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DO EMERGENCY MEDICAL SYSTEM RESPONSE TIMES MATTER FOR HEALTH OUTCOMES?[†]

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The introduction of technology aimed at reducing the response times of emergency medical services has been one of the principal innovations in crisis care over the last several decades. These substantial investments have typically been justified by an assumed link between shorter response times and improved health outcomes. However, current medical research does not generally show a relationship between response time and mortality. In this study, we explain the discrepancy between conventional wisdom and mortality; existing medical research fails to account for the endogeneity of incident severity and response times. Analyzing detailed call-level information from the state of Utah's Bureau of Emergency Medical Services, we measure the impact of response time on mortality and hospital utilization using the distance of the incident from the nearest EMS agency headquarters as an instrument for response time. We find that response times significantly affect mortality and the likelihood of being admitted to the hospital, but not procedures or utilization within the hospital. Copyright © 2012 John Wiley & Sons, Ltd.

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1. INTRODUCTION

Emergency medical services (EMS) have experienced dramatic technological change over the last several decades. In the 1960s and 1970s, ambulance services primarily offered basic transportation (Reines *et al.*, 1988; University of Southern Alabama, 2005; Blackwell and Kaufman, 2002; System, 2006). Since the 1980s, though, ambulances have become sophisticated mobile intensive-care units that are staffed by licensed and trained professional paramedics and emergency medical technicians (Office of Rural Health Policy, 2006). Technological advances, such as computer-aided dispatch services and mobile geographic information system units on ambulances, allow ambulances to reach patients far more quickly.

The push to reduce response times is predicated on the widely-held belief that faster responses will improve health outcomes. Despite the assumption that response times matter, and the substantial investments that have been made to reduce them, very little is actually known about the impact of response times on the mortality and morbidity of patients (Pons *et al.*, 2005; Swor and Cone, 2002). The current evidence on the effectiveness of reduced response times is largely drawn from observational studies of patients suffering from a few very specific medical conditions—most commonly cardiac arrest, which has a high rate of mortality but accounts for just 1% of EMS calls (Pons *et al.*, 2005). These studies examining the relationship between mortality and response times for cardiac arrest victims typically find that patients with higher response times have lower

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rates of survival. Unfortunately, very few studies in the medical literature have examined the relationship between response times and outcomes for people suffering from conditions other than cardiac arrest or heart-related complaints, although these patients generate the vast majority of EMS calls. These studies have generally found no association between response times and survival.

There are several reasons for this knowledge gap. One problem is the scarcity of good data: few states maintain databases that can be used to link response times to patient outcomes. Another challenge lies in the endogeneity of response times. EMS dispatchers collect important information about each incident that produces a call, and they can take actions that result in lower response times for the most critical cases. EMS personnel may respond more quickly to the most serious and life-threatening situations. Such triage makes it difficult to obtain unbiased estimates of the benefits of lower response times, even when data are available. Even detailed call reports cannot capture all of the information communicated by dispatchers to ambulance drivers—communication, which may be as subtle as the dispatcher's tone of voice. If this endogeneity of response time is ignored, then estimates of the "effects" of response times on patient outcomes will be biased downward toward finding no effect.

This paper contributes to the existing literature examining the relationship between EMS response times and health outcomes by using a novel identification strategy and extensive set of covariates on a patient population for which there is little if any evidence: all patients including calls for reasons other than cardiac arrest, heart conditions, trauma, or motor vehicle accidents. The direct impact of distance—measured as the length between the agency garage and the "incident", or the location where a patient needs to be picked up—on response times is examined along with the standard econometric model of response times. Then, using distance to closest authorized EMS agency headquarters as an instrument for response time, the extent to which shorter response times affect health outcomes is measured. The impact of response times for men and women and for patients of different ages is also analyzed for the first time. This is also the first paper, to our knowledge, to analyze the relationship between response times, emergency department admissions, procedures, and hospital expenses.

We find that distance is positively and significantly correlated with mortality. Without accounting for the endogeneity of response times, there is no statistically significant relationship between response time and mortality. However, the instrumental variable estimates of the impact of response times on outcomes show that, on average, a minute increase in response times increases mortality by between 8 (measured 1 day after the initial incident) and 17% (measured 90 days after the initial incident). Women and those over age 65 appear to be most affected. Patients with longer response times are also more likely to be admitted to the emergency department.

2. METHODS

2.1. Data

The primary data in this study come from the 2001 Utah Prehospital Incident Dataset, a collection of prehospital incident reports collected in Utah between 1 January 2001 and 31 December 2001 (Utah Department of Health, 1999-2005a). Utah was chosen because of the quality and availability of their data; after any incident for which an ambulance is dispatched and the EMS personnel provide care, the paramedics or EMTs are required to complete a "bubble" sheet including response times, patient demographics, the incident address, the date, and a description of each of the patient's illness or injuries. (Appendix A provides background on EMS services).

Response time was defined as the difference between the time that the ambulance is dispatched and the time that the ambulance arrives at the scene (Scott *et al.*, 1978; Stueven *et al.*, 1989; Cummins *et al.*, 1991; Grossman *et al.*, 1997; Athey and Stern, 1998; Key *et al.*, 2003; Lerner *et al.*, 2003). The measure of distance to the closest EMS agency was constructed by calculating the straight line distance from the incident location to the agency address of the closest provider in the territory in which the incident occurred. The census block group for each incident was identified using ARCMap Version 9.1.

Utah mortality records (2001–2002) and the Utah Emergency Department Encounter Dataset (2001) provided outcome data (Utah Department of Health, 1999-2005b; Utah Department of Health, 2001). The Utah mortality records, which come from Utah Office of Vital Statistics, included the name, age, race, time, and

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location of death for all deaths of Utah residents that occur within the state. Utah law also required that all hospitals in the state provide reports of every Emergency Department (ED) admission to the state Department of Health. These reports contain the name, admission date, admission time, birth date, mortality risk, condition severity, outcome, total charge, number of procedures, and primary diagnosis for each patient. Additional details of the construction of the dataset are contained in Appendix B. Mortality and ED records were linked to the prehospital records using probabilistic linking software LinkPlus. Details of the probabilistic matching procedure are contained in Appendix C. Using ARCMap, we also identified the census block group for each incident, and linked census 2000 demographic summary data to incident information (Bureau, 2000). Weather data were matched using the date, time and the latitude and longitude of each incident and the closest weather station within the state of Utah (National Climactic Data Center, 2001). Duplicated prehospital reports, cancelled calls or calls without a name were excluded from the analysis. Incident reports, which did not have descriptions of the patients' primary complaint, response time, or geocoded incident address, were also dropped from the analysis. Respondents missing census block group characteristics or the distance to the closest EMS agency were also excluded. The analysis was restricted to incidents occurring in the Salt Lake City area. In some cases, EMTs and paramedics from more than one ambulance provided care to the patient. When this occurred, there were multiple reports for the same patient from the same incident. Only the report from the first EMS on scene was included in the analysis (Nichol *et al*., 1996a; Fischer *et al*., 2000)(Figure 1).

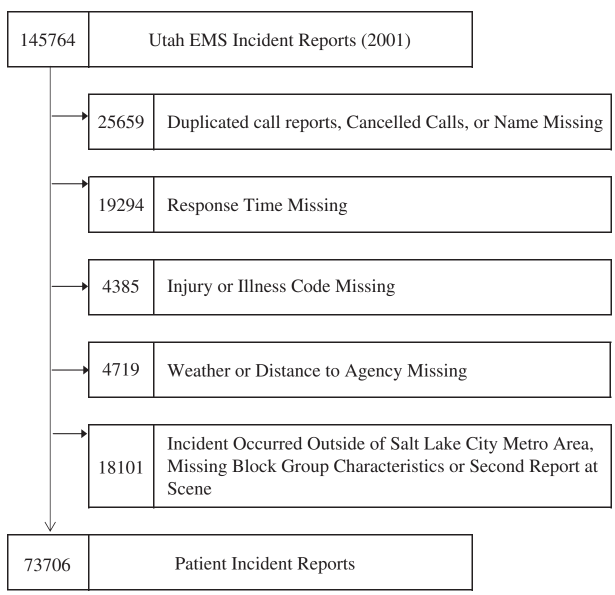

Figure 1. Study cohort

2.2. Econometric framework

In the standard econometric framework in the medical literature, outcomes are modeled as a function of response times. We present the standard model as a linear probability model rather than a logistic regression for ease of presentation.

$$\mathrm{Y}_{\mathrm{ics}} = \alpha + \mathrm{RT}_{\mathrm{i}}\delta + \mathbf{X}_{\mathrm{i}}\mathbf{b} + \varepsilon_{\mathrm{i}}, \tag{1}$$

where

$\mathrm{Y}_{\mathrm{ics}}$ = Outcome for individual-incident i
RT_{i} = Response Time for individual-incident i

$\mathbf{X}_i$ = A vector of incident characteristics, and
ε_i = An error term.

We propose that ε_i can be decomposed into two terms:

$$\varepsilon_i = \mu_i + \theta_i$$

where

μ_i = A residual component of severity that is not observed by the ambulance driver or the researcher and
θ_i = A measure of severity which is observed by the ambulance driver, but unobserved by the researcher.

Because the ambulance driver knows θ_i, response time may depend in part on it. As long as $E(\varepsilon_i\,RT_i < 0)$, then OLS estimates of mortality on RT will be negatively biased. This may explain why regressions which fail to account for the endogeneity of response times often find no significant relationship between mortality and response times. To address this endogeneity, we used an instrumental variable—the straight line distance from incident address to the address of the closest indicated provider agency—which was correlated with response time but uncorrelated with severity. Distance to the closest indicated agency is not the distance actually travelled by the responding ambulance. For example, the responding ambulance may leave from places other than the agency headquarters and may not travel in a straight line.

We estimated the following:

$$Y_{ics} = \gamma + RT_i\sigma + \mathbf{X}_i\mathbf{\Pi} + v_i, \tag{2}$$

$\check{R}T_i$ is the predicted value resulting from regressing response time on the instrument, $Z_{i,}$ distance to the closest indicated agency and a vector of incident characteristics, having removed the component of RT_i, which was correlated with ε_i:

$$RT_i = \lambda + Z_i\theta + \mathbf{X}_i\boldsymbol{\psi} + \mu_i \tag{3}$$

A valid instrument satisfies two criteria. First, it is sufficiently correlated with the endogenous variable $(E(Z_i\ RT_i \neq 0))$. Second, it is not correlated with the error term $(E(Z_i\varepsilon_i = 0))$. We tested the first condition with an F test on the instrument in the first stage regression (3). Unfortunately, it is impossible to prove the second condition or exclusion restriction because the error term is unobserved. However, we do present several tests of its validity. Given that these two criteria are met, the parameter σ will provide an unbiased estimate of the impact of response time on mortality—identified off of the variation in response times which is correlated with the distance to the closest EMS agency and uncorrelated with ε_i.

We controlled in both the OLS and IV estimates for a wide variety of factors including weather, month, the illnesses identified by the EMS as the reasons for calling, weekend interacted with hour-of-day fixed effects, and primary complaint indicator variables—so that we are only comparing patients with the same primary complaint. We also included census block group characteristics: area, total population, density, the proportion of community members living below the poverty line, the proportion of the population not receiving government assistance, the median income, the proportion of the block group that is rural, and the proportions of the population that are, respectively, younger than 5, between 16 and 65, and older than 65.

Any variables that might be considered endogenous to response time are excluded, including time at scene, distance to hospital, and treatments and medications which might potentially be affected by time to scene. We explored several of these intermediate outcome variables in a later section, as we tried to determine the mechanism through which response time affects outcomes.

The reduced form regression of mortality on distance was estimated for each of the five mortality outcomes: death within 1 day, 2 days, 30 days, 90 days, and 1 year after the initial incident. The standard econometric regression of mortality on response times was estimated as was the instrumental variables specification where distance was the instrument for response times. IV regressions run separately by gender and, for major age

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categories (<15, 15–25, 25–65, and over 65), showed the extent to which response times differ across gender and age. Because Utah's population is more than 89% non-Hispanic white, there were not enough calls by nonwhites to estimate treatment effects separately by race (Bureau, 2000).

We also explored the mechanism through which response time may affect mortality. To do this, we measured the impact of response time on several intermediate outcomes, including the probability of being admitted to the emergency department, on total hospital expenditures, and the total number of procedures within the hospital. All results are reported with robust standard errors. Additional tests of validity and sensitivity analyses are described in detail below.

3. RESULTS

There were 73 706 observations in the final analysis sample. The majority of observations excluded from the analysis sample were either cancelled, missing a name, response time, not in the Salt Lake City area, or not the first responder on the scene. Patients using EMS in Utah are much more likely to be over age 65 and slightly more likely to be white and female than the general population of Utah. Utah is considerably younger and more white than the rest of the USA (Table I).

Table I. Utah 2001 prehospital sample demographic characteristics

Variable	Utah 2001 prehospital sample*	Utah census 2000	US census 2000
Age			
Less than 15	0.09	0.27	0.21
15 to 24	0.17	0.20	0.14
25 to 64	0.47	0.45	0.52
65 and over	0.27	0.09	0.12
N = 62 982			
Gender			
Female	0.52	0.50	0.51
N = 73 556			
Race			
White	0.91	0.89	0.75
Black	0.02	0.01	0.12
Native American/Alaskan Native	0.01	0.01	0.01
Asian/Pacific Islander	0.02	0.02	0.04
Other	0.06	0.06	0.08
N = 45 164			

*Sample sizes vary because of missing values.

Table II. Descriptive statistics for Utah 2001 prehospital sample

	Mean	Standard deviation
Incident characteristics:		
Time from dispatch to arrival at scene (minutes)	8.46	6.64
Distance to agency (miles)$	3.25	5.74
Outcomes:		
Death within 1 day of incident*	1.69	12.90
Death within 2 days of incident*	1.97	13.91
Death within 30 days of incident*	4.28	20.25
Death within 90 days of incident*	5.95	23.66
Death within one calendar year of incident*	9.77	29.69
Admitted to ED	70.02	45.82
Number of ED procedures for ED patients*	33.12	85.90
Total hospital expenses For ED patients	2934.34	9841.07

$:Distance to agency is defined as distance to the closest agency covering the territory that the incident occurs. *Scaled by 100 for ease of interpretation. # For number of ED procedures and total hospital expenses, N = 51 607. For all other outcomes, N = 73 706.

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The mean response time is 8.46 minutes, with an average distance between the incident location and the closest EMS agency of 3.25 miles (Table II). Approximately 2% of EMS patients die within 1 or 2 days of the incident, 4% die within 30 days, 6% within 90 days, and around 10% die within 1 year. Around 70% of patients are admitted to the emergency department after an EMS incident. Those that are admitted have an average hospital expenditure of around $3000. Most patients do not have a procedure within the hospital.

Row 1 of Table III contains the reduced form estimates of the impact of distance to closest non-mutual aid EMS agency on mortality. As the increment since the incident increases, the coefficient on distance increases. Incidents that occur farther from agencies are more likely to result in deaths. The coefficient on distance in the regression of 1-day mortality on distance was 0.0150—suggesting a two hundredth of a percentage increase in mortality for every mile increase in distance between the incident and the closest agency in the territory. The coefficient on distance 1 year after the initial incident is 0.1392—approximately a tenth of a percent. The coefficient on distance for all but the first measure of mortality is statistically significant.

Row 2 of Table III contains ordinary least squares estimates of the regression of mortality on response times, where mortality is an indicator equal to 100 for those who were matched to the mortality records. The coefficient on response time is not statistically significantly different from 0 for any of the estimates.

Row 3 of Table III contains the instrumental variable estimates of the impact of response time on mortality measured at different intervals. The coefficients vary in magnitude from 0.1363 to 1.2617 percentage points and increase as the interval over which response time is measured increases. On average, a minute increase in response time increases mortality by between 8 and 17%. The coefficient on distance in the first stage of the instrumental variables analysis is 0.1103 (SE of 0.0084)—the marginal impact of an additional mile in distance to the closest indicated ambulance station is a less than 10-second increase in response times. Note that the distance from the incident to the nearest ambulance headquarters is not a proxy, intended replacement, or representation of the distance that the ambulance actually travels in each incident, although they are correlated. The appropriate interpretation of the coefficient in the first stage is that the farther from an EMS agency headquarters that an incident occurs, the slower, on average, the response time for responding ambulances. The first stage F-statistic is 172.62.

Table III. Coefficients from reduced form regression of mortality on distance, ordinary least squares regression of mortality on response time and instrumental variables regression of mortality on response time where distance is an instrument for response time

	Dependent variable:				
	1-day mortality	2-day mortality	30-day mortality	90-day mortality	1-year mortality
Reduced form regression of mortality on distance	0.0150 (0.0083)	0.0342 (0.0123)*	0.0780 (0.0177)*	0.1112 (0.0200)*	0.1392 (0.0232)*
OLS regression of mortality on response time	−0.0077 (0.0063)	−0.0058 (0.0069)	0.0205 (0.0124)	0.0276 (0.0149)	0.0157 (0.0176)
IV regression of mortality on response time	0.1363 (0.075)	0.3099 (0.1139)*	0.7080 (0.1648)*	1.0084 (0.1854)*	1.2617 (0.0209)*
Mean	1.6932	1.9741	4.2819	5.9520	9.7713
			Dependent variable:		
	Response time	Response time	Response time	Response time	Response time
First stage (coefficient on distance)	0.1103 (0.0084)*	0.1103 (0.0084)*	0.1103 (0.0084)*	0.1103 (0.0084)*	0.1103 (0.0084)*
R^2	0.0093	0.0093	0.0093	0.0093	0.0093
F Stat	172.62	172.62	172.62	172.62	172.62
N	73 706	73 706	73 706	73 706	73 706

Notes: All specifications include block group characteristics, hour, week, week by hour, month, illness, and weather indicators. Robust standard errors in parentheses. *Indicates significant at 5% level.

Table IV. Coefficients on response time for instrumental variables regression of mortality on response time where distance is an instrument for response time by gender and age

	Dependent variable:				
	1-day mortality	2-day mortality	30-day mortality	90-day mortality	1-year mortality
Coefficient on RT:					
Utah 2001 prehospital sample	0.1363	0.3099	0.7080	1.0084	1.2617
(N = 73 706)	(0.0754)	(0.1139)*	(0.1648)*	(0.1854)*	(0.0209)*
	1.6932	*1.9741*	*4.2819*	*5.9520*	*9.7713*
Men	0.0773	0.3208	0.5080	0.8478	1.0286
(N = 35 645)	(0.1087)	(0.1893)	(0.2221)*	(0.2499)*	(0.2808)*
	2.0620	*2.3454*	*4.6795*	*6.3431*	*10.3128*
Women	0.1797	0.2829	0.8949	1.1610	1.5070
(N = 37 911)	(0.0993)	(0.1187)*	(0.2416)*	(0.2724)*	(0.3098)*
	1.3532	*1.6328*	*3.9250*	*5.6079*	*9.3007*
Age less than 15	0.0831	0.0566	0.0201	0.1759	0.1528
(N = 5328)	(0.1015)	(0.1036)	(0.1136)	(0.1769)	(0.1857)
	0.6006	*0.6569*	*0.9384*	*1.0323*	*1.5390*
Age 15–24	0.0167	0.0261	0.1679	0.5778	0.5881
(N = 10 670)	(0.0774)	(0.0759)	(0.1459)	(0.2345)*	(0.2519)*
	0.5061	*0.5248*	*0.6279*	*0.8247*	*1.3683*
Age 25–64	0.0321	0.2895	0.3657	0.3687	0.4246
(N = 29 792)	(0.1247)	(0.2397)	(0.2648)	(0.2730)	(0.2990)
	1.5675	*1.7320*	*3.0512*	*4.0078*	*6.7166*
Over 65	0.2232	0.4848	1.0470	1.3183	1.2972
(N = 17 192)	(0.2332)	(0.2869)	(0.5421)	(0.6068)*	(0.6666)*
	4.0426	*4.9325*	*12.3895*	*17.7408*	*28.9204*

Notes: All specifications include block group characteristics, hour, week, week by hour, month, illness, and weather indicators. Robust standard errors in parentheses. Dependent variable means in italics. *Indicates significant at 5% level.

Table IV shows the instrumental variables estimates of mortality on response time for the complete 2001 analysis sample, for men, women, those less than 15, between the ages of 15 and 24, between 25 and 64, and those above age 65. For each group, the impact of response time is increasing with the time since the incident: for example, the IV estimate of the coefficient on response time in the regression of 1-year mortality for women is 1.5070, whereas the estimated impact of a minute change in response time on 1-day mortality is 0.1797—a less than 1% change (Row 3). Table IV shows that women and those over 65 appear to be most affected by response time, with coefficient estimates larger than the estimates from the entire 2001 Analysis Sample. However, it is worth emphasizing that, although base mortality rates for male and female EMS patients are similar, average mortality rates differ considerably by age: over 28% of those over 65 who call EMS die within 1 year but less than 7% of those between 25 and 65 and less than 2% of those less than 25 die within 1 year.

4. INSTRUMENT VALIDITY

Some may be concerned that the coefficient on the instrument in the first stage is small: it appears that a 1-mile increase in distance increases response time by less than 1 minute. However, interpreting this coefficient as an indicator of the speed of the ambulance responding to the scene is incorrect. The coefficient captures the change in response time from a 1-mile change in distance to the closest indicated agency from the incident—not the change in response time associated with a 1-mile change in *actual* distance travelled by the ambulance

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responding to the incident; we do not know how far the ambulance actually travelled except for a small subset of calls. For that subset of calls, we know that a 1-mile increase in distance to closest agency corresponds to a 0.20-mile increase in distance travelled. This implies a travelling speed far lower than observed by looking at the coefficient on the first stage alone (by a factor of five). Clearly, distance to closest indicated agency is correlated with the actual distance travelled by the ambulance (presumably explaining why the instrument is correlated with response time), but this relationship is far from one-to-one, and nor need it be to be a valid instrument. A valid instrument needs to be correlated with the endogenous variable and uncorrelated with the unobserved error in the equation relating the dependent variable (mortality) to the endogenous variable (response time). Even if one interpreted the instrument as a flawed measure of the distance actually travelled by the ambulance, the IV estimate would be unbiased as long as the measurement error is classical, uncorrelated with the endogenous variable, other regressors, and error terms (Appendix part D).

To test the first condition required for a valid instrumental variable, we conducted a F test on the first stage regression of response time on distance. Given that we were not accounting for road structure, traffic lights, number of lanes, and speed limits and not capturing the true distance travelled by the ambulance, all of which would seem to be important predictors of response time, it is surprising that our instrument satisfied the first condition of instrument validity: the first-stage F test value is well over 10 (Table III).

Satisfying the second condition required for instrumental validity is more difficult. The primary limitation of our work is that the instrument may identify patients who are different in ways that may be correlated with both response times and outcomes—for instance, because sick people locate near EMS headquarters or EMS headquarters locate near sick people or because among those living far away, only the sickest patients call EMS. If severity and distance are positively correlated (and response time and distance to closest agency), then this would bias our IV coefficients upward and would suggest that our estimates of the impact of response time on outcomes were too high.

We address this in several ways. First, to reduce the potential of such bias, we control for 36 detailed injury or illness categories, such as chest pain, falls, and fevers. This means that all respondents are only compared with those suffering from the same condition, with (presumably) similar levels of severity.

We also control for census block group characteristics, thereby identifying response time off of variations in distance to the closest EMS agency within socioeconomically and demographically homogenous territories. That is, we only compare patients with other patients, suffering the same complaint, in the same block group. As an additional robustness check on the identification strategy, we also ran specifications where we explicitly controlled for block group fixed effects. The F statistic on the first stage is slightly less strong in the specifications, which include block group fixed effects (F-statistic of 16.47), but the IV results are similar to those reported in Table III, as can be seen in Appendix E, Table I, although the IV coefficients and standard errors increase in size.

Next, even controlling for census block group characteristics and injury or illness category, one might still be concerned that the instrument may be correlated with unobserved severity. To examine this, we regressed indicators for distance to closest hospital, race, gender, individual age categories, and years of education (available only for those who died) on the distance to the closest provider agency. Because one might also be concerned that the experience or training of staff or that the characteristics of the unit responding to the incident differs systematically with distance and is correlated with unobserved severity, we also regress the experience level of the most experienced member of the responding ambulance team (calculated using the number of trips taken by each paramedic in calendar year 2001 by the time of the incident), an indicator for whether the unit responding is licensed to provide advanced life support care and an indicator for whether the type of unit responding is a ground ambulance, on distance.

As Table V shows, we found that all of these observable characteristics are significantly correlated with distance, with the exception of experience and education (a proxy for SES). However, including distance to closest hospital, race, gender, age, education, provider experience, unit type, or unit certification levels as right-hand side variables, as presented in Table V, does not appreciably affect the IV results, as one might expect if these characteristics were correlated with the unobserved error. Being correlated with the instrument, alone, is not enough to invalidate the instrument. Including provider fixed effects does not affect these results (row 4 in Table V).

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Table V. Instrument validity

	Distance to closest hospital (miles)	Black	Female	Patient age > 65	EMS personnel experience	Paramedic unit certification	Ground ambulance	Years of education
OLS: Coefficient on distance (dependent variable: column heading)	0.0345 (0.0027)*	−0.0004 (0.0001)*	0.0012 (0.0003)*	0.0026 (0.0004)*	−0.0082 (0.1257)	−0.0056 (0.0003)*	0.0056 (0.0005)*	0.0053 (0.0043)
IV 1: Coefficient on RT controlling for block group characteristics (dependent variable: 30-day mortality)	0.7076 (0.1648)*	1.4241 (0.3027)*	0.7024 (0.1648)*	0.6902 (0.1862)*	0.7776 (0.2052)*	0.6320 (0.1497)*	0.6320 0.1497	1.6888 (0.9074)*
IV 2: Coefficient on RT controlling for block group characteristics and column variable (dependent variable: 30-day mortality)	0.7462 (0.1756)*	1.4162 (0.3029)*	0.7074 (0.1643)*	0.4980 (0.1846)*	0.7775 (0.2050)*	0.6547 (0.1571)*	0.6267 0.1534	1.6902 (0.9076)
IV 3: Coefficient on RT with provider Fixed effects, controlling for column variable (dependent variable: 30-day mortality)	0.8711 (0.2224)*	1.8995 (0.4293)*	0.7139 (0.1958)*	0.5157 (0.2332)*	0.8190 (0.2566)*	0.6133 (0.1708)*	0.6153 (0.1714)*	1.8143 (1.2551)*
N	73 706	45 164	73 556	62 982	58 018	71 316	71 316	14 716

Note: Sample is defined using report which includes the shortest response time to scene; distance is that of closest non-mutual aid agency. Mortality outcomes are multiplied by 100 for ease of coefficient interpretation. Robust standard errors in parentheses. Row one contains the coefficient from the reduced form regression of the covariate of interest (i.e. distance to closest hospital) on distance, controlling for hour, week, week by hour, month, weather, and injury illness fixed effects as well as block group characteristics. Row 2 (IV 1) contains the instrumental variable estimate of response time on mortality measured at 30 days, controlling for hour, week, week by hour, month, weather and injury illness fixed effects as well as block group characteristics, and restricting the sample to observations which contain nonmissing values of the column variable. Row 3 (IV 2) contains the instrumental variable estimate of response time on mortality measured at 30 days, controlling for hour, week, week by hour, month, weather and injury illness fixed effects as well as block group characteristics, including the column variable as a covariate. Row 4 (IV 3) contains the instrumental variable estimate of response time on mortality measured at 30 days, controlling for hour, week, week by hour, month, weather and injury illness fixed effects as well as agency fixed effects, and includes the column variable as a covariate. *Indicates significant at 5% level. Education is defined only for individuals in the mortality dataset; the experience of EMS personnel represents the number of trips so far this year made by the most experienced responding EMT; unit type is defined as ground ambulance, quick response unit, or rescue unit. Unit certification is the highest level of care that the unit is licensed to provide: basic, basic IV, intermediate, intermediate advanced, intermediate interfacility, paramedic, or paramedic interfacility. For comparison purposes, for the standard sample (without additional covariates), the coefficient on response time is 0.7097 (0.1963) with provider fixed effects (N = 73 706).

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We also explored the relationship between our measure of distance and characteristics measured at the block group level within the Salt Lake City Metropolitan Area for the sample, controlling for all of the other characteristics in the main regression specification except for other block group census characteristics. We ran regressions including census tract fixed effects, place, zip, city, county fixed effects, and no fixed effects at all. In all specifications, we found that the percent without government assistance is significantly positively related to distance, that the poverty rate is significantly negatively related to distance, and that percent rural is positively related to distance to closest EMS agency (Appendix E, Table II).

Finally, it is possible that when agencies divide block groups into separate jurisdictions, they do so to avoid (or to capture) sicker patients. Our informal conversations with EMS agency directors suggested that these agency borders largely follow natural boundaries (mountains/rivers), railroad tracks, community/township lines, county lines, and major roads. Of course, this does not rule out endogeneity. However, if agencies divide block groups into jurisdictions based on unobserved patient characteristics, then including provider fixed effects should eliminate such differences. In all cases, the instrumental variable estimates including provider fixed effects were not very different from the main specification. For 1-day mortality, the IV estimate including provider fixed effects was 0.165 (0.089). For 2-day mortality, the IV estimate was 0.354 (0.1367), the 30-day mortality IV estimate was 0.709 (0.1963), the 90-day mortality IV estimate was 0.979 (0.219), the 1-year mortality IV estimate was 1.161 (0.246), and the 4-year mortality IV estimate was 2.069 (0.322).

5. SENSITIVITY ANALYSES

We tested the sensitivity of our results to alternate specifications. Our results are equivalent using logistic and probit models. The significance and direction of the coefficients are also robust to using the logarithm of response time and increase with the time interval over which mortality is measured (Appendix E, Table III).

We also tested the sensitivity of our results to alternate definitions of response time. We used distance as an instrument for an indicator for response times less than 2 minutes, less than 3 minutes, and so on, up to 10 minutes. Response times of less than 2 minutes produced the greatest reductions in mortality. Although response times less than 10 minutes still reduced mortality relative to longer response times, these reductions were far less than those which resulted from response times of less than 2 minutes, 3 minutes, 4 minutes, or 5 minutes. Other regressions, in which we used grouped distance measures as instruments for three response time indicators (less than 5 minutes, between 5 and 7 minutes, and more than 7 minutes), were consistent with these results which showed that response times less than 5 minutes appear to be most predictive of mortality.

We also excluded the particular groups that we thought might be driving our main results. However, none of the results are significantly affected by the following: excluding transfers (Appendix E, Table IV), excluding mutual aid calls, excluding those labeled as DOA, excluding patients (incidents) outside of Utah, and restricting the sample to incidents with only one report or one patient.

We were also concerned that our results were sensitive to our choice of included covariates, but the results were not affected by excluding weekend, month, or day fixed effects; excluding weather variables; not controlling for the primary complaint. Likewise, including different permutations of hour-of-day or day-of-week interactions, dispatch codes instead of the primary complaint, indicators for patient location and incident location (playground, home, etc.), including traffic measures, indicators for Olympic location or tourist location, hourly EMS call congestion numbers, temperature, indicators for daylight savings time, or indicators for the incident occurring before or after sunset or sunrise also did not affect the main results. Nor were the substance of the results affected by including race; gender and age covariates; or characteristics of tracts, places, zip codes, or counties on the right-hand side or by interacting mortality with the score assigned by LinkPlus for each match or restricting matches to those with scores greater than 20 (Appendix E, Table V and Table VI). Including the distance to the closest hospital also did not affect the main results (Appendix E, Table VII).

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6. MECHANISM

There are several potential mechanisms through which EMS response times could affect patient outcomes. The first mechanism that we propose is one in which delays in response time reduce the patient's underlying health in ways which are unobservable to the researcher; this "damage" takes time to manifest and affect mortality and would explain why the impact of a 1-minute change in response time on mortality appears to be increasing with the interval over which response time is measured. In a second mechanism, which we explore, the increasing relationship between a minute change in response time and mortality can be explained by a compounding effect from living farther away from EMS headquarters. In short, patients who call from farther away, who have longer response times, may be more likely to experience bad outcomes, increasing the likelihood of making a call for EMS care again, possibly from a similarly "far away" place, thus experiencing a long response time, which leads to a bad outcome, and so on, leading to the measured increasing relationship between response time and mortality after the initial incident.(Note that although the coefficients in Table IV are increasing in absolute value from column 1 to column 6, these coefficients are relatively consistent as a proportion of total deaths across all time intervals.)

In the first mechanism that we discuss, earlier EMS arrivals stop the deterioration and limit the extent of additional damage to patients' health. The sooner the paramedics arrive, the less the damage, and the smaller the later chance of death. Some existing literature supports this mechanism. An article comparing survivorship between systems with EMTs versus systems with paramedics found that "intravenous medication and intubation has survival benefits" (Cummins *et al*., 1991). This evidence suggests that the timing of treatments matters: presumably patients served by EMTs would have access to any of these treatments after reaching the hospital. More recently, randomized controlled trials have supported existing evidence on "the importance of early access to defibrillation for improved survival in out-of-hospital cardiac arrest" (Callans, 2004). Researchers who placed defibrillators in random locations throughout a community found that reducing the time to defibrillation significantly increased survival (Callans, 2004; Hallstrom *et al*., 2004).

This mechanism would explain why the probability of dying at any point is higher for patients with longer response times. These patients with more "damage" may or may not have worse vital signs, as measured at the scene, because vital signs may not capture "damage". Nevertheless, they should have higher hospital admission rates and should be, conditional on hospital admission, in worse shape in the emergency department. Finally, EMTs and paramedics should choose hospitals, which are closer for these patients because they are in more danger of dying, which is also consistent with the data. (One might also expect these patients to use overall more health resources in the years after the initial prehospital incident because they are in worse health.) This explanation does not suggest that the treatments or medications provided to patients experiencing longer response times will be any different from those provided to patients with shorter response times; nor would the time at the scene be any different because the treatments and medications are equivalent. Rather, it is the timing of the medications and treatments, which is essential; that is what differentiates patients with longer and shorter response times, rather than any disparity in the substance of caregivers' interventions.

Table VI shows how response times affect emergency department (ED) admission, total ED-related charges (expressed in natural logs), the number of procedures within the hospital conditional on admission to the ED, the probability that a patient in the ED is assessed as having a very severe condition or being at high risk of mortality, and the distance from the incident address to the hospital (for admitted patients), health index 1 and health index 2 (two predictors of 48-hour mortality based on vital signs), which are measured at the scene and time at scene. We do not look at the impact of response time on individual health measures (blood pressure, pulse, Glasgow coma score, or respiration) because, individually, these do not provide a reliable picture of the patient's condition at the scene. It is not clear how response times should affect costs. Patients made sicker by longer response times might have higher costs if they require more intensive treatment. Conversely, they may have lower costs because they are more likely to die (Diehr *et al*., 1999). Because laboratory procedures and emergency department expenditures are distributions with many zeros and long right tails, it is typical to transform them into the log scale. This 'shortens the long right tail, lessens heteroscedasticity, and decreases

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Table VI. Intermediate outcomes

	Dependent variable:								
	Indicator for admitted to ED**	Total hospital expenditures (natural log)	Total number of procedures**	High mortality risk (ED)**	Severe injury or illness (ED)**	Distance from incident to hospital (miles)	Health index 1**	Health index 2**	Time at scene
Mean (dependent variable)	70.0174	6.8250	33.1195	5.9661	7.1359	7.7004	98.3040	98.3250	18.2731
Reduced form regression of dependent variable on distance (coefficient on distance)	0.1622 (0.0358)*	0.0008 (0.0011)	0.0217 (0.0672)	0.0627 (0.0226)*	0.0528 (0.0239)*	−0.1111 (0.0273)*	0.0070 (0.0046)	0.0038 (0.0064)	−0.0077 (0.0102)
OLS (coefficient on RT)	−0.1568 (0.0274)*	−0.0027 (0.0010)*	−0.2332 (0.0571)*	0.0041 (0.0166)	−0.0043 (0.0174)	0.0252 (0.0197)	0.0050 (0.0030)	0.0030 (0.0037)	−0.2403 (0.0118)*
IV (coefficient on RT)	1.4709 (0.3038)*	0.0067 (0.0091)	0.1722 (0.5334)	0.4966 (0.1816)*	0.4182 (0.1904)*	−0.8843 (0.2165)*	0.0597 (0.0391)	0.0325 (0.0543)	−0.0677 (0.0889)
	Dependent variable:								
	Response time	Response time	Response time	Response time	Response time	Response time	Response time	Response time	Response time
First stage (coefficient on distance)	0.1103 (0.0083)*	0.1258 (0.0108)*	0.1258 (0.0108)*	0.1263 (0.0110)*	0.1263 (0.0110)*	0.1256 (0.0108)*	0.1169 (0.0094)*	0.1169 (0.0094)*	0.1140 (0.0088)*
N	73 706	51 607	51 607	50 519	51 607	51 579	67 519	67 519	66 813

Note: Sample is defined using report including the shortest response time to scene; distance is that of closest non-mutual aid agency. All specifications include block group characteristics, hour, week, week by hour, month, and injury illness fixed effects. **Indicates dependent variables are multiplied by 100 for ease of coefficient interpretation. Robust standard errors in parentheses. *Indicates significant at 5% level.

the influence of outliers' and, in practice, makes the distribution close to normal (Diehr *et al.*, 1999). In this project, for ease of coefficient interpretation, we used the natural log of ED expenditures and the number of ED procedures multiplied by 100 as measures of health care utilization.

Table VI follows the same basic format as Table III. The first row contains the reduced form of outcomes on distance, the second row contains the OLS estimates, the third row contains the IV estimates, and the final row contains the first stage results. The basic specification is that of the mortality specification with month, weekend by hour-of-day fixed effects, primary complaint indicators, weather indicators, and block group characteristics. All results are reported with robust standard errors. The first column includes the entire regression sample, but columns (2) - (6) only include patients admitted to the hospital. Columns (7)–(9) have smaller sample sizes because of missing data.

These results show that response times affect the likelihood of being admitted to the ED. However, conditional on being admitted to the ED, response time does not significantly affect healthcare utilization: the IV estimates of the impact of response time on the number of ED procedures and total ED expenses are not significantly different from zero. Response times also significantly affect the condition of the patient as assessed in the ED. Patients with longer response times are more likely to be considered at high risk of mortality and to have more severe conditions, as Columns (4) and (5) in Table VI shows. It appears that response times also affect the choice of hospital; response time is negatively correlated with the distance from the incident to the hospital to which patients are admitted. The implication is that EMTs and paramedics take patients with longer response times to closer hospitals, whereas those patients who have shorter response times are transported to more distant facilities. This may be because paramedics grant patients less influence over the choice of hospital when they are in worse condition, or paramedics may simply want to get patients to the closest possible hospital.

It is not particularly surprising that response times do not significantly affect either health index, as these health indices are measured at the scene and are predictive only of short-term mortality (within 48 hours of the incident), and are not necessarily measures indicative of long term health. Response times also do not affect the time that EMTs and paramedics spend at the incident scene. In regressions not reported here, we find that response time does not consistently predict medication usage or treatments. A complete list of the medications and treatments provided to EMS patients is included in Appendix E, Table IIX.

A second potential explanation for increasing mortality over time is that patients who experience initially longer response times are more likely to make additional calls to EMS and, therefore, experience longer response times again. We ruled out this mechanism. Because 39% of EMS calls occur at home, if an initially longer response time causes damage and also increases the likelihood of making additional EMS calls, then later EMS calls will likely compound this effect. This mechanism implies that patients with longer response times experience more subsequent EMS calls, and the hazard of death conditional on survival for those with initially long response times should be increasing over time as opposed to constant.

To evaluate these claims, we created identifiers for any person who appears in the prehospital data set. Then, we calculated the average number of EMS calls following the initial call. We found that this number averaged zero for both patients above and below the mean of the distance from the incident to the provider, suggesting that a mass of so-called 'additional' EMS calls are not responsible for causing increasing damage to patients farther from agency locations. Second, looking directly at the hazard of mortality for EMS patients who experienced initially longer response times, even after controlling for survival from initial periods, there appears to be a continued but not increasing impact of longer response times on mortality. What we call a hazard here is simply the IV estimate of the impact of the initial response time on mortality in this period conditional on survival to the previous period. For example, the IV estimate for the hazard of mortality in day 2 conditional on survival to day 1 is 0.1803 (with a standard error of 0.0906). The hazard of mortality by day 30 conditional on survival to day 2 is 0.4236 (0.1288), whereas the hazard of mortality by day 90 conditional on survival to day 30 is 0.3375 (0.0952). The hazard of mortality by day 365 conditional on survival to day 90 is 0.3320 (0.1175), and the hazard of mortality by day 1460 conditional on survival to day 365 is 1.2389 (0.2230). If this explanation were true, the hazard of mortality should be increasing, and the number of subsequent EMS calls for patients with distances to their providers above the mean should be greater than zero, which is not what we find.

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7. DISCUSSION

Many factors affect the quality of EMS services. Existing research on EMS by economists largely focuses on the factors which affect the supply of EMS. For example, EMS may be supplied in many ways: publicly provided through a fire department or police department or privately provided by a for-profit or not-for-profit entity. The probability of being private seems to be related to the community's distance to other cities, the population, and the number of hospitals in the city (all but the former negatively associated with private provision)(David and Chiang, 2009).

Several researchers have used response times as a measure of quality. David and Harrington found that after controlling for population density, differences between blacks and whites in response time disappeared (David and Harrington, 2010). Concannon *et al*. found that distance, time of day, race, and gender predict longer total response times, and population density, racial composition (percentage white) and ER bypass are associated with delays of more than 15 minutes (Concannon *et al*., 2009).

Other factors affecting response time include worker fatigue, experience, human capital depreciation, and turnover. More experienced workers respond faster to EMS calls—a one standard deviation increase in trauma runs correlates with a 35-second reduction in out of hospital time (David and Brachet, 2009). Longer shifts, time of day, and worker turnover are also correlated with longer response times (Brachet *et al*., 2010; David and Brachet, 2011)

We see this article as a natural extension of those existing articles that focus on the supply of EMS. Although many have looked at the factors that predict response time, the current evidence on the impact of reduced response times on outcomes is limited. One meta-analysis of a small set of case studies found that, on average, that shorter response times were associated with higher survival rates (Nichol *et al*., 1996a). In that meta-analysis, a one-minute decrease in mean response time was associated with an increase in survival of 0.4 percentage points in a one-tier system (mean survival rate: 5.2%) and an increase of 0.7 percentage points in a two-tier system (mean survival rate: 10.4%) (Nichol *et al*., 1996a). As a proportion of total deaths, this suggests that a minute change in response time appears to cause a 8% change in survival to hospital discharge for cardiac arrest victims in a one tier system and a 7% change in survival to hospital discharge for cardiac arrest victims in a two tier system. This provides a benchmark of sorts for our estimates: we find that a one minute increase in response times causes an 8% change in survival within one day of the initial incident.

Only a handful of studies have examined the relationship between response times and outcomes for people suffering from conditions other than cardiac arrest. Presumably, this is based on the assumption that response times are very important for survival from cardiac arrest but less important for survival from other conditions. These studies have generally found no association between response times and survival (Newgard *et al*., 2010; Esposito *et al*., 1995; Pons and Markovchick, 2002). A few studies have looked at outcomes after motor vehicle accidents with mixed results, but two of the studies were analyses of means only (Sanchez-Mangas *et al*., 2010; Esposito *et al*., 1995; Gonzalez *et al*., 2009).

Two studies analyzed outcomes for trauma patients and found no difference in survival based on response times (Pons and Markovchick, 2002; Newgard *et al*., 2010). A third paper looking at mortality and response time for trauma patients found no survival benefit from a paramedic response time of less than 8 minutes, and a survival benefit for response times of less than 4 minutes for a subset of patients (those considered to be of 'intermediate' or 'high' risk of mortality, as defined by the study authors)(Pons *et al*., 2005).

Just two studies, to our knowledge, have looked at the impact of response times on a broad selection of EMS calls, rather than examining only incidents involving trauma or cardiac arrest (Blackwell and Kaufman, 2002; Blackwell *et al*., 2009). Blackwell and Kaufman study all patients with emergency responses of priority 1 or priority 2 who were transported to a Level 1 trauma center and compare means between survivors and non survivors, finding no significant difference in median response times between survivors and nonsurvivors and a slight benefit when response times are less than 5 minutes of around 1%. A second paper studying emergency, life-threatening transports compared mortality outcomes for those with response times of greater

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than 10:59 with a random sample of patients with response times less than 10:59 and found no association but suggestive evidence that response times less than 5 minutes might be beneficial (Blackwell *et al*., 2009).

There are many reasons to think that the endogeneity of response times is a very real problem for these analyses. Dispatchers tell drivers and paramedics the basic circumstances of incidents, including information, which allows drivers to determine whether to rush to the scene. Because riding 'hot' can carry significant risks for EMS personnel, the decision about whether to activate lights and sirens and travel quickly to the scene is almost always at the discretion of the paramedics. Empirical evidence supports this. After one community instituted a priority dispatch system, response times for more severe calls dramatically decreased, but they increased significantly for less severe calls (Slovis *et al*., 1985). Pons and Markovchick also found that ambulance drivers who take longer to arrive at the scene take longer to get from the scene to the hospital(Pons and Markovchick, 2002). This evidence supports discretion on the part of ambulance drivers.

Our results support this explanation: when we estimated the standard econometric model of response times on mortality, we found no statistically significant relationships and both positive and negative point estimates. However, when we instrumented for response times, our point estimates went up and become statistically significant, varying between 0.1363 and 1.2617 percentage points, a change of between 8%, one day after the incident, and 17%, 90 days after the incident. These results match the results of three related relevant papers.

Athey and Stern explore how the introduction of 911 and enhanced 911 services influence the outcomes of heart patients (Athey and Stern, 2002). Although they do not show the direct evidence of 911 on response times, they find that 911 services reduce mortality by 11%, presumably partially by lowering response times (Athey and Stern, 2002). This number is close to our 1- and 2-day mortality estimates.

A second paper accounts for the endogeneity of total out of hospital time—different from response time—by examining the impact of ambulance diversion on mortality among patients with acute myocardial infarction (Shen and Hsia, 2011). When an ambulance is diverted from a hospital and forced to drive to another hospital, it will take longer for the patient to receive definitive care; the total out of hospital time for the patient will be longer than it otherwise would be. As in our results, the authors find that the impact of a diversion of more than 12 hours increases over the time interval in which death is estimated: patients who experienced a diversion of more than 12 hours experienced more of a mortality increase a year out than they do after 30 days—an estimated 3%. Of course, diversion may affect outcomes for other reasons other than through total out of hospital time, but the pattern of results matches our own.

Finally, Buchmueller *et al*. (2006) estimate the direct relationship between deaths in a zip code and the distance from the population centroid of a patient's residential zip code to the closest hospital. They find that a one-mile increase in distance to the closest hospital increases mortality for heart attack victims within a zip code by 6.45%, a number not too different from our estimates of the impact of a minute change in response times on mortality ((Buchmueller *et al*., 2006). One might argue that one of the mechanisms through which distance to the hospital matters for health would be through response times.

8. CONCLUSION

This is the first study to examine the impact of changes in response time on mortality using an instrumental variable. It is also the first study to examine the impact of response time on emergency department admissions, procedures, and expenses. Several studies have found no significant relationship between response times and survival to hospital discharge. Using the empirical methods employed by previous researchers, we reproduce those results. However, our instrumental variables estimates show a strong relationship between response time and mortality. Higher response times also lead to a higher probability of hospital admission. As we continue to invest more resources in health care in the USA, it is important to know how our medical care affects outcomes throughout the life course. The benefits of reducing response times must be weighed against the considerable cost.

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