

## RESEARCH ARTICLE

# The effect of rural hospital closures on emergency medical service response and transport times

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## Abstract

**Objective:** To examine the effect of rural hospital closures on EMS response time (minutes between dispatch notifying unit and arriving at scene); transport time (minutes between unit leaving the scene and arriving at destination); and total activation time (minutes between 9-1-1 call to responding unit returning to service), as longer EMS times are associated with worse patient outcomes.

**Data Sources/Study Setting:** We use secondary data from the National EMS Information System, Area Health Resource, and Center for Medicare & Medicaid Provider of Service files (2010-2016).

**Study Design:** We examined the effects of rural hospital closures on EMS transport times for emergent 9-1-1 calls in rural areas using a pre-post, retrospective cohort study with the matched comparison group using difference-in-difference and quantile regression models.

**Principal Findings:** Closures increased mean EMS transport times by 2.6 minutes ( $P = .09$ ) and total activation time by 7.2 minutes ( $P = .02$ ), but had no effect on mean response times. We also found closures had heterogeneous effects across the distribution of EMS times, with shorter response times, longer transport times, and median total activation times experiencing larger effects.

**Conclusions:** Rural hospital closures increased mean transport and total activation times with varying effects across the distribution of EMS response, transport, and total times. These findings illuminate potential barriers to accessing timely emergency services due to closures.

## KEYWORDS

barriers to access, emergency medical services, hospital closures, prehospital emergency care, rural

## 1 | INTRODUCTION

Rural hospitals provide critically needed services to local communities but have historically struggled to maintain financial viability.<sup>1-4</sup> From 2013 to 2017, 64 rural hospitals have closed, a rate of closure double that of the previous five-year period.<sup>1,5</sup> Rural hospital closures

increase the distance to nearest hospital or emergency department (ED) for rural residents.<sup>6-9</sup> In the United States, the mean EMS response times for rural ZIP codes are nearly double that of urban ZIP codes.<sup>10</sup> Increases in EMS times are associated with worse patient outcomes.<sup>11-13</sup> Using Utah's Bureau of Emergency Services data, Wilde (2013) found a "one-minute increase in EMS response time increases mortality by 8 percent and 17 percent."<sup>14</sup> Thus, as the distance to

nearest hospitals increases due to closures, patients may experience delayed or decreased access to emergency medical services (EMS), exacerbating already considerable disparities in response times which lead to increased risk of poor outcomes.

The objective of this analysis was to examine the effect of the recent rural hospital closures on EMS times in communities served by the hospital. In our analysis, we estimated the mean and distributional effects of rural hospital closures on EMS times using difference-in-difference and quantile regression models with a propensity score-matched comparison group.

## 2 | BACKGROUND

EMS are an important element of the health care system. Although most admissions to the ED are not via EMS, those that are via EMS tend to be far more acute (eg, myocardial infarction) and for trauma such as motor vehicle collision, where timely response is a key determinant of survival.<sup>12,15,16</sup> Nationwide, service times are longer in rural ZIP codes, nearly double that of urban ZIP codes.<sup>10</sup> This disparity in timely access to care is likely a large driver of urban-rural mortality differences in emergency conditions, such as AMI and motor vehicle collision.

Rural hospital closure rates have received increased attention recently.<sup>1</sup> When hospitals close, there are several mechanisms by which the closure could influence EMS times. First, when a hospital closes, the hospital-based EMS agency may also close. Notably, approximately 6 percent of EMS agencies are hospital-based.<sup>17,18</sup> Second, when a hospital closes, someone in need of timely emergency care will potentially face a longer travel time from the scene of the incident to the nearest ED. The average distance from a closed hospital to the next closest hospital in rural areas was 12 miles,<sup>19</sup> which could lead to a considerable increase in time to care. Given evidence that minor delays in care for certain conditions can lead to a significant increase in mortality,<sup>14,16</sup> closures of rural hospitals could lead to mortality increases in affected communities.<sup>20</sup>

Because of the importance of timely response, EMS records are designed to include granular details on the nature of the service. For example, key events in a typical call include the following: (a) call arrives at dispatch (9-1-1), which then notifies the EMS unit (ambulance); (b) EMS arrives at scene; (c) EMS arrives at patient side; (d) EMS leaves the scene; (e) EMS arrives at destination; and (f) EMS returns to service. Please see Figure 1 for greater detail.

A hospital closure may increase these times in various manners. For example, if a hospital closure reduces EMS availability in the area, dispatch-to-scene time may increase as the EMS unit travels farther distances. There is little reason to suspect scene-to-patient time to change due to a closure. Scene-to-destination (ie, transport) time is almost certain to increase as the distance to nearest hospital increases. Notably, a minute of increased service times may not have equal effect on outcomes. For example, Brown et al<sup>15</sup> examined the association of prehospital times on mortality in patients suffering traumatic injuries and found prolonged time at the scene was

### What this Study Adds

- The number of rural hospital closures has increased dramatically in recent years.
- The effects of the recent rural hospital closures on emergency medical service (EMS) times in communities served by the closing hospitals are unknown.
- We found closures increased EMS transport times and total activation times on average.
- Rural hospital closures are a potential barrier to accessing timely emergency services, which may impact patient outcomes.

associated with increased odds of mortality in certain populations. Ultimately, increased response times may have a cumulative effect leading to longer response times overall and additional stress on EMS systems.

## 3 | METHODS

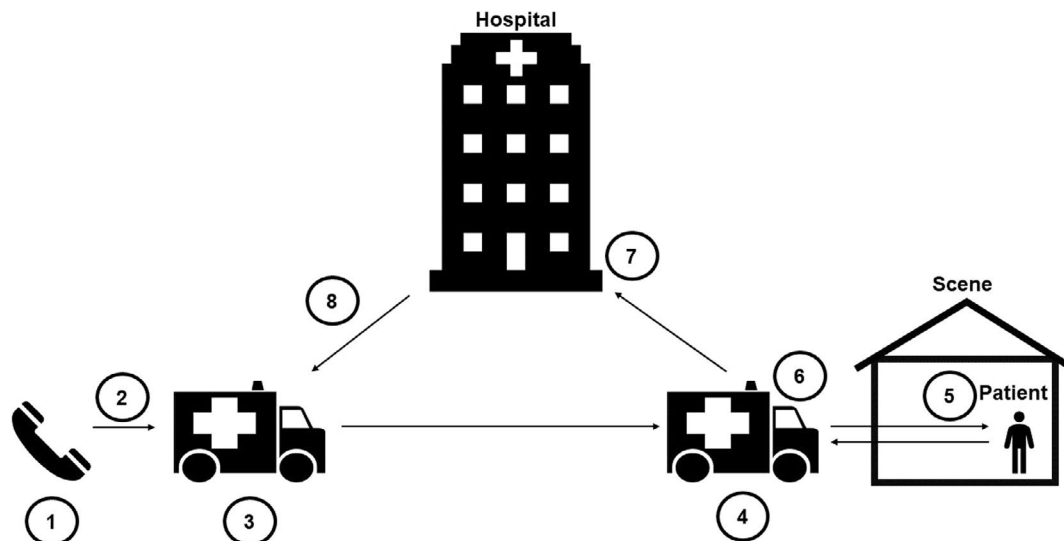
### 3.1 | Study design and data sources

Using a retrospective, cohort design with a propensity score-matched comparison group, we estimated changes in EMS times before and after a rural hospital closure. The study used the Centers for Medicare & Medicaid Services (CMS) Provider of Service (POS) files (2010-2016); the National EMS Information System (NEMSIS) database (2010-2016); and the Area Health Resource File (AHRF) (2010).

The CMS POS files provide a list of all hospitals in the United States and the corresponding ZIP code. Using the 2010-2016 files, we identified ZIP codes with at least one hospital and calculated the distance for each ZIP code in the United States to the nearest ZIP code with a hospital for each year. See Appendix S1 for additional details.

NEMSIS is a publicly available dataset that includes EMS information from over 49 states and territories.<sup>21</sup> State decisions to contribute data to NEMSIS are voluntary; thus, NEMSIS is a convenience sample. NEMSIS includes information on patient encounter EMS times, transportation destination, patient disposition, and demographic and chief complaint variables. The change in distance to the nearest hospital from year  $t$  to year  $t + 1$  for each ZIP code in the United States was matched to the ZIP code of incident for all patient encounters recorded in the NEMSIS dataset for years 2010-2016.

Finally, we used the publicly available, county-level AHRF 2010 data for variables thought to predict rural hospital closure in the propensity matching analysis.<sup>22</sup> The AHRF is a publicly available dataset produced and maintained by the Health Resources & Services Administration.<sup>23</sup>



**FIGURE 1** Timeline of a 9-1-1 call. (1) Time 9-1-1 call is made. (2) Dispatch notifies EMS unit of 9-1-1 call. (3) EMS unit is en route to the patient incidence where the 9-1-1 call was made, the scene. (4) EMS unit arrives at the scene. (5) EMS unit arrives at patient side. (6) EMS unit departs scene. (7) EMS unit arrives at destination. (8) EMS unit returns to service, that is, ready to accept next call. Icons and graphics in this publication were used in accordance with Microsoft Office 365 licensed product guidelines. The images are free to use. There is no royalty or copyright. License information retrieved from <https://support.office.com/en-us/article/insert-icons-in-microsoft-office-e2459f17-3996-4795-996e-b9a13486fa79>. Last accessed: November 29, 2019

### 3.2 | Outcomes

The primary outcome of interest was EMS transport times, defined as the time between when the unit leaves the scene (patient location where 9-1-1 was called) and arrives at destination (ED/hospital), corresponding line between #6 and #7 in Figure 1. The secondary outcomes of interest were (a) system response time, defined as the time between when the unit was notified by dispatch until EMS arrival at scene, corresponding lines between #1 and #4 in Figure 1, and (b) total activation time, defined as the time between the 9-1-1 call and EMS responders have completed encounter and return to service, corresponding line between #1 and #8 in Figure 1.<sup>24</sup> We also examined scene-to-patient time, defined as the time between EMS arrival at the scene and arrival at the patient's side<sup>24</sup> for a falsification test. Rural hospital closure should have no impact on this time interval.

### 3.3 | Study cohort

The study cohort includes emergent EMS encounters originating in ZIP codes designated by NEMSIS as rural or wilderness (or frontier) areas, as informed by the 2003 Urban Influence Codes. Emergent encounters are defined as encounters requiring lights and sirens at any point during EMS response. Encounters from Hawaii, Alaska, and Puerto Rico (ie, not the continental United States) were excluded due to the fundamental difference in rurality of the non-continental United States. Total activation times were limited to no longer than 24 hours.<sup>21</sup> Observations with an EMS system response, transport time, or scene-to-patient time greater than or equal to the total activation time were excluded from analysis due to data quality

concerns. This resulted in approximately 4.54 percent of the overall records to be excluded with 5.31 percent and 3.34 percent of records excluded from the treated and comparison groups, respectively.

### 3.4 | Exposure of interest

The primary explanatory variable of interest is an indicator of a patient encounter occurring in a county affected by a rural hospital closure. If the minimum distance for a ZIP code to the closest ZIP code with a hospital increased by two or more miles from the year prior to the current year, the ZIP code was coded as experiencing a rural hospital closure. Finally, we aggregated ZIP codes to the county level to match on county characteristics. If at least one ZIP code in a rural county had a closure, then the county was coded as having a closure. Please see Appendix S1 for additional details.

### 3.5 | Statistical analysis

First, we identified a propensity score-matched comparison group to address concerns about underlying differences in counties that experience a closure compared to those that do not. Second, we identify the EMS times prior to and postclosure for counties with hospital closure and the matched comparison group. Third, we estimated the mean effect of rural hospital closure on each outcome through a difference-in-differences approach with the matched comparison group. Finally, because we wanted to consider effects across the distribution, not just on average, we examined the treatment effect of rural hospital closure across the distribution of EMS

times using quantile regression compared to the matched comparison group.

### 3.5.1 | Propensity score matching

Hospital closures are not random events. Underlying systematic differences between counties experiencing a closure and counties not experiencing a closure may exist. Thus, we predicted the probability of a closure for each county using a multivariable probit model.<sup>25</sup> Using 2 to 1 nearest-neighbor matching with replacement, we then matched counties not experiencing closure to those experiencing a closure with similar observed baseline characteristics. We applied trimming to meet the common support assumption, which requires overlap between the distribution of treatment and control group propensity scores for matched observations.<sup>26</sup> See Appendix S2 for additional details.

### 3.5.2 | Explanatory variables in the propensity score model

The model included explanatory variables of county-level characteristics including the following: demographic and economic status, access to medical care, and state indicators. The following county-level demographic and economic variables were classified into quartiles: total square miles, population density, housing density, percent of population aged 65 or greater, percent of population white, and percent of population living in poverty. To account for differential access to medical care, we included indicator variables for full, partial, or no county designation as a health provider shortage area in primary care; full, partial, or no county designation as a health provider shortage area in dentistry; and full, partial, or no county designation as a health provider shortage area in mental health care. After matching, we achieved balance for almost all baseline covariates and outcomes

in the preperiod immediately prior to closure, suggesting we have successfully matched counties not experiencing a closure with similar observed characteristics to counties experiencing a closure. The final matched sample retained 21 states. We defined balance as standardized mean difference  $\leq 0.10$ .<sup>25,27,28</sup> See Appendix S2 for additional details.

### 3.5.3 | Explanatory variables in the outcome models of EMS time

Covariates included patient-specific characteristics, such as age and indicators for gender, suspected alcohol and/or drug use by the patient, and chief complaint organ system requiring EMS: pulmonary, cardiac, or obstetrics/gynecology. The chief complaint organ system is the "primary organ system of the patient injured or medically affected."<sup>24</sup> Suspected alcohol and/or drug use is indicated if disclosed by the patient, suspected due to "alcohol/drug paraphernalia at the scene," and/or "smell of alcohol on breath."<sup>24</sup>

### 3.5.4 | Difference-in-difference

Using the propensity score-matched analytic cohort, we used a multivariable, ordinary least-squares (OLS) regression with frequency weights to account for multiple matches and bootstrapped (500 repetitions) standard errors clustered at the county level to estimate the effect of a hospital closure on the EMS times. A difference-in-differences analysis assumes (a) time trends prior to the exposure (hospital closure) in the treatment and comparison groups would have continued in the absence of the exposure during the study period, and (b) the group composition does not vary over time inconsistently between groups.<sup>29,30</sup> Thus, we estimate the mean difference in outcomes in the treatment group pre- and postexposure periods compared to the matched comparison group (see Equation

**TABLE 1** Weighted baseline descriptive statistics, period immediately prior to closure

	Overall N = 58 487	Patient encounters in county experiencing rural hospital closure N = 37 318	Patient encounters in matched counties not experiencing rural hospital closure N = 21 169	Standardized mean difference <sup>a</sup>
Patient characteristics				
Age, mean (SD)	55.66	55.56 (0.12)	55.84 (0.16)	0.01
Female, %	52.46	52.78	51.90	0.02
Chief complaint, %				
Cardiac	10.56	9.89	11.73	0.06
Pulmonary	7.89	7.50	8.56	0.04
OB/GYN	1.10	1.12	1.05	0.01
Alcohol/drug use, %	4.40	4.64	3.99	0.03

<sup>a</sup>A standardized mean difference of  $\leq 0.10$  is commonly used to suggest balance, or no statistically significant differences, between the two matched counties not experiencing a hospital closure and counties experiencing a hospital closure based on observed characteristics.

(1). Specifically, we examine data two years prior to closure and two years following closure. The coefficient of interest is the interaction of the treatment and postexposure periods. Specifically, we focus on the interaction term of the second postexposure period as we could only identify the year of a hospital closure, not the specific date of closure, to ensure temporal consistency of measurement of treatment and outcomes. We examined explanatory variables for collinearity prior to modeling.

$$\begin{aligned}
 Y_{igt} = & \alpha + \beta_1 \text{Treat}_g + \beta_2 \text{Period}_{\text{Pre-2}} + \beta_3 \text{Period}_{\text{Post1}} + \beta_4 \text{Period}_{\text{Post2}} \\
 & + \beta_5 (\text{Treat}_g * \text{Period}_{\text{Pre-2}}) + \beta_6 (\text{Treat}_g * \text{Period}_{\text{Post1}}) \quad (1) \\
 & + \beta_7 (\text{Treat}_g * \text{Period}_{\text{Post2}}) + \beta_8 X_{igt} + \beta_9 \text{Year}_t + \epsilon_{igt}
 \end{aligned}$$

In Equation (1) above,  $Y_{igt}$  is the outcome of interest, that is, EMS system response and transport, time, for individual  $i$  having an encounter occurring in a county  $g$  and time  $t$ ;  $\text{Treat}_g$  represents whether the encounter occurred in a county experiencing a hospital closure;  $\text{Period}_{\text{Pre-2}}$  represents whether the encounter occurred 2 years prior to a closure;  $\text{Period}_{\text{Post1}}$  represents whether the encounter occurred 1 years post a closure;  $\text{Period}_{\text{Post2}}$  represents whether the encounter occurred 2 years post a closure;  $X_{igt}$  represents a vector of patient demographics as defined above in “Explanatory Variables in the Outcome Models of EMS Time”;  $\text{Year}_t$  represents year fixed effects; and  $\epsilon_{igt}$  represents the error component which is comprised of any remaining time-invariant error and time-varying error. As the data are time-to-event but the treatment occurs at the county level where an EMS unit is not censored after completing a single 9-1-1 call response, the difference-in-difference model and specification tests were also examined as a generalized linear model (GLM) with a gamma distribution and log link which has been used to model wait times between Poisson events.<sup>31</sup> We present the GLM results in Appendix S3.

### 3.5.5 | Quantile regression

We used quantile regression to capture differing treatment effects across the distribution of the outcomes. Quantile regression is a semiparametric analytic approach to reflect how the exposure may have varying treatment effects across the distribution of the outcome (ie, EMS times).<sup>30</sup> For example, rural hospital closure may have different effects on service times at different points in the distribution of service times (eg, 10th percentile compared to 90th percentile). Using the propensity score-matched cohort and the same independent variables as the difference-in-difference model, we estimated each outcome using quantile regression with frequency weights to account for multiple matches (see Appendix S2) and bootstrapped (100 repetitions) standard errors clustered at the county level at the 10th, 30th, 50th, 70th, and 90th percentiles.

All statistical testing was 2-sided with a level of significance set at 0.05. All analyses were conducted using Stata, version 14/15 (StataCorp LLC). The Duke University Institutional Review Board reviewed and determined the research to be exempt from IRB review.

TABLE 2 Outcome descriptive statistics

	Immediately prior to rural hospital closure(s)		Immediately post-rural hospital closure(s)	
	Patient incident in county experiencing rural hospital closure N = 37 318	Patient incident in matched rural hospital closure N = 21 169	Patient incident in county experiencing rural hospital closure N = 37 878	Patient incident in matched counties not experiencing rural hospital closure N = 20 596
Overall N = 58 487	11.0 (0.04)	11.5 (0.07)	11.6 (0.06)	11.5 (0.07)
EMS <sup>a</sup> system response time, <sup>b</sup> mean (SD)	10.8 (0.06)	11.5 (0.07)	11.5 (0.07)	11.6 (0.13)
EMS scene-to-patient time, <sup>c</sup> mean (SD)	1.6 (0.02)	1.6 (0.03)	1.7 (0.02)	1.8 (0.03)
EMS <sup>a</sup> transport time, <sup>d</sup> mean (SD)	23.3 (0.09)	26.0 (0.15)	24.2 (0.09)	25.5 (0.16)
EMS total activation time, <sup>e</sup> mean (SD)	77.9 (0.22)	82.5 (0.39)	79.6 (0.22)	80.7 (0.37)

<sup>a</sup>Emergency medical services (EMS).

<sup>b</sup>EMS system response time is defined as the time in minutes from the unit notification of call by dispatch to time of arrival at scene.

<sup>c</sup>EMS scene-to-patient time is defined as the time it takes from EMS responders arriving at the scene to the time responders reach the patient's side.

<sup>d</sup>EMS transport time is defined as the time in minutes from when the EMS responders leave the scene of patient origination until arrival at the destination, a hospital, or ED.

<sup>e</sup>EMS total activation time is defined as the time in minutes from the 9-1-1 call to the time when the EMS responders have completed service for the patient encounter and are back in service—ready to accept the next call.

TABLE 3 Model results

Point estimate (SE)	System response time	Scene-to-patient time	Transport time	Total EMS activation time
<b>Treatment</b>				
Patient incident in a county not experiencing rural hospital closure	-ref-	-ref-	-ref-	-ref-
Patient incident in a county experiencing rural hospital closure	-0.50 (0.94)	0.031 (0.18)	-3.77 (3.00)	-8.03 -7.57
<b>Period</b>				
Preperiod: -2	0.98 (0.94)	0.01 (0.14)	3.78* (2.27)	2.21 -5.15
Preperiod: -1	-ref-	-ref-	-ref-	-ref-
Postperiod: 1	-0.13 (0.63)	-0.19 (0.13)	0.81 (1.69)	-0.05 -3.8
Postperiod: 2	-0.07 (1.23)	-0.19 (0.22)	-0.41 (2.54)	-2.6 -7.77
<b>Interaction of treatment and postperiods</b>				
Preperiod -2 × Treatment	-1.38 (0.99)	-0.09 (0.19)	-2.44 (2.92)	1.72 -5.61
Preperiod -1 × Treatment	-ref-	-ref-	-ref-	-ref-
Postperiod 1 × Treatment	0.99 (0.67)	0.41*** (0.13)	2.58* (1.53)	7.17** -3.04
Postperiod 2 × Treatment	0.97 (0.99)	0.29 (0.18)	4.65** (1.98)	9.45* -5
<b>Patient encounter characteristics</b>				
Age	-0.00 (0.00)	0.00 (0.00)	-0.04*** (0.01)	-0.03 -0.02
Female	-0.31*** (0.10)	-0.21*** (0.03)	-1.45*** (0.27)	-4.36*** -0.63
<b>Chief complaint</b>				
Cardiac	0.23 (0.26)	0.22*** (0.08)	3.43*** (0.89)	8.71*** -2.21
Pulmonary	0.49** (0.20)	0.17** (0.07)	0.65 (0.85)	1.9 -2.09
Obstetrics/Gynecological	0.40 (0.34)	0.31* (0.17)	8.13*** (1.42)	10.16*** -3.34
Alcohol and/or drug use	0.62* (0.37)	0.03 (0.10)	-1.37 (1.16)	2.45 -3.23
<b>Year fixed effects</b>				
2010	-ref-	-ref-	-ref-	-ref-
2011	0.69 (0.84)	-0.06 (0.21)	4.67 (3.05)	12.74** -5.7
2012	0.22 (1.01)	-0.12 (0.21)	1.78 (3.91)	6.9 -7.94
2013	0.32 (1.24)	0.024 (0.22)	0.11 (3.95)	6.54 -9.33
2014	1.60 (1.84)	0.32 (0.36)	7.17 (5.23)	11.84 -12.85

(Continues)

TABLE 3 (Continued)

Point estimate (SE)	System response time	Scene-to-patient time	Transport time	Total EMS activation time
2015	2.54 (1.97)	0.48 (0.44)	4.77 (5.43)	8.76 -14.61
2016	1.67 (1.84)	0.38 (0.52)	6.94 (6.35)	12.52 -20.06
Constant	10.96*** (1.30)	1.61*** (0.23)	24.01*** (4.15)	74.77*** -7.69
Observations	204 850	204 850	204 850	204 850
R-squared	.004	.003	.025	.012

Note: Standard errors in parentheses.

\*\*\* $P < .01$ .

\*\* $P < .05$ .

\* $P < .1$ .

## 4 | RESULTS

### 4.1 | Descriptive statistics

Table 1 presents weighted descriptive statistics in the preperiod for the overall analytic cohort, the treatment group, and the matched control group. Overall, the sample had a mean age of 55.66 years old, 52.46 percent female, 10.56 percent with a chief complaint of cardiac, 7.89 percent with a chief complaint organ system of pulmonary, 1.10 percent with a chief complaint organ system of obstetrics and gynecology, and 4.40 percent with suspected or confirmed alcohol or drug use. Compared to the matched comparison group, patients in the treatment group were approximately the same age with slightly higher proportions of females and obstetrics/gynecology chief complaints and alcohol and/or drug use indicated encounters, but lower proportion of cardiac and pulmonary chief complaints. Approximately 1 percent of the treatment group and 1 percent of the matched comparison died during EMS response immediately preclosure period; 1.5 percent of the treatment group and 1.5 percent of the matched comparison died during EMS response in the immediate postperiod. Approximately 0.12 percent of the overall analytic cohort were transported via helicopter, with 0.15 percent and 0.02 percent of the treated and the comparison groups transported via helicopter.

Table 2 presents descriptive statistics of the outcomes of interest across the treated and matched comparison groups prior to and post-rural hospital closure. In the preperiod, the overall cohort had a mean transport time of 23.3 minutes; system response time of 11.0 minutes; and total activation time of 77.9 minutes. In the preperiod, patient encounters experiencing a closure had mean transport times of 21.8 minutes; system response times of 10.8 minutes; and total activation times of 75.3 minutes. Comparatively, the matched comparison group had a mean transport time of 26.0 minutes; system response time of 11.5 minutes; and total activation time of 82.5 minutes.

From the period immediately postclosure compared to immediately prior to closure, the change in average minute times in closure counties and their matched controls, respectively, was (a) system

response time (+0.7, +0.1), (b) transport time (+1.7, -0.5), and (c) total activation times (+3.7, -1.8). Finally, we found an increase in average scene-to-patient times of 0.1 minutes. Patient encounters occurring in a county experiencing a closure increased the average time by 0.2 minutes, while the matched comparison group mean average scene-to-patient times decreased by 0.1 minutes.

#### 4.1.1 | Difference-in-differences

We tested the parallel trend assumption testing for systematic differences in coefficients using seemingly unrelated estimation and concluded that the coefficients (ie, trends of the pre-exposure outcomes) were not statistically significantly different. Controlling for patient encounter characteristics and year fixed effects, in the year of a closure we found a closure increases in the transportation time (time from scene to hospital) by 2.6 minutes ( $P = .09$ ; 95% CI [-0.42, 5.57]) and total activation time (time from 9-1-1 call to time EMS will accept next call) by 7.2 minutes ( $P = .02$ ; 95% CI [1.21, 13.12]) compared to the year prior to closure. Controlling for patient encounter characteristics and year fixed effects, in the subsequent year postclosure (the primary interaction of interest), we found a closure increases transportation times (time from scene to hospital) by 4.7 minutes ( $P = .02$ ; 95% CI [0.76, 8.54]) and increases total activation times (time from 9-1-1 call to time EMS will accept next call) by 9.5 minutes ( $P = .06$ ; 95% CI [-0.35, 19.24]) compared to the year prior to closure. We found no effect of a closure on system response times (time from 9-1-1 call to EMS arrival at scene), the year of closure (0.99 minutes;  $P = .17$ ; 95% CI [-0.32, 2.30]), or subsequent year (0.97 minutes;  $P = .32$ ; 95% CI [-0.97, 2.91]). See Table 3 for complete results.

#### 4.1.2 | Quantile regression

Quantile regression identified heterogeneous treatment effects of rural hospital closure across the distribution of transport

(scene-to-hospital time), total activation (from 9-1-1 call to EMS unit returns to service), and system response (9-1-1 call to EMS arrival at scene) call times. Table 4 presents complete results. We found that in the 30th, 50th, 70th, and 90th percentiles of transport times, patient encounters occurring in counties with rural hospital closure experienced increased transport times (effects ranging from 4.5 to 8.8 minutes,  $P < .05$ ) compared to patient encounters in matched counties not experiencing rural hospital closure in the subsequent year postclosure. We found that in the 30th and 50th percentiles of total activation call times, patient encounters occurring in counties with rural hospital closure experienced increased total activation times by 7.1 minutes in the 50th percentile the year of hospital closure. We also found in the subsequent year postclosure that compared to patient encounters in matched counties not experiencing rural hospital closure, patient encounters in counties with rural hospital closure experienced increased total activation times of 10.5 minutes and 13.3 minutes at the 30th and 50th percentiles, respectively ( $P < .05$ ). We found that in the 10th percentiles of system response times, patient encounters occurring in counties with rural hospital closure experienced increased transport times in the year of closure (1.0 minutes,  $P < .05$ ) compared to patient encounters in matched counties not experiencing rural hospital closure in the subsequent year postclosure. Among all other percentiles examined, we found no statistically significant effects of closures.

#### 4.1.3 | Falsification tests

We found no statistically significant differences between the treatment and matched controls in the preperiod and postperiod, as defined as standardized mean differences  $\leq 0.10$ . However, controlling for patient encounter characteristics and year fixed effects, we found rural hospital closures slightly increased scene-to-patient times by 0.4 minutes ( $P < .01$ ; 95% CI [0.15, 0.66]) in the year of the closure and no effect on scene-to-patient times in the year after a closure (0.3 minutes  $P = .09$ ; 95% CI [-0.04, 0.63]).

## 5 | DISCUSSION

After controlling for patient encounter characteristics and year fixed effects, we found rural hospital closures increased mean EMS transport and total activation times in the subsequent year after a closure. We found a slight increase in times of the proposed falsification test during the year of a closure, which may suggest a closure strains the whole EMS system with other stressors on EMS response times, leading to delays in arrival to patient side after arriving at the scene. However, this effect is not seen in the second year postclosure, the primary period of interest. While the average treatment effect in a linear regression model masks effects of rural hospital closures for encounters with longer EMS times, quantile regression allows for the magnitude and significance of the treatment effects to vary at different percentiles of the outcome, thus providing a more nuanced

understanding of treatment effects which may be masked by the average treatment effect.

The quantile regression in this study revealed that those most affected by rural hospital closures are those patients experiencing low to high transport times, mid-total activation times, and low system response times. In the subsequent period postclosure, encounters at 70th percentile of system response time experienced nearly a two-minute increase (1.8 minutes) in system response time due to a hospital closure. There is some evidence that an effect of this magnitude is clinically significant. Specifically, using a sample of EMS encounters in Utah, Wilde (2013) determined a "one-minute increase in EMS response time increases mortality by 8 percent and 17 percent" and increases the likelihood of an emergency department admission.<sup>14</sup> In the second year postclosure, closure was estimated to cause an increase in transport time across the distribution, with larger effects in higher quintiles. Larger effects in higher quintiles align with the proposed theory that closures increase time in transit to the next nearest hospital. Moreover, closures may disproportionately impact more rural counties with transport times at the higher quintiles. It is unclear the mechanism by which rural hospital closures impact only the middle quintiles of the total activation times. Further research into the types of EMS agencies servicing the patients in the lower and higher quintiles of total activation times could help inform the context of these findings. Finally, encounters at the lowest percentile of the distribution may have experienced increased system response times due to a closure if the calls were not prioritized in the EMS response, for example, due to lower acuity.<sup>14</sup>

In addition to the effect of rural hospital closures on EMS times, we also provide evidence of a baseline (immediate preclosure period) difference in mean EMS times. Our descriptive analysis indicates that the average times in rural areas are already greater than 8 minutes. Best practices suggest that system response time should be equal to or less than 8-9 minutes.<sup>32</sup> Given that minutes are critical in emergency medicine, these descriptive findings in addition to the increase in times due to a closure suggest rural hospital closures may further delay emergency medical care to patients already experiencing mean wait times outside of the gold standard.

The analysis is subject to several limitations. First, NEMSIS is a convenience sample; thus, although the analysis includes 21 states, we cannot state that the results are nationally representative. Additionally, NEMSIS defines rurality and wilderness/frontier based on Urban Influence Codes.<sup>24</sup> Due to the requirements to maintain a de-identified dataset, we used the rurality indicators available in the NEMSIS dataset, which use the Urban Influence Codes. Urban Influence Codes have been successfully used in research projects to identify rural areas in the United States historically.<sup>33</sup> Second, driving distances instead of straight mile distances would be preferred, but were not possible given data access limitations. Third, we assume time-invariant ZIP codes and counties. Finally, while the matched cohort was balanced across covariates, systematic differences between the treated and controls may persist due to unobserved factors. Thus, we used rigorous statistical techniques, such as propensity matching and difference-in-difference, to control for

TABLE 4 Quantile regression results

Quantile	System response times					Transport times	
	10	30	50	70	90	10	30
<b>Treatment</b>							
Patient encounter in a county not experiencing rural hospital closure	-ref-	-ref-	-ref-	-ref-	-ref-	-ref-	-ref-
Patient encounter in a county experiencing rural hospital closure	-1.00 (0.65)	-0.67 (0.68)	-1.04 (1.05)	-0.89 (1.30)	-0.72 (1.68)	-1.02 (0.97)	-4.21* (2.32)
<b>Period</b>							
Preperiod: -2	-0.00 (0.46)	0.67 (0.55)	0.88 (0.77)	1.15 (1.23)	1.58 (1.62)	0.32 (0.78)	2.70 (2.46)
Preperiod: -1	-ref-	-ref-	-ref-	-ref-	-ref-	-ref-	-ref-
Postperiod: 1	0.00 (0.30)	-0.33 (0.50)	-0.40 (0.56)	-0.55 (0.74)	-0.58 (1.50)	0.32 (0.79)	0.28 (2.00)
Postperiod: 2	0.00 (0.53)	-0.33 (0.67)	-0.68 (0.97)	-0.88 (1.21)	-0.79 (2.47)	0.86 (0.92)	0.51 (2.66)
<b>Interaction of treatment and postperiods</b>							
Preperiod (-2) × Treatment	0.00 (0.60)	-1.00 (0.80)	-1.34 (1.20)	-1.68 (1.65)	-2.64 (1.73)	0.16 (0.81)	0.34 (2.27)
Preperiod (-1) × Treatment	-ref-	-ref-	-ref-	-ref-	-ref-	-ref-	-ref-
Postperiod 1 × Treatment	1.00** (0.46)	0.67 (0.55)	0.76 (0.51)	1.20* (0.67)	2.29 (1.57)	0.16 (0.81)	1.61 (2.07)
Postperiod 2 × Treatment	1.00* (0.56)	0.67 (0.57)	1.32 (0.84)	1.80* (0.98)	2.44 (1.81)	0.32 (0.91)	4.48** (2.21)
<b>Patient encounter characteristics</b>							
Age	0.00 (0.00)	0.00 (0.00)	-0.004 (0.003)	-0.006 (0.005)	-0.01 (0.01)	-0.02*** (0.00)	-0.03*** (0.0071)
Female	-0.00 (0.0116)	-0.00 (0.05)	-0.33* (0.17)	-0.47* (0.26)	-0.59** (0.29)	-0.22* (0.11)	-0.71*** (0.20)
<b>Chief complaint</b>							
Cardiac	-0.00 (0.20)	0.00 (0.15)	0.29 (0.23)	0.53 (0.40)	0.60 (0.54)	0.8** (0.32)	2.38*** (0.65)
Pulmonary	-0.00 (0.30)	0.33 (0.34)	0.58 (0.39)	0.70* (0.38)	0.54 (0.49)	0.34 (0.36)	1.25** (0.62)
Obstetrics/Gynecology	0.00 (0.29)	0.33 (0.36)	0.41 (0.37)	0.47 (0.50)	0.06 (0.76)	2.72* (1.44)	8.62*** (1.51)
Alcohol and/or Drug Use	-0.00 (0.15)	0.67 (0.45)	1.05*** (0.40)	1.19*** (0.46)	1.17* (0.65)	0.42 (0.27)	0.29 (0.89)
<b>Year fixed effects</b>							
2010	-ref-	-ref-	-ref-	-ref-	-ref-	-ref-	-ref-
2011	0.00 (0.47)	0.67 (0.56)	0.81 (0.80)	1.12 (1.19)	0.86 (1.79)	0.44 (0.85)	4.20 (2.69)
2012	0.00 (0.48)	0.33 (0.70)	0.52 (0.98)	0.66 (1.45)	-0.14 (2.21)	0.18 (0.80)	3.14 (2.23)
2013	0.00 (0.53)	0.33 (0.77)	0.21 (1.10)	0.32 (1.82)	0.09 (2.87)	-0.46 (0.78)	0.14 (2.01)

Total activation times							
50	70	90	10	30	50	70	90
-ref-	-ref-	-ref-	-ref-	-ref-	-ref-	-ref-	-ref-
-6.88*	-5.38	-3.40	-7.69*	-10.00	-9.11	-6.00	-1.38
(4.15)	(4.17)	(5.65)	(3.96)	(7.48)	(7.50)	(9.19)	(13.34)
3.13	4.10	6.24	0.31	2.00	4.09	6	5.63
(3.13)	(3.33)	(5.50)	(3.53)	(2.30)	(5.33)	(7.60)	(9.22)
-ref-	-ref-	-ref-	-ref-	-ref-	-ref-	-ref-	-ref-
0.13	0.52	0.61	-1.04	-0.50	0.39	-0.00	1.50
(2.83)	(2.77)	(4.05)	(3.21)	(4.05)	(4.00)	(4.66)	(6.98)
-1.59	-2.10	-4.67	0.39	-2.50	-3.40	-4.00	-3.87
(3.77)	(4.06)	(5.42)	(4.91)	(6.22)	(8.40)	(9.54)	(12.71)
0.93	-1.59	-7.77	6.37	7.00	4.31	-1.00	-11.78
(4.21)	(4.51)	(4.98)	(4.60)	(6.48)	(7.16)	(7.77)	(9.50)
-ref-	-ref-	-ref-	-ref-	-ref-	-ref-	-ref-	-ref-
3.92	3.79	2.55	2.57	5.50	7.13**	8.00	7.47
(2.70)	(2.60)	(2.73)	(2.94)	(3.48)	(3.53)	(4.09)	(6.22)
8.76***	7**	7.10*	1.82	10.50**	13.28**	11.00	6.64
(3.25)	(3.26)	(3.76)	(4.54)	(4.95)	(5.64)	(6.78)	(10.15)
-0.04***	-0.03**	-0.02	0.02*	0.00	0.01	0.00	-0.06
(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)	(0.03)	(0.04)
-1.11***	-1.55***	-2.54***	-0.98***	-2.00***	-3.47***	-5.00***	-8.52***
(0.4)	(0.4)	(0.55)	(0.28)	(0.41)	(0.68)	1.06	(1.34)
3.61***	4.35***	4.42**	6.02***	8.50***	9.21***	9.00***	10.27**
(0.93)	(1.21)	(1.73)	(1.02)	(1.84)	(2.06)	(2.47)	(4.50)
1.21	0.69	-0.02	3.47***	3.50*	3.01	1.00	-1.48
(0.94)	(0.99)	(1.35)	(1.10)	(1.85)	(2.00)	(2.25)	(3.92)
8.82***	9.28***	7.50**	7.65***	9.00**	9.52**	11.00**	10.15
(2.14)	(2.06)	(2.66)	(1.87)	(3.06)	(3.82)	(4.50)	(7.32)
	-1.41	-3.82**	5.04*	5.00	4.58	3.00	-1.85
(1.44)	(1.24)	(1.68)	(2.00)	(3.12)	(3.28)	(3.31)	(5.03)
-ref-	-ref-	-ref-	-ref-	-ref-	-ref-	-ref-	-ref-
7.62*	8.14*	4.65	7.67*	13.00**	16.64**	17.00*	15.01
(4.21)	(4.92)	(5.35)	(4.00)	5.60	(5.66)	(8.73)	(12.34)
4.69	3.90	-0.05	6.71	10.50	11.34	10.00	4.22
(4.42)	(6.75)	(8.17)	(4.52)	(6.78)	(7.09)	(10.65)	(16.64)
1.65	2.21	-1.31	4.86	9.00	9.85	10.00	5.79
(4.72)	(7.10)	(8.51)	(5.87)	(8.01)	(8.41)	(11.49)	(18.34)

(Continues)

TABLE 4 (Continued)

Quantile	System response times					Transport times	
	10	30	50	70	90	10	30
2014	0.00 (0.71)	1.00 (0.93)	1.20 (1.25)	1.62 (2.20)	1.95 (3.28)	0.06 (1.94)	5.59 (3.94)
2015	0.00 (0.77)	1.33 (1.06)	1.83 (1.38)	2.60 (2.25)	3.55 (4.97)	0.06 (1.23)	3.42 (3.51)
2016	0.00 (0.83)	1.33 (1.14)	1.84 (1.60)	2.31 (2.15)	2.08 (4.19)	0.28 (2.34)	4.41 (4.68)
Constant	4.00*** (0.62)	6.00*** (0.72)	9.21*** (1.09)	12.72*** (1.60)	20.86*** (2.46)	5.48*** (1.03)	10.82*** (3.32)
Observations	204 850	204 850	204 850	204 850	204 850	204 850	204 850

Note: Robust standard errors in parentheses.

\*\*\* $P < .01$ .

\*\* $P < .05$ .

\* $P < .1$ .

observed and unobserved heterogeneity between the treated and comparison groups.

Notably, indicators of patient encounters due to obstetrics/gynecology or cardiac chief complaints were statistically significant across almost all models. Future research should consider examining, first, the impact of rural hospital closures on mortality rates of a heterogeneous patient population using a multistate approach. Existing research examining the effects of increased prehospital times on mortality have focused on populations defined by specific characteristics, for example, state-specific (Wilde 2013, Gujral 2019), Medicare enrollees (Carroll 2019), or disease group, for example, trauma cases (Brown et al 2016). Second, future research should consider examining encounters related to obstetrics/gynecology or cardiac events or examine distance to nearest obstetrics unit as rates of rural hospitals closing obstetrics units have increased in recent years.<sup>5,34</sup> Given recent increases in rural hospital closures, this analysis provides evidence contributing to understanding the impact of rural hospital closures on timely provision of emergency medical services. When considering policy solutions to better support the fiscal health of rural hospitals, policy makers should also consider investments in and optimal reimbursement policies for local EMS agencies to ensure patients maintain access to critical services in cases of emergencies.

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			Total activation times				
50	70	90	10	30	50	70	90
9.53	9.79	9.82	5.55	13.00	16.74	17.00	13.55
(6.40)	(8.72)	(10.83)	(7.98)	(11.60)	(11.58)	(15.99)	(23.34)
5.57	5.17	8.74	6.14	8.50	10.68	12.00	10.08
(6.42)	(8.85)	(13.59)	(8.31)	(11.94)	(13.34)	(17.66)	(26.22)
7.77	7.90	15.55	4.12	11.00	13.56	16.00	17.71
(6.79)	(10.11)	(14.83)	(13.02)	(15.49)	(18.48)	(22.04)	(34.04)
18.71***	28.21***	48.44***	29.35***	44.00***	58.85***	79.00***	128.80***
(4.67)	(6.12)	(8.38)	(5.49)	(6.81)	(7.25)	(9.70)	(17.18)
204 850	204 850	204 850	204 850	204 850	204 850	204 850	204 850

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## SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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