, such differences between treatment and control groups must be stable over time and changes in treatment exposure should not be linked to changes in the distribution of covariates (Wing et al., 2018). Differences between control and treatment HSAs noted here are consistent with several previous studies examining hospital closures using different data sets from different time periods. As the distributions of the covariates appear consistent with expectations from prior work, and as there are no differences at all in the co-morbidities, the treatment and control groups seem well-balanced.

4.3 General Impact of Hospital Closures

When no distinction is made between HSAs affected due to rural closures vs. due to urban closures, there is no measurable impact of hospital closure on inpatient mortality. Marginal effects for treatment variables are presented in Table 8.

Table 8: General Impact of Hospital Closures

Variable	Marginal Effect (Std. Error)
Treat Post	0.0008
	(0.0011)
Treat	-0.0014
	(0.0011)
R^2	0.147
N	2,736,593

Standard errors are reported in parentheses.
Errors are clustered by patient residential zip codes.
+ p<0.10, * p<0.05. None of the variables presented in this table were statistically significant.

This lack of a measurable general impact of hospital closures is a finding consistent with Joynt et al. (2015); Hsia et al. (2012); Rosenbach and Dayhoff (1995), which also do not find any measurable impact of hospital (or ED) closures on mortality. As mentioned earlier in Section 3.3 and as noted in Hsia et al. (2012), readmissions or morbidity may prove to be better measures for estimating adverse patient outcomes due to hospital closures. As such, the results presented would be conservative estimates of the general impact of hospital closures.

Additionally, as Hsia et al. (2012) note, a majority of patients in California experience a less than 10 minutes increase in driving time post-ED closure. If changes in driving times post-hospital closures are similar, then detecting mortality differences through such a channel would be difficult. Furthermore, positive patient outcomes from mechanisms of higher efficiency and/or higher quality of care at open hospitals post-closures, which are cited as theoretical possibilities in the literature, may be at play in offsetting potentially negative effects due to closures, leading to an overall null result.

Moreover, as these findings are based on data from California, which tends to be relatively more urban than the country (Hsia et al., 2012), the impact of urban closures may be driving the general impact of closures, potentially masking adverse impact of rural closures. As driving times, transportation barriers, and spillover effects post-rural closures may differ from effects post-urban closures, the differential impact of rural and urban closures must be analyzed. Results from studying differential impacts of rural and urban closures are thus presented in Section 4.4.

4.3.1 Subgroup Analyses - General Impact of Hospital Closures

In this section, separate estimates of the general impact of hospital closures are presented for each of the four diagnostic conditions. Marginal effects for the treatment variables are present in Table 9.

Table 9: Subgroup Analyses - General Impact of Hospital Closures

Variable	Sepsis	Stroke	Asthma/COPD	AMI
Treat Post	-0.0021	0.0033*	-0.0014*	0.0033*
	(0.0024)	(0.0017)	(0.0005)	(0.0014)
Treat	-0.0004	-0.0045*	0.0006	-0.0008
	(0.0025)	(0.0017)	(0.0006)	(0.0014)
R^2	0.111	0.054	0.187	0.159
N	724,182	678,069	956,206	691,516

Standard errors are reported in parentheses.
Errors were not clustered by patient residential zip codes because the model did not converge with clustering.
+ p<0.10, * p<0.05

Similar to the results for all conditions combined, presented in Section 4.3 above, there is no measurable impact of hospital closures for sepsis patients. However, closures increase mortality for stroke patients by 3.1% and for AMI patients by 4.5%, whereas closures decrease mortality by 8.8% for Asthma/COPD patients[19] This differential effect across Asthma/COPD and AMI and stroke patients is similar to differential findings across the same diagnostic categories in Buchmueller et al. (2006) (although they find a null result for COPD patients, when studying the effect of change in distances post-urban closures in LA county). As AMI and stroke are relatively more time-sensitive condition than asthma/COPD, results suggest that negative effects of closures may be stronger for more time-sensitive conditions, and that patients with other diagnostic conditions may be experiencing net effects of closures that are positive (similar to reduced mortality for patients with chronic conditions, noted in Buchmueller et al. (2006)), potentially owing to higher efficiency at open hospitals. Further examination of the underlying mechanisms and of the various diagnostic conditions is needed for targeting and improving protective policy measures undertaken post-closures.

4.4 Differential Impacts of Rural and Urban Closures

In this section, the differential impacts of rural and urban closures on inpatient mortality are presented. Marginal effects for the treatment variables for the subgroup analyses are presented in Table 10.[20] It is seen that rural hospital closures increase inpatient mortality by 0.46% points (an increase of 5.9%) whereas urban closures have no measurable impact on inpatient mortality. These results are consistent with Song and Saghafian (2019); Carroll (2018); Liu et al. (2014), which suggest that hospital closures and ED closures increase patient mortality. Song and Saghafian (2019) find that hospitals experience greater demand post-closure, and respond by using a "speed-up behavior," i.e. by reducing service duration rather than bed idle time. This leads to increased efficiency, which is nonetheless accompanied by a 3% increase in mortality. Carroll (2018) finds that rural hospital closures increase mortality by 5%. (Liu et al., 2014) finds that hospitals neighboring closing EDs experience an increase in inpatient mortality of 5% for the general patient population, and experience increases of higher magnitudes for three of the four time sensitive conditions: sepsis, 8%, stroke 10%, and AMI 10%. Although direct comparisons with prior studies are not possible due to different data sets and differing approaches, the estimates of mortality due to closures are similar, ranging from 3%-10%.

[19]Average inpatient mortality rate for the control group with time-sensitive conditions studied were as follows: sepsis, 17.1%; stroke 10.6%; asthma/COPD 1.6%; AMI, 7.3%.

[20]Marginal effects for all variables are presented in Table 13 in Appendix B

Table 10: Differential Impacts of Rural and Urban Closures

Variable	Marginal Effect (Std. Error)
Rural Treat Post	0.0046*
	(0.0020)
Urban Treat Post	0.0009
	(0.0011)
Rural Treat	-0.0069*
	(0.0024)
Urban Treat	-0.0013
	(0.0012)
R^2	0.147
N	2,736,593

Standard errors are reported in parentheses.
Errors are clustered by patient residential zip codes.
+ p<0.10, * p<0.05

4.4.1 Subgroup Analyses - Differential Impacts of Rural and Urban Closures

Each time-sensitive condition is also separately examined. Marginal effects of treatment variables are presented in Table 11. For sepsis patients, rural closures increase inpatient mortality by 1.54% points (an increase of 9.0%).[21] This is consistent with the 8% increase in mortality for sepsis patients due to nearby ED closures in California owing to delayed care and overcrowded EDs, noted in Liu et al. (2014).

Urban closures increase inpatient mortality for AMI patients by 0.30% points (a 4.1% increase), similar to Buchmueller et al. (2006), which suggests a 6.5% increase in cause-specific mortality due to urban closures in LA county for AMI patients. Yet, urban closures decrease inpatient mortality for asthma/COPD patients by .10% points (about 6.3% decrease). A similar differential effect of urban closures across heart attack and COPD patients is noted in Buchmueller et al. (2006), although they find a null result for COPD patients and focus on the impact of change in distance. A negative effect for AMI, which is more time-sensitive than asthma/COPD, may be suggestive of increased distance, travel time, and/or overburdened emergency care mechanisms dominating other mechanisms for conditions that are relatively more time-sensitive. Reduced patient mortality for asthma/COPD patients, in contrast, may reflect patient welfare-improving mechanisms of hospital closure being more dominant for conditions that are less time-sensitive (similar to reduction in mortality post-closure for chronic patients (Buchmueller et al., 2006)). In any case, note that combining these diagnostic conditions, for which the effects are opposing, can result in a null result when all conditions are combined, as is the case for results presented in Table 10.

Overall, the results for sepsis and AMI patients are consistent with expectations of delayed or forgone care. However, further research on each of the underlying mechanisms for the various diagnostic conditions is needed for identifying exact channels and cautionary steps to be taken post-closure.

[21] Baseline mortality for the time-sensitive conditions studied were as follows: sepsis, 17.1%; stroke 10.6%; asthma/COPD 1.6%; AMI, 7.3%.

Table 11: Subgroup Analyses - Differential Impacts of Rural and Urban Closures

Variable	Sepsis	Stroke	Asthma/COPD	AMI
Rural Treat Post	0.0154*	0.0038	-0.0015	0.0009
	(0.0044)	(0.0033)	(0.0009)	(0.0026)
Urban Treat Post	-0.0025	0.0029	-0.0010+	0.0030*
	(0.0026)	(0.0018)	(0.0006)	(0.0015)
Rural Treat	-0.0268*	-0.0145*	0.0001	0.0021
	(0.0050)	(0.0038)	(0.0014)	(0.0033)
Urban Treat	0.0018	-0.0039*	0.0005	-0.0009
	(0.0026)	(0.0018)	(0.0006)	(0.0015)
R^2	0.111	0.054	0.187	0.159
N	724,182	678,069	956,206	691,516

Standard errors are reported in parentheses.
Errors were not clustered by patient residential zip codes because the model did not converge with clustering.
+ p<0.10, * p<0.05

4.4.2 Sensitivity Analyses

The results presented in Section 4.4 are robust to several sensitivity checks. Firstly, one may believe that the negative impact of rural closures picks up only the effect on rural patients, which may be driven by changes in trends across rural and urban patients that are not controlled for. However, this notion is ruled out, as very similar negative effects of rural closures are observed even when restricting the analysis to include only urban patients. This also points to spillover effects of rural closures leading to increased mortality for urban patients. Marginal effects for treatment variables are presented in Table 18 in Appendix D.

Secondly, as the results for subgroup analyses could not be clustered by zip codes when analyzing each condition separately, a model with clustered errors is run for sepsis, stroke, and AMI conditions combined (i.e. excluding asthma/COPD patients). As these three conditions are relatively more time-sensitive than asthma/COPD, the adverse impact of hospital closures should be larger for these conditions than all four conditions combined. As expected, the results are stronger for these conditions, i.e. rural closures increase mortality by 0.93% points (an increase of 8.0%).[22] Marginal effects for treatment variables are presented in Table 19 in Appendix D.

Next, as length of stay can be correlated with quality of care, the impact of hospital closures on length of stay (LOS) is also examined. Rural closures increase LOS by 5.5 hours. For sepsis, stroke, and AMI patients combined, rural closures increase LOS by 8 hours, whereas no impact is noted when analyzing only asthma/COPD admissions - a pattern that coincides with the mortality impact of hospital closures. Marginal effects for treatment variables for both of these analyses are presented in Table 20 and 21 in Appendix D. Nevertheless, while longer LOSs are associated with lower efficiency, the link between LOSs and quality is less clear. Shorter LOSs can be indicative of poor quality of care as hospitals respond to financial pressures by reducing service durations and discharge patients earlier than is appropriate. At the same time, poor quality of care or ED crowding may lead to complications, resulting in longer LOSs. However, despite the recent trend of shortening LOSs, most recent studies (Tran et al., 2018) do not find that shorter LOSs are linked to increased mortality (although they may be linked to readmissions). Instead, there is evidence linking increased LOS with poor quality of care and mortality (McRae et al., 2017; Chaou et al., 2016; Pines et al., 2010; Thomas et al., 1997). Regardless, even if increased LOSs are not caused

[22] Average inpatient mortality rate for the control group with sepsis, stroke, and AMI admissions combined was 11.6%

by poor quality of care, they can contribute significantly to overcrowding (Henneman et al., 2010). Thus, the coinciding pattern of hospital closure's impact on LOS and on mortality is suggestive of underlying overcrowding.

Finally, one may be concerned that as rural areas suffer from declining populations, the observed results are driven by shrinking populations. However, these results are robust to the inclusion of average HSA-level population density growth from 2000 to 2010. Marginal effects for treatment variables are presented in Table 22 in Appendix D.Thus, the results observed do not seem driven by changes in population density.

4.4.3 Discussion

The differential impacts of rural and urban closures are consistent with expectations, and offer one possible explanation for the difference in results across studies that find no impact of closures vs. studies that find an adverse impact. That is, rural closures may have an overall more adverse impact on patient mortality than urban closures.

It is generally well known that patients from rural areas travel longer distances to seek care, compared to urban patients. However, distance tends not to be the only issue; several transportation barriers add to delayed or forgone patient care. In case studies of hospital closures in Kansas, Kentucky, and South Carolina, respondents from all studies indicated the need to ensure emergency transportation to neighboring hospitals post-closure (Wishner et al., 2016). Many rural communities lack adequate public transportation systems, implying that patients without cars or patients that do not drive must rely on someone to drive them. As many of the elderly cannot drive, travel tends to pose greater issues for them. Additionally, patients in rural areas worry they may not have transportation to go back from the hospital. Such transportation issues in rural areas, which lead to delayed care and foregone care, are exacerbated post-hospital closures (Wishner et al., 2016). Similar access concerns for the elderly and low-income populations have been noted in the context of California's urban hospital closures and trauma center closures (Hsia and Shen, 2011; Buchmueller et al., 2006), but such concerns and perceived reduction in access to care do not seem to affect California's population at large (Hsia et al., 2012; Buchmueller et al., 2006).

As mentioned earlier, Troske and Davis (2019) find that rural patients experience an ambulance time increase of 76% (11 minutes) in the year post-closure (within their zip code), compared to before closure. Additionally, they spend more time in an ambulance, compared to urban patients facing closure, who experience no change in ambulance time post-closure (similar to small change in distances post ED-closures, noted in (Hsia et al., 2012)).

Furthermore, rural hospital closures lead to an outmigration of health care professionals, and worsen pre-existing challenges to access. For instance, when large hospital systems in Kansas, Kentucky, and South Carolina, that had employed local physicians, closed, physicians were offered competitive salaries at other hospitals in the hospital owners' systems, causing physician relocations. In some cases, physicians were banned from entering into contracts with hospitals in the closure area. Such relocation sometimes even occurred before the hospital closed. Thus, physician relocation due to hospital closure exacerbates existing recruitment difficulties and systemic workforce shortages in rural areas (Wishner et al., 2016).

Overall, rural closures negatively impact economic measures in a community, such as poverty level, income, unemployment, and home values, in both the short- and long-term. Note that rural closures lead to job loss not just in healthcare, but also in other industries and occupations (Manlove and Whitacre, 2017). Although the direct link between unemployment and health outcomes suggests an improvement in health outcomes (mostly due to healthier behaviors) during times of unemployment Strumpf et al. (2017); Ruhm (2007, 2005, 2000), hospital and ED closure literature emphasizes disproportionately worse outcomes post-closure for lower-income populations, as these populations are most affected by access barriers (Song and Saghafian, 2019; Hsia and Shen, 2011; Buchmueller et al., 2006). Thus, such economic impacts of rural closures may have long lasting negative impacts on access to health care that lead to deteriorated patient health for these communities.

Apart from exacerbated transportation and economic problems affecting rural patients, spillover effects of hospital (and ED) closures, which appear substantial according to Song and Saghafian (2019); Liu et al. (2014), may differ for rural closures compared to urban closures. Communities surrounding rural closures are more likely to experience longer-term spillovers, spillovers from disproportionately longer ambulance transportation times, and additional overcrowding owing to patients seeking primary care at hospitals, compared to communities surrounding urban closures.

This paper is unable to pinpoint which mechanisms play a larger role in the differential results of rural and urban closures observed. Nevertheless, these results demonstrate the extent to which negative effects of rural closures are masked when no distinction is made between treatment groups. As such, these results offer a crucial potential explanation for the lack of consensus among scholars regarding the impact of hospital (and ED) closures: rural hospital closures have a differential impact on patient mortality than urban closures.

5 Conclusions

With the rise in hospital closures, and especially with increasing rates of rural closures, lack of studies on the impact of closures on patient outcomes and the lack of consensus across existing studies pose barriers to policy implementation. Among the handful of studies examining the impact on patient mortality due to hospital (and ED) closures, about half find no impact, while the remaining studies find increased mortality for certain diagnostic conditions yet no clear impact for others. Additionally, rampant discrepancies exist across most studies regarding the number (and identity) of California's closed hospitals in a given time period. This paper attempts to reduce the aforementioned gaps and reconcile differences across prior studies. Firstly, the paper explicitly outlines its methodology for identifying closures and closure years, compiling a more complete list of California's hospital closures, 1995-2011, which is compared to closure lists from other sources. The paper also suggests methodological improvements for tracing detrimental impacts of hospital closure which may have appeared elusive or nonexistent based on prior research. Finally, this is one of the very few papers that studies the impact of hospital closures on Medicare as well as non-Medicare patients, and to our best knowledge, is the first paper to examine patient mortality impact of rural closures in California. As California has historically had and continues to have a high number of hospital closures, understanding the impact of hospital closures, and not just ED closures, is critical. Despite limitations to generalizability that come with a state-specific study, the paper's primary contributions are likely applicable beyond the context of California.

To summarize, the paper finds no impact of hospital closures when all closures are considered alike. However, when studying each diagnostic condition separately, closures are found to increase mortality for stroke patients by 3.1%, for AMI patients by 4.5%, and to decrease mortality for asthma/COPD patients by 8.8%. When differentiating between rural and urban closures, rural hospital closures increase mortality by about 5.9% overall, whereas urban hospital closures have no measurable impact. When studying each diagnostic condition separately, it is seen that rural closures increase mortality for sepsis patients by 9.0%, urban closures increase mortality for AMI patients by 4.1%, and urban closures decrease mortality for asthma/COPD patients by 6.3%.

The paper emphasizes the extent to which detrimental impacts of rural closures can get masked in an analysis that does not distinguish between rural and urban closures. Similarly, as illustrated through the subgroup analyses, combining different diagnostic conditions, which may have opposite effects, can be problematic when studying several conditions combined. Additional research that distinguishes between rural and urban closures must be conducted for various diagnostic conditions separately in order to deepen and refine the understanding of patient mortality impact of hospital closures.

As mentioned earlier, although this paper captures multiple channels through which hospital closures can impact patient mortality, it is unable to distinguish between these mechanisms. Further research is needed for understanding each individual channel of impact, keeping in mind that adverse effects on mortality may be sparsely distributed across these channels. Using an intermediate measure of adverse patient outcomes, such as readmission or co-morbidity instead of mortality, may be particularly helpful for studies attempting to isolate the impact of a given channel.

Nevertheless, regardless of the underlying mechanisms, this paper contributes to the emerging concord in very recent studies that hospital (or ED) closures do lead to increased patient mortality, ranging from about 3-10%, which may be distributed across various channels. Overburdening of the health care system post-closure and rural closures are particularly concerning. While policy instruments that tackle root causes for closures and macroeconomic effects of rural closures appear less straightforward, there seems to be a clear need to ensure emergency transportation post-closures, especially for vulnerable populations, and to identify strategies that help surrounding hospitals manage increased and potentially differential health-care demands post-closures.

A Appendix - Sample Summary Statistics

Table 12: Sample Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
In-hospital death	0.086	0.281	0	1
Urban Treat Post	0.434	0.495	0	1
Urban Treat	0.355	0.478	0	1
Rural Treat	0.069	0.254	0	1
Rural Treat Post	0.042	0.202	0	1
Age Categories (Base=Under 1 year or missing				
1-17 years	0.049	0.216	0	1
18-34 years	0.027	0.162	0	1
35-64 years	0.306	0.46	0	1
65 years & over	0.605	0.488	0	1
Gender (Base = Male)				
Female	0.523	0.499	0	1
Other	0.000	0.001	0	1
Race (Base = White)				
Black	0.085	0.278	0	1
Native American/Eskimo/Aleut	0.000	0.030	0	1
Asian/Pacific Islander	0.060	0.238	0	1
Other	0.064	0.244	0	1
Missing	0.103	0.304	0	1
Expected Payment (Base=Medicare)				
Medi-Cal	0.152	0.359	0	1
Private Coverage	0.208	0.406	0	1
Indigent	0.017	0.130	0	1
Self-Pay	0.027	0.164	0	1
Other or Missing	0.012	0.112	0	1
Admission Source Site (Base=Home)				
Residential Care Facility	0.015	0.121	0	1
Ambulatory Surgery	0.003	0.058	0	1
Skilled Nursing/Intermediate Care	0.056	0.231	0	1
Acute/Inpatient Hospital Care	0.047	0.213	0	1
Other (Inpatient) Hospital Care	0.005	0.073	0	1
Newborn	0.000	0.004	0	1
Prison/Jail	0.000	0.030	0	1
Other	0.007	0.083	0	1
Missing	0.000	0.016	0	1
Admission Source Site License (Base=This Hospital)				
Another hospital	0.061	0.24	0	1
Not a hospital	0.927	0.259	0	1
Missing	0.000	0.015	0	1
Patient Route (Base=Admitting hospital's ER)				
No ER or another facility's ER	0.191	0.393	0	1
Missing	0.000	0.015	0	1
Hospital Control Type (Base=City/County)				
District	0.069	0.253	0	1
Investor	0.164	0.370	0	1
Non-profit	0.720	0.448	0	1
State	0.002	0.050	0	1
Proportion of Medi-Cal Days	0.216	0.173	0	0.871
No. of Medical Staff	0.461	0.349	0	2.309
Available Beds/Licensed Beds	0.941	0.102	0.093	1.670
Rural admission	0.048	0.215	0	1
County unemployment rate	7.511	3.348	2	29.8
Pop. dens. per sq. mile by 10,000	0.606	0.624	0.002	4.983

Table 12 Continued: Sample Summary Statistics

HSA Admissions/10000	0.312	0.358	0.006	1.891
HHI-HSA for open hospitals	5618.7	3444.4	0	10000
Elixhauser Comorbidities				
Congestive Heart Failure	0.220	0.414	0	1
Cardiac Arrhythmias	0.260	0.438	0	1
Valvular Disease	0.069	0.254	0	1
Pulmonary Circulation Disorders	0.031	0.175	0	1
Peripheral Vascular Disorders	0.069	0.253	0	1
Hypertension, Uncomplicated	0.431	0.495	0	1
Paralysis	0.089	0.285	0	1
Other Neurological Disorders	0.120	0.325	0	1
Chronic Pulmonary Disease	0.447	0.497	0	1
Diabetes, Uncomplicated	0.219	0.413	0	1
Diabetes, Complicated	0.066	0.248	0	1
Hypothyroidism	0.095	0.294	0	1
Renal Failure	0.116	0.321	0	1
Liver Disease	0.034	0.183	0	1
Peptic Ulcer Disease Excluding Bleeding	0.012	0.109	0	1
AIDS/HIV	0.002	0.05	0	1
Lymphoma	0.008	0.089	0	1
Metastatic Cancer	0.020	0.14	0	1
Solid Tumor Without Metastasis	0.034	0.183	0	1
Rheumatoid Arthritis/Collagen Vascular	0.026	0.159	0	1
Coagulopathy	0.044	0.206	0	1
Obesity	0.083	0.276	0	1
Weight Loss	0.055	0.228	0	1
Fluid and Electrolyte Disorders	0.264	0.441	0	1
Blood Loss Anemia	0.009	0.098	0	1
Deficiency Anemia	0.026	0.161	0	1
Alcohol Abuse	0.036	0.186	0	1
Drug Abuse	0.026	0.16	0	1
Psychoses	0.018	0.134	0	1
Depression	0.076	0.266	0	1
Hypertension, Complicated	0.125	0.33	0	1
Admission Year (Base=1995)				
1996	0.049	0.216	0	1
1997	0.052	0.222	0	1
1998	0.053	0.225	0	1
1999	0.054	0.226	0	1
2000	0.049	0.217	0	1
2001	0.058	0.235	0	1
2002	0.058	0.234	0	1
2003	0.056	0.23	0	1
2004	0.048	0.215	0	1
2005	0.056	0.23	0	1
2006	0.06	0.239	0	1
2007	0.055	0.228	0	1
2008	0.069	0.254	0	1
2009	0.070	0.255	0	1
2010	0.077	0.267	0	1
2011	0.080	0.272	0	1
N	2,736,593			

B Appendix - Differential Impacts of Rural and Urban Closures - Marg. Effects for all variables

Table 13: Differential Impacts of Rural and Urban Closures - Marg. Effects for all variables

Variable	Marginal Effect (Std. Error)
Rural Treat Post	0.005*
	(0.002)
Urban Treat Post	0.001
	(0.001)
Rural Treat	-0.007*
	(0.002)
Urban Treat	-0.001
	(0.001)
Age Categories (Base=Under 1 year or missing)	
1-17 years	-0.002*
	(0.001)
18-34 years	0.030*
	(0.001)
35-64 years	0.055*
	(0.001)
65 years & over	0.090*
	(0.001)
Gender (Base = Male)	
Female	0.006*
	(0.000)
Other	0.136
	(0.127)
Race (Base = White)	
Black	-0.018*
	(0.001)
Native American/Eskimo/Aleut	-0.031*
	(0.005)
Asian/Pacific Islander	-0.007*
	(0.001)
Other	-0.007*
	(0.001)
Missing	0.012*
	(0.001)
Expected Payment (Base=Medicare)	
Medi-Cal	0.006*
	(0.001)
Private Coverage	-0.004*
	(0.001)
Indigent	-0.042*
	(0.002)
Self-Pay	0.028*
	(0.002)
Missing	0.006*
	(0.002)
Admission Source (Base=Home)	
Residential Care Facility	0.015*
	(0.001)
Ambulatory Surgery	-0.039*
	(0.002)
Skilled Nursing/Intermediate Care	0.050*
	(0.001)

Table 13 Continued: Diff. Impacts. - Marg. Effects for all variables

Acute/Inpatient Hospital Care	0.015*
	(0.002)
Other (Inpatient) Hospital Care	0.023*
	(0.003)
Newborn	-0.025
	(0.031)
Prison/Jail	-0.008
	(0.007)
Other	0.025*
	(0.003)
Missing	0.023
	(0.030)
Admission Source Site License (Base= This Hospital)	
Another hospital	-0.056*
	(0.003)
Not a hospital	-0.060*
	(0.003)
Missing	-0.001
	(0.051)
Patient Route (Base=Admitting hospital's ER)	
No ER or another facility's ER	-0.024*
	(0.001)
Missing	-0.057*
	(0.017)
Hospital Control Type (Base=City/County)	
District	-0.008
	(0.009)
Investor	-0.007
	(0.009)
Non-profit	-0.010
	(0.008)
State	-0.009*
	(0.004)
% of Medi-Cal Days	0.006
	(0.005)
No. of Medical Staff/1000	0.004*
	(0.001)
Available Beds/Licensed Beds	-0.003
	(0.003)
Rural admission	0.004*
	(0.002)
County unemployment rate (%)	-0.000
	(0.000)
Pop. dens. per sq. mile/10000	0.002*
	(0.001)
HHI-HSA for open hospitals/1000	-0.001*
	(0.000)
HSA Admissions/10000	0.004*
	(0.001)
Elixhauser Comorbidities	
Congestive Heart Failure	0.028*
	(0.000)
Cardiac Arrhythmias	0.037*
	(0.000)
Valvular Disease	-0.010*
	(0.001)
Pulmonary Circulation Disorders	0.029*

Table 13 Continued: Diff. Impacts. - Marg. Effects for all variables

	(0.001)
Peripheral Vascular Disorders	0.018*
	(0.001)
Hypertension, Uncomplicated	-0.016*
	(0.000)
Paralysis	-0.005*
	(0.001)
Other Neurological Disorders	0.037*
	(0.001)
Chronic Pulmonary Disease	-0.050*
	(0.001)
Diabetes, Uncomplicated	-0.005*
	(0.000)
Diabetes, Complicated	-0.011*
	(0.001)
Hypothyroidism	-0.008*
	(0.001)
Renal Failure	0.043*
	(0.001)
Liver Disease	0.065*
	(0.001)
Peptic Ulcer Disease Excluding Bleeding	-0.020*
	(0.002)
AIDS/HIV	0.018*
	(0.003)
Lymphoma	0.041*
	(0.001)
Metastatic Cancer	0.060*
	(0.001)
Solid Tumor Without Metastasis	0.031*
	(0.001)
Rheumatoid Arthritis/Collagen Vascular	0.007*
	(0.001)
vCoagulopathy	0.057*
	(0.001)
Obesity	-0.023*
	(0.001)
Weight Loss	0.024*
	(0.001)
Fluid and Electrolyte Disorders	0.046*
	(0.000)
Blood Loss Anemia	-0.009*
	(0.001)
Deficiency Anemia	-0.040*
	(0.001)
Alcohol Abuse	0.012*
	(0.001)
Drug Abuse	0.001
	(0.001)
Psychoses	-0.028*
	(0.001)
Depression	-0.026*
	(0.001)
Hypertension, Complicated	-0.028*
	(0.001)
Admission Year (Base=1995)	
1996	-0.004*

Table 13 Continued: Diff. Impacts. - Marg. Effects for all variables

	(0.001)
1997	-0.003*
	(0.001)
1998	-0.003*
	(0.001)
1999	-0.000
	(0.002)
2000	0.002
	(0.002)
2001	0.003*
	(0.001)
2002	0.001
	(0.001)
2003	-0.002
	(0.001)
2004	-0.001
	(0.001)
2005	-0.003*
	(0.001)
2006	-0.004*
	(0.002)
2007	-0.008*
	(0.002)
2008	-0.013*
	(0.001)
2009	-0.020*
	(0.002)
2010	-0.027*
	(0.002)
2011	-0.030*
	(0.002)
R^2	0.147
N	2,736,593

Standard errors are reported in parentheses.
Errors are clustered by patient residential zip codes.
The model also includes hospital fixed effects.
+ p<0.10, * p<0.05

C Appendix - Sensitivity analysis using alternate definition of "closure year"

The following tables present results using an alternate definition of "closure year." For these analyses, "closure year" was defined as the very year in which a hospital's admissions dropped to 10 or less (instead of using the year *prior*, as is the case for the analysis presented in the main text of the paper). These results are very similar to those presented in the paper.

Table 14: General Impact of Hospital Closures, Alternate "closure year"

Variable	Marginal Effect (Std. Error)
Treat Post	0.0013
	(0.0010)
Treat	-0.0017+
	(0.0010)
R^2	0.147
N	2,729,670

Standard errors are reported in parentheses.
Errors are clustered by patient residential zip codes.
+ p<0.10, * p<0.05. None of the variables presented in this table were statistically significant.

Table 15: Subgroup Analyses, General Impact of Hospital Closures, Alternate "closure year"

Variable	Sepsis	Stroke	Asthma/COPD	AMI
Treat Post	-0.0043*	0.0042*	-0.0007	0.0037*
	(0.0022)	(0.0016)	(0.0005)	(0.0013)
Treat	0.0013	-0.0047*	0.0001	-0.0010
	(0.0023)	(0.0016)	(0.0005)	(0.0013)
R^2	0.111	0.054	0.187	0.159
N	720,254	677,323	954,339	690,201

Standard errors are reported in parentheses.
Errors were not clustered by patient residential zip codes because the model did not converge with clustering.
+ p<0.10, * p<0.05

Table 16: Differential Impacts of Rural and Urban Closures, Alternate "closure year"

Variable	Marginal Effect (Std. Error)
Rural Treat Post	0.0053*
	(0.0019)
Urban Treat Post	0.0015
	(0.0010)
Rural Treat	-0.0077*
	(0.0023)
Urban Treat	-0.0016
	(0.0011)
R^2	0.147
N	2,729,670

Standard errors are reported in parentheses.
Errors are clustered by patient residential zip codes.
+ p<0.10, * p<0.05

Table 17: Subgroup Analyses - Differential Impacts of Rural and Urban Closures, Alternate “closure year”

Variable	Sepsis	Stroke	Asthma/COPD	AMI
Rural Treat Post	0.0152*	0.0054	-0.0008	0.0017
	(0.0042)	(0.0033)	(0.0010)	(0.0026)
Urban Treat Post	-0.0044+	0.0037*	-0.0005	0.0037*
	(0.0023)	(0.0016)	(0.0005)	(0.0014)
Rural Treat	-0.0269*	-0.0149*	-0.0010	0.0005
	(0.0048)	(0.0037)	(0.0013)	(0.0032)
Urban Treat	0.0037	-0.0040*	0.0001	-0.0014
	(0.0024)	(0.0016)	(0.0006)	(0.0014)
R^2	0.111	0.054	0.187	0.159
N	720,254	677,323	954,339	690,201

Standard errors are reported in parentheses.
Errors were not clustered by patient residential zip codes because the model did not converge with clustering.
+ p<0.10, * p<0.05

D Appendix: Other Sensitivity Analyses

Table 18: Differential Impacts of Rural and Urban Closures - Urban Patients Only

Variable	Marginal Effect (Std. Error)
Rural Treat Post	0.0044+
	(0.0023)
Urban Treat Post	0.0006
	(0.0011)
Rural Treat	-0.0038
	(0.0031)
Urban Treat	-0.0012
	(0.0012)
R^2	0.148
N	2,602,432

Standard errors are reported in parentheses.
Errors are clustered by patient residential zip codes.
+ p<0.10, * p<0.05

Table 19: Differential Impacts of Rural and Urban Closures - Sepsis, Stroke, AMI admissions combined

Variable	Marginal Effect (Std. Error)
Rural Treat Post	0.0093*
	(0.0029)
Urban Treat Post	0.0021
	(0.0016)
Rural Treat	-0.0102*
	(0.0033)
Urban Treat	-0.0019
	(0.0016)
R^2	0.104
N	1,867,244

Standard errors are reported in parentheses.
Errors are clustered by patient residential zip codes.
+ p<0.10, * p<0.05

Table 20: Differential Impacts of Rural and Urban Closures - Length of Stay (LOS) as dependent variable

Variable	Marginal Effect (Std. Error)
Rural Treat Post	0.2259*
	(0.0661)
Urban Treat Post	0.0248
	(0.0365)
Rural Treat	-0.0775
	(0.0826)
Urban Treat	-0.0128
	(0.0319)
R^2	0.157
N	2,736,902

Standard errors are reported in parentheses.
Errors are clustered by patient residential zip codes.
+ p<0.10, * p<0.05

Table 21: Differential Impacts of Rural and Urban Closures - LOS as dependent variable; Sepsis, Stroke, AMI admissions combined

Variable	Marginal Effect (Std. Error)
Rural Treat Post	0.3305*
	(0.0736)
Urban Treat Post	0.0389
	(0.0468)
Rural Treat	-0.0655
	(0.0849)
Urban Treat	-0.0091
	(0.0407)
R^2	0.154
N	1,867,503

Standard errors are reported in parentheses.
Errors are clustered by patient residential zip codes.
+ p<0.10, * p<0.05

Table 22: Differential Impacts of Rural and Urban Closures - Inpatient mortality as dependent variable; controlling for growth in population density from 2000 to 2010

Variable	Marginal Effect (Std. Error)
Rural Treat Post	0.0047*
	(0.0020)
Urban Treat Post	0.0010
	(0.0012)
Rural Treat	-0.0070*
	(0.0002)
Urban Treat	-0.0013
	(0.0012)
R^2	0.147
N	2,736,593

Standard errors are reported in parentheses.
Errors are clustered by patient residential zip codes.
+ p<0.10, * p<0.05

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