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Do Response Times Matter? The Impact of EMS Response Times on Health Outcomes

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ABSTRACT

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. But, current medical research does not actually show a significant relationship between response time and mortality. In this study, I explain the discrepancy between conventional wisdom and current medical research; existing research fails to account for the endogeneity of incident severity and response time. Analyzing detailed call-level information from the state of Utah's Bureau of Emergency Medical Services, I 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. I find that response times significantly affect mortality, but not hospital utilization. A cost benefit analysis suggests that the anticipated benefits of a response time reduction exceed the costs and I discuss free-rider problems that might be responsible for the inefficiently high response times I observe.

JEL: I12, I18, I10

Key Words: Emergency Medical Services, response time, mortality, cost-benefit analysis, free-rider

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1 INTRODUCTION

Emergency Medical Services (EMS) experienced dramatic technological change over the last several decades. In the 1960's and 1970's, ambulance services primarily offered basic transportation to medical care. Frequently, funeral home directors doubled as emergency-services providers, using their hearses to haul patients. These volunteers typically had little, if any, knowledge of first aid.[1] 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 Care Policy 2006). Technological advances, such as computer-aided dispatch services and mobile Geographic Information System (GIS) units on ambulances, allowed ambulances to reach patients far more quickly (see Athey and Stern 2000 for an evaluation of one such technology, enhanced 911).

The push to reduce response times is predicated on the widely-held belief that faster responses will improve health outcomes. Response time is a commonly-used measure of EMS quality (Pons, Haukoos, Bludworth, Cribley, Pons, and Markovchick 2005, Bailey and Sweeney 2003). One of the goals of Healthy People 2010, a broad federal initiative aimed at alleviating the major preventable threats to Americans' health, is to "increase the proportion of people who can be reached by EMS within 5 minutes in urban areas and within 10 minutes in rural areas" (Emergency Medical Services 2001). The National Fire Protection Association (NFPA) recommends that, for at least 90 percent of EMS calls, Basic Life Support (BLS) services should get to the scene of a medical incident within four minutes. The association says that Advanced Life Support (ALS) providers should arrive within eight minutes for all EMS calls (Ludwig 2005, Pons and Markovchick

[1] University of Southern Alabama 2004, Blackwell and Kaufman 2002, Reines and Bartlett and Chudy and Kiragu and McKnew 1988, Emergency Medical Services: At the Crossroads 2006, Emergency Medical Services in Frontier Areas 2006.

2002, Blackwell and Kaufman 2002, Pons et al. 2005).

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. In the words of two medical researchers, "justification of specific time criteria for specific medical or traumatic emergencies is lacking" (Pons and Markovchick 2002). 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. Such triage makes it difficult to obtain unbiased estimates of the benefits of lower response times, even when data are available.

In this paper, I take advantage of comprehensive EMS records from the state of Utah, which include detailed patient and provider information, to identify the impact of response times on patient outcomes. I examine 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. Then, using distance to closest authorized EMS agency headquarters as an instrument for response time, I measure the extent to which shorter response times affect health outcomes, including mortality and hospital utilization. I also examine whether the impact of response times varies depending on a patient's medical condition (i.e., strokes, falls, or fainting) and population subgroup (for example, age and/or gender).

Section two provides a basic background on Emergency Medical Services. Section three reviews prior research on the impact of emergency response times on health and other outcomes. Section four describes the data. Section five introduces the econometric strategy. Section six presents the main results and results for various subgroups. Section seven explores potential mechanisms through which response times affect outcomes.

Section eight provides a cost-benefit analysis for reducing response times, explains why response times may be inefficiently high and provides potential policy recommendations. Section nine concludes.

2 EMERGENCY MEDICAL SERVICES BACKGROUND

Emergency Medical Services are structured and funded in a variety of ways. Services are operated locally, generally at the town or county governmental level, although EMS jurisdictions may not perfectly match political boundaries (Emergency Medical Services, 2001). EMS agencies are typically operated by fire departments, police forces, hospitals, private ambulance companies (for-profit and not-for-profit), or special administrative districts. Emergency medical systems may be "one-tier," offering either advanced life support (ALS) or basic life support (BLS) ambulances, or "two-tier," providing both BLS and ALS. In 1996, approximately 75 percent of urban areas in the U.S. were served by two-tier systems (Nichol, Detsky, Stiell, O'Rourke, Wells, and Laupacis 1996). In urban areas, Emergency Medical Technicians (EMTs) and paramedics are typically full-time professionals, while rural agencies are generally staffed by trained volunteers. Emergency Medical Services are funded through a combination of municipal taxes, cell phone and telephone taxes, user fees, private donations, intergovernmental grants, and subscription fees. State-level regulators typically oversee local EMS agencies by monitoring EMT and paramedic training and licensing, but they are not involved in day-to-day agency operations (Emergency Medical Services, 2001).[2]

Despite variation in the administrative structure of local EMS agencies, most follow similar protocols when responding to calls. Typically, a caller reporting a medical emergency will call 911 or a seven-digit number and reach a dispatcher. The dispatcher may begin by providing medical advice over the phone, but most likely he or she will only

[2] For a more thorough introduction to Emergency Medical Services, see Nichol et al (1996), Emergency Medical Services at the Crossroads (2006), Emergency Medical Services in Frontier Areas (2006) or Braun, McCallion, and Fazackerley (1990).

assess the severity of the situation, determine the patient's address and then dispatch relevant medical resources to the scene. If there are no ambulance units available for this answering agency, then the dispatcher will contact another nearby community or agency to request mutual aid.

The type of service dispatched depends on what is reported in the call. The dispatcher might activate a first responder (FR) unit of police or firefighters; BLS units that are staffed by EMTs; or ALS ambulances that are staffed by paramedics. EMTs provide basic first aid, but they can only offer a limited number of other treatments to patients. Paramedics can treat severe trauma and also provide more advanced care, including "administering drugs, inserting intravenous lines, and opening airways through endotracheal intubation" (Emergency Medical Services 2001). After driving to the scene and finding the patient, the EMTs or paramedics provide medical care. Sometimes, they aim only to stabilize the patient before transporting him or her to a higher-order care facility. Other times, they provide life-saving treatments immediately, under the standing orders of a physician. In most cases, the patient is transported to a hospital or other medical facility where he or she can receive more advanced care. Then, after filling out paperwork, the EMS personnel return to service (Emergency Medical Services 2001).

Emergency medical services in Utah, the state examined in this paper, are typical of the services offered in most states. Within Utah, there are 201 licenses for EMS. Some agencies have multiple licenses, covering a number of territories or service levels, but these generally do not cover territories that precisely match up with political boundaries. Excluding air ambulances, there are 137 unique providers of ambulance services in Utah, including both ALS and BLS providers. In Utah, EMS is primarily funded through user fees (personal conversations with agency directors and Utah Bureau of EMS, 2006). All EMS agencies in the state follow the same protocol in treating patients. Calls are answered in the order in which they are received, and dispatchers follow cue cards in ascertaining the severity of the condition. By state law, EMS agencies cannot discriminate on the basis of race or ability to pay (Emergency Medical Services 2001).

3 RELEVANT LITERATURE

The current evidence on the effectiveness of reduced response times is extremely limited. It was largely drawn from observational studies of patients suffering from a few very specific medical conditions—most commonly cardiac arrest, which accounts for just one percent of EMS calls. These studies, which often had very small samples, typically found a negative correlation between cardiac-arrest response times and survival. A meta-analysis of studies which reported mean response times and survivorship showed that, on average, shorter response times were associated with higher survival likelihood (Nichol et al. 1996). In that meta-analysis, a one-minute decrease in mean response time was associated with an increase in survival in a one-tier system of 0.4 percentage points (mean survival rate: 5.2 percent). In a two-tier system, the increase was 0.7 percentage points (mean survival rate: 10.4 percent) (Nichol et al. 1996).

Only a handful of studies have examined the relationship between response times and outcomes for people suffering from conditions other than cardiac arrest, even though these patients generate the vast majority of EMS calls. These studies have generally found no association between response times and survival. One of them analyzed outcomes for trauma patients who were transported to one particular trauma center over a two-year period. It found that, after controlling for the trauma category, age group, and other factors, there was no difference in survival based on response times (Pons and Markovchick 2002). Patients who might have been most affected by response times–specifically, those who were dead on arrival–were excluded from the study.[3] Pons and Markovchick also found that ambulance drivers who take longer to arrive at the scene

[3] Other studies of trauma patients have found no association between total out-of-hospital time and survival (Pepe, Wyatt, Bickell, Bailey, and Mattox 1987). However, this evidence is difficult to interpret, since out-of-hospital time includes both response time to the scene and time spent treating the patient at the scene.

take longer to get from the scene to the hospital. This evidence is consistent with discretion on the part of ambulance drivers, which I discuss below.

Just two studies 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 (Pons et al. 2005, Blackwell and Kaufman 2002). Like the examination of trauma patients discussed above, these studies find no association between response times and patient survival. However, both studies suffer from significant weaknesses. One is that they examine only patients who were admitted to hospitals. Blackwell and Kaufman focus solely on patients experiencing "emergencies" who were transported to a particular trauma hospital. Both studies exclude patients who were dead on arrival. Pons et al. (2005) do not control for incident location or any characteristics of the incident location; Blackwell and Kaufman (2002) do not control for any community or individual characteristics – such as illness or demographic indicators – that might have influenced both response times and outcomes. Despite these methodological shortcomings, Pons et al. conclude that "there is no effect of paramedic response time on patient outcomes."[4] Blackwell and Kaufman state that "there is little evidence to support reducing the current adopted emergency response times," although they did detect a slight benefit when response times are less than five minutes

None of these studies account for a key factor that almost certainly impacts response times: EMS personnel may respond more quickly to the most serious and life-threatening situations. If this endogeneity of response time is ignored, then estimates of the "effects" of response times on patient outcomes will be biased downwards. There are many reasons to think that endogeneity of response times is a very real problem in doing such analyses. Even detailed call reports cannot capture all of the information communicated by dispatchers to ambulance drivers—communication which may be as subtle as the dis-

[4]Pons et al. find no survival benefit from a paramedic response time of less than 8 minutes, but do find a survival benefit for response times of less than four minutes for a subset of patients (those considered to be of "intermediate" or "high" risk of mortality, as defined by the study authors).

patcher's tone of voice. Dispatchers tell drivers and paramedics the basic circumstances of incidents, including information which allows drivers to determine whether or not 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. A study of one community supports the idea that EMS personnel do adjust their response times in response to the severity of the incident. After this community instituted a priority dispatch system, response times for more severe calls dramatically decreased, but they increased significantly for less severe calls (Slovis, Carruth, Seitz, and Elsea 1985).

One way to account for endogeneity of response times is to examine how technological changes that affected response times altered patients' outcomes. This approach is taken by Athey and Stern, who examine how 911 and enhanced 911 services influence the outcomes of heart patients (Athey and Stern 1998, 2000, 2002). The adoption of 911 capacities may improve outcomes by reducing response times. One paper's results indicate that enhanced 911 services significantly reduce average response time but, in the reduced form, do not significantly affect mortality (Athey and Stern 1998, Table 6 and Table 9). The most recent Athey and Stern paper, which uses a somewhat different specification, indicates that 911 services do improve outcomes for heart patients (Athey and Stern 2002). However, this article does not present evidence on the effects of 911 on response times. One potential problem with this general identification strategy is that the expansion of 911 services reflects policy decisions and technological advances, and policy decisions could be influenced by factors correlated with patient health. In addition, as discussed above, heart incidents represent only a small fraction of EMS calls.

I contribute to the existing literature in several ways. First, I resolve an empirical puzzle. Despite the widespread belief that response times matter, existing medical research shows no significant impact from response times on outcomes except in a few very special cases. I explain why this is so. Second, I introduce a new way of handling the endogeneity of response times which does not rely upon policy changes which might themselves be endogenous. I instrument for response times with the distance from the incident location to the provider. Third, I provide more accurate estimates of the impact of response times for all conditions, not only cardiac incidents, by controlling for covariates including census block group characteristics not previously available to researchers. I also look at the impact of response times for particular population subgroups, as well as for many health outcomes never previously studied. Fourth, I suggest a mechanism through which response times affect health outcomes. Finally, I provide an explanation for the inefficiently high response times which I observe in the data.

4 THE DATA

The primary data in this study came from the 2001 Utah Prehospital Incident Dataset, a collection of all prehospital incident reports collected in Utah between January 1, 2001 and December 31, 2001 (Utah Prehospital Incident Data 1999-2005). In Utah, every dispatched ambulance is required to complete a detailed incident report which includes patient demographics (such as age, race, name, and birth date), the incident address, a description of the patient's major complaint, the medications and treatments administered, the patient's vital signs at the scene, and the outcome of the incident.[5]

I defined response time as the difference between the time that the ambulance is dispatched and the time that the ambulance arrives at the scene. This definition was consistent with the work of several other researchers (Athey and Stern 1998, Key et al. 2002, Lerner, Billittier, Moscati, and Adolf 2002, Cummins at al. 1991, Stueven, Waite, Troiano, and Mateer 1989, Grossman, Kim, Macdonald, Klein, Copass, and Maier 1997, Scott, Factor, and Gorry 1978). For a small proportion of the Prehospital Incident sample, I knew the time of the initial call, when the dispatcher was notified, and when

[5]Appendix A contains a more detailed description of this data.

the paramedic or EMT arrived at the patient's side (Utah Prehospital Incident Data). On average, as shown in Table 3, two of these three additional response-time components added 0 minutes or less to the total response time. The third additional response-time component (time from arrival at scene to arrival at patient's side) is measured for less than 300 patients and isn't from a representative population of patients. Therefore, it is likely that these unrecorded response-time components would increase total response times by a small amount, an assumption that makes sense because most homes and businesses in the Salt Lake City metropolitan area are not in densely populated areas or tall buildings.[6]

I used two sources of outcome data: the Utah Emergency Department Encounter Dataset (2001) and Utah mortality records (2001-2002). Utah law requires 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, birthdate, mortality risk, condition severity, outcome, total charge, number of procedures, and primary diagnosis for each patient.[7]

The Utah death data, which come from the state Office of Vital Statistics, include the name, age, race, time and location of death for all deaths of Utah residents that occur within the state. These death records allowed me to capture mortality outcomes for all patients, not just those who died within hospitals, so that my analysis includes patients who were dead when EMS arrived.

I merged the Utah Emergency Department data and mortality records with the pre-hospital records using probabilistic linking software LinkPlus (Utah Prehospital Incident Data 1999-2005, Utah Death Data 1999-2005). I include complete details of this merging

[6] Morrison et al. documented a median scene-to-patient time of 1.43 minutes in a study of ambulance response times for high-priority patients in an area with high population density and a high density of high-rise buildings, suggesting that even if there were many calls to tall buildings, the additional cost in response time would not be very high (Morrison, Angelini, Vermeulen, and Schwartz 2005). Other studies have found similar results (Campbell, Gratton, Salomone, and Watson 1993).

[7] The Utah Department of Health is currently merging records from Emergency Department data with Utah Ambulatory Surgery and Hospital Discharge data records, so that I can look at other outcomes.

process in Appendix B.

To construct the instrument for response time, I standardized and geocoded each incident, provider and hospital address using ARCMap Version 9.1. I used the latitude and longitude of each of these locations to calculate the distance between the patient and the provider and the patient and the hospital (if admitted). Using ARCMap, I also identified the census block group for each incident, and merged census 2000 demographic summary data with incident information (Census 2000 Summary File 3 2000).

I identified weather, traffic and daylight conditions for each incident. To capture weather conditions, I merged hourly weather readings from the Utah weather station closest to each incident (Integrated Surface Hourly Database 2001). To capture local traffic conditions, I linked hourly measures of traffic congestion (volume) from the closest Utah Department of Transportation traffic station (Utah Automatic Traffic Counter Data 1990-2005). I identified whether an incident occurred before or after sunrise and sunset using the latitude and longitude of the county of each incident and daily sunrise and sunset data provided by the Canadian government (Sunrise/Sunset/Sun Angle Calculator 2007).

I restricted the regression sample in several ways. I excluded cancelled and standby calls, and I dropped duplicated prehospital reports. In some cases, EMTs and paramedics from more than one ambulance may provide care to the patient. When this occurred, there were multiple reports for the same patient from the same incident. I included only the report from the first EMS on scene, following Nichol et al (1996), and Fischer, O'Halloran, Littlejohns, Kennedy, and Butson (2000). However, using different individual incident reports for cases in which there were multiple reports did not affect the results of my analysis.[8]

In some cases, multiple individuals were involved in one incident, i.e. a traffic acci-

[8] My results are not sensitive to using other reports taken at the scene, including the report with the longest measured time at scene, longest time to arrival at scene, and the report with fewest missing values.

dent. In such cases, there would be even greater reason for concern about the endogeneity of response times. If there were ten people at the scene, presumably the EMS would first help the patient who was most severely injured. Even though I measured response times from dispatch to arrival at scene (and not arrival at the patient), this might still be a concern for my analysis. However, regressions which excluded patients involved in incidents with multiple patients produced results very similar to the original regressions.

Finally, I observed all patients who used any EMS in Utah in 2001. I saw some patients more than once. If patient outcomes within individual are correlated across time, then by treating each incident as an independent event, I may be overstating the true variation in the dataset. As a specification check, I excluded individuals who appeared in the dataset more than once (in different incidents) and my results were unaffected.[9]

I excluded calls which did not have descriptions of the patients' major complaints, the response times, or geocoded incident addresses. For reasons discussed below, I excluded patients outside of the Salt Lake City metropolitan area, defined by the following counties: Weber, Morgan, Davis, Salt Lake, Summit, Utah, and Toelle. These represented 86 percent of the calls in the prehospital database. Appendix Table 9A contains a count of the number of observations lost due to each of these restrictions.

Figure 1 provides a visual representation of a typical community in the Salt Lake City metropolitan area; census block groups are outlined with a thin line, EMS incidents are identified with diamonds, circles identify hospitals, and EMS agency headquarters are represented with squares. The boundary for each EMS territory is identified with a thick line.

[9] I also clustered the observations along the following dimensions: individual ID; incident ID; emergency medical technician id; block group; tract; zip code; and county. In these cases when I clustered along a single dimension, the results were similar to the current regression specification, which does not involve clustering. In addition, I experimented with clustering on multiple dimensions (Cameron, Gelbach, and Miller 2006). And in all cases, the variance estimate had negative elements on the diagonal, which according to Cameron et al., "primarily occurs when there is actually no need to cluster in more than one dimension" (Cameron et al. 2006). For this reason, all results are reported using robust standard errors.

Table 1 shows demographic characteristics for the Utah Prehospital Regression Sample. Patients using EMS 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, more homogenous, and more white than the rest of the United States.

Table 2 presents the distribution of patient complaints and shows how I combine these descriptions into larger categories of complaints, as well as the 1-year mortality rates for each complaint. The most common patient complaints are traffic accidents (16 percent of all calls) and transfers between hospitals (nine percent of calls). It may not be obvious why I include transfers in the analysis. In fact, EMS are often used to transport trauma patients (or patients who are otherwise very ill) from hospitals or clinics to trauma centers, and not just for scheduled "non emergency" transfers.[10] Heart and breathing problems, fainting, and trauma are also quite common.

Table 3 provides summary statistics on response time, the distance from the closest provider agency to the incident, and the distance from the incident to the intake hospital. Patients admitted to hospital emergency departments (EDs) are, on average, closer to their EMS providers than to their hospitals. In general, paramedics and EMTs spend more than twice as much time (18 minutes) at the scene as they do getting to the scene (eight minutes); it also takes longer to arrive at the final destination than it did to arrive at the scene (12.9 minutes, on average).

Table 4 supplies summary statistics for several outcome variables. First, I report mortality within one, two, 30, and 90 days and 1 year and four years of the incident. Approximately two percent of EMS patients die within two days; four percent die within 30 days, and around 10 percent die within one year. Next, I provide summary statistics for two intermediate health indices constructed using information gathered at the scene (Athey and Stern 2000). I constructed the first index by regressing an indicator for two-day survival on four Glasgow trauma score categories, four respiration-rate categories,

[10] My results are robust to the exclusion or inclusion of transfers (please see appendix Table 5A).

four blood-pressure categories, and an indicator for whether the patient's pulse is greater than 40; these coefficients are multiplied on the patient's own characteristics and used to predict two-day survival.

I constructed the second index by regressing an indicator for two-day survival on five revised trauma score categories; I again used these coefficients to predict the likelihood of 48-hour survival. A higher score represents a higher survival probability for both indices.[11]

Finally, Table 4 also shows the average number of ED procedures, the total charge for ED care, and the probability, conditional on being admitted to the ED, of being at high risk of mortality or of having a severe injury, as assessed by the hospital.

Table 1A in the appendix contains definitions and sources for each of the variables used in the basic specification.

5 ECONOMETRIC FRAMEWORK

In the standard econometric framework in the medical literature, outcomes are modeled as a function of response times[12]:

$$Y_i = \alpha + RT_i\delta + X_i\beta + \varepsilon_i \tag{5.1}$$

Where:

Y_i = Outcome for individual-incident i

RT_i= Response Time for individual-incident i measured from time of dispatch to time at scene, first responder at scene

X_i = A vector of individual incident characteristics (i.e. age, gender, dispatch code,

[11] When I restrict the sample to only heart patients, the coefficients in both probit regressions are very similar to those reported by Athey and Stern (2000).

[12] I present the standard model as a linear probability model rather than a logistic regression for ease of presentation.

local demographics, traffic and weather conditions).

ε_i= error

I propose that ε_i can be decomposed into two terms:

$$\varepsilon_i = \mu_i + \theta_i \tag{5.2}$$

where:

θ_i= a residual component of severity that is not observed by the ambulance driver or the researcher

and

μ_i= a measure of severity which is observed by the ambulance driver, but unobserved by the researcher.

Because the ambulance driver knows μ_i, response time may depend in part on it, and $E(\varepsilon_i RT_i) \neq 0$.As long as $E(\varepsilon_i RT_i) < 0$, then ordinary least squares (OLS) estimates of mortality on RT will be negatively biased. This may explain why ordinary least squares (or logistic 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, I used an instrumental variable (IV) – distance from incident address to address of closest assigned provider agency – which is correlated with response time, but uncorrelated with severity. This instrument allowed me to estimate the true effect of response times on outcomes. I also controlled for a wide variety of factors which might affect both outcomes and response time, including weather, month, weekend interacted with hour-of-day fixed effects, and primary complaint indicator variables.

I 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 five, between 16 and 65, and older than 65.[13]

I exclude any variables that might be considered endogenous to response time, including time at scene, distance to hospital, and treatments and medications which might potentially be affected by time to scene. I explore these intermediate outcome variables in a later section, as I try to determine the mechanism through which response time affects outcomes.

Instrument validity

One concern with the instrument is that it may identify patients who live in exurban areas, and who are different in ways which may be correlated with both response times and outcomes. For example, "distance" may identify patients who live very far away and only call EMS when they are very sick.[14] For this reason, I identified response times from the variation in distance to providers within census block groups within the Salt Lake City metropolitan area. In my basic regression specification, I included census block group characteristics, so that I could identify and control for health variations between block groups. Block groups are the smallest census unit for which summary data are readily available; they fall within census tracts which are already "designed to be homogeneous with respect to population characteristics, economic status, and living conditions" (Geographic Area Description: Census Block Groups 2000, Geographic Area Description: Census Tracts 2000). In the Salt Lake City metropolitan area, block groups have a mean area of 5.36 square miles with an average population of 1,631.

Within block groups, the variation in distance from incident to closest agency comes from two sources: differences in the distance to the provider when only one provider covers the entire the block group, and variation in the distance to the provider when

[13] I tried specifications including fixed effects for ambulance ID, EMT ID, individual patient ID and incident ID fixed effects, but these variables did not do a good job explaining outcomes and had little effect on the coefficient of interest.

[14] One study, using Veterans' Administration (VA) patients, identified a correlation between distance and mortality; "Patients living more than 20 miles from their admitting hospital were more likely to die independent of their likelihood of receiving VA outpatient follow-up" (Piette and Moos 1996). Piette and Moos suggest that these differences in mortality were due to the quality of the follow-up care, but they cannot rule out the possibility that people who live farther away from medical facilities are sicker.

more than one provider covers territory within the block group.[15] To test whether sicker individuals intentionally locate near ambulance agencies within block groups, I explored whether the distance to the provider differs significantly by observable patient characteristics.[16]

I regressed indicators for individual age categories, race, and gender on the distance to closest provider agency, and I find that these observable characteristics are significantly correlated with distance to agency. Neither the first stage nor the IV estimates in regressions which include race, gender, or age as right-hand-side variables differ appreciably from the regressions which do not include these variables, suggesting that even though these observed characteristics are correlated with distance, unobserved severity is not significantly correlated with these variables. I also regress years of education (available only for those in the mortality dataset) on distance to closest EMS agency and find that there is no significant relationship within this subsample between education (a proxy for SES) and distance. Finally, it is possible that when agencies divide block groups into separate jurisdictions, they do so to avoid (or to capture) sicker patients. My 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. But because there are few census block groups that contain multiple provider jurisdictions, this appears to be a minor threat to the validity of my instrument.[17]

[15] 80 percent of the variation in distance is between block group variation and 20 percent is absorbed by block group fixed effects.

[16] Conversely, agencies might locate near areas where many sick people live.

[17] I interpreted the coefficient on response time in the instrumental variables estimate as an average treatment effect rather than a local average treatment effect. In this context, the marginal patient whose average treatment effect is measured by the IV is actually the representative patient using prehospital care – and not a member of a unique subset of prehospital patients. Although distance might appear to be a more relevant predictor of response time for the patients with the highest unobserved severity, this does not change the interpretation of δ which represents the average treatment effect of response time on outcomes, equivalent to that measured if response time were randomly assigned within the population.

6 RESULTS FOR RESPONSE TIME AND MORTALITY

I first present results for the impact of response times on mortality, measured within one day, two days, 30 days, 90 days, 1 year and 4 years of the incident. Row 1 of Table 5 contains the reduced form estimates of the impact of distance to closest non-mutual aid EMS agency on mortality. Row 2 of Table 5 contains ordinary least squares estimates of the impact of response times on mortality, where mortality is an indicator equal to 100 for all of those who were identified in the mortality records within the allotted calendar amount after the prehospital incident. Finally, Row 3 of Table 5 contains the instrumental variables estimates of the impact of response time on mortality, measured at different intervals. Row 4 contains the first stage: the estimated impact of distance on response time. All specifications include month, weekend, hour of day, and weekend by hour of day fixed effects, as well as weather indicators and block group characteristics. In all regressions I also include indicators for the primary patient complaint.[18] All results are reported with robust standard errors.

Table 5 shows that response times matter. I consider six outcome measures, and I present OLS and IV estimates, the latter shown both as the reduced-form effect of distance on outcomes and as the implied effect of response times. Reduced-form coefficients of the impact of distance on mortality show that incidents that occur farther from agencies are more likely to result in deaths. The coefficients are positive and, for all but one-day mortality, statistically significant. An extra one-tenth of a mile is estimated to increase the probability of mortality within 365 days by more than two-tenths of a percentage point.

The first-stage estimates show that distance predicts response time. The marginal impact of a mile on response time is approximately a tenth of a minute, and this relationship is highly significant with a t statistic>10, indicating that I do not need to

[18] For a small proportion of calls (less than 1%), the patient is listed as Dead upon Arrival at the scene by EMS (DOA); these patients are included in the analysis, although the results are not sensitive to their exclusion.

worry about weak instruments.[19] Response times differ considerably by complaint: for example, all else equal, the average response time for cardiac arrests calls is almost two minutes less than the omitted category (abdominal pain); electrocution and choking also had considerably shorter average response times, along with a number of other complaints. The OLS estimate of the impact of response time one-day mortality is negative. The OLS estimates for mortality measured over longer periods are mostly positive, but are never statistically significant. These point estimates imply that a one-minute increase in response time affects mortality by less than three-tenths of a percentage point. Overall, these results are consistent with the limited previous research in the medical literature, though these earlier analyses do not account for the endogeneity of response times.

Finally, the instrumental variables impact of response time on mortality is positive and significant in all but the first day after the incident, and increasing over time. The coefficients on indicators for stab and gunshot wounds, strokes, breathing problems, cardiac arrest incidents were particularly noteworthy; all are positive and significant. In the reduced-form regression of mortality on distance, the coefficient on distance is also positive and significant for all but one-day mortality, and it increases when mortality is measured over longer periods. The marginal impact of a response-time increase of one minute on mortality at 365 days is approximately 1.26 percentage points (which, given a mean mortality rate of 9.8 percent, represents an approximately 13 percent change). Note that if the instrument was correcting for classical measurement error, I would expect the coefficient on response time in the IV regression to increase in absolute value in the same direction as the OLS coefficient. This is not what I find. Therefore, these results are consistent with the presence of an omitted variable, "severity," which is negatively correlated with response time, and missing from the OLS equation.

[19] For a small subset of the sample, I have odometer measures of the actual distance travelled by the ambulance enroute to the call; in the first stage for this subsample, the coefficient on distance is approximately .19 with a standard error of .09.

My estimates are larger than the estimates from the only article in the medical research which attempts to measure the impact of response times on overall patient survival, Pons et al (2005), which finds no significant impact of response times on patient outcomes except for response times less than four minutes.[20] My measured impact of response times on mortality (13 percent) is also higher in percentage terms than results found in observational studies in the cardiac literature, which suggest a three- to seven-percent decrease in mortality following a one-minute decrease in response times (Athey and Stern 2000, Larsen et al. 1993).

I have explored a variety of other specifications which I discuss here. One specification check involved investigating functional form. For ease of interpretation, I estimated all models using linear probability models, but the results are equivalent using both logistic and probit models. The significance and direction of the coefficients are also robust to using the logarithm of response time (Table 3A). I also ran specification checks where I excluded particular groups which I thought might be particularly influential. None of the results are significantly affected by any of the following actions: excluding transfers; 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. Including 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. I thought that other covariates may be significantly correlated with response times and outcomes - such that omitting these covariates would significantly bias my results. But my results are not affected by including different permutations of hour-of-day or day-of-week interactions; excluding weekend, month or day fixed effects; excluding weather variables; including indicators for patient location and incident location (playground, home, etc.); including traffic measures; including indicators for Olympic location or tourist location; including hourly EMS call congestion numbers;

[20] Blackwell and Kaufman limit their sample to "emergencies."

not controlling for the primary complaint; or including dispatch codes instead of the primary complaint. Nor does including race, gender and age covariates, or characteristics of tracts, places, zip codes, or counties on the right hand side. As an additional robustness check on the identification strategy, I also ran additional specifications where I control 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, but the IV results are similar to those reported in Table 5, as can be seen in appendix Table 2A. The IV coefficients and standard errors increase in size with the inclusion of block group fixed effects. Including the distance to the closest hospital as a covariate does not affect the main results either, as Table 4A shows.

Heterogeneous Treatment Effects

The effects of response times for outcomes may vary across different types of incidents. To examine whether this is the case, I divided the primary complaints into the six categories listed in Table 2: transfers, traffic accidents, strokes/falls/fainting, heart problems/breathing problems/cardiac arrests, ear/eye/psychiatric problems, and trauma (electrocution, gunshot wound, etc.). These groups are of similar sizes. Each type of complaint is interacted with response time. I created the distance instrument similarly. In Table 6, I report the Cragg Donald Test statistic (equivalent to the first stage F statistic used to determine whether instruments are weak, but used with multiple endogenous regressors), and the complete instrumental variables results.[21] Distance is highly significant in the first-stage equation with a Cragg Donald test statistic of 15. In the OLS results not reported here, more than one-third of the response-time coefficients are negative. In only one instance are the response-time coefficients consistently positive and significant (traffic accidents).

The IV estimates shown in Table 6 are quite different from the OLS estimates and

[21] Rather than estimate the effect of response time separately for each condition or major category, I constrain the impact of other covariates to be the same and estimate the effects jointly. Splitting the sample by condition pushes too hard on the data – given the number of covariates in the basic specification and the frequency of some of the conditions.

generally indicate that lower response times reduce mortality across all incident types, with the possible exception of trauma. In the instrumental variables regressions, the relevance of response times to outcomes generally increases as mortality is measured over a longer time period. For four of the complaint categories, response times positively and significantly affect mortality measured at 30 days and 1 year and for five out of six complaint groupings, instrumented response time is significant for mortality at 90 days and mortality measured at 4 years. For all specifications, the impact of response time on mortality differs significantly between complaint categories. In general, the instrumental variables estimates for the impact of response times on mortality are more positive for transfers and other issues than the overall IV estimates and less positive than the overall IV results for other categories, including cardiac issues. It may seem somewhat surprising that the effect of response times on mortality is high for transfers and other issues, and relatively small for heart problems and trauma. But transfers include transfers between, for example, airports and nursing homes to secondary hospitals (and therefore populations which may be very sick), and other issues include a wide variety of complaints (such as fever and diarrhea) for which prompt intervention may be especially important.[22]

To see whether the impact of response times differs across gender and age, I also ran IV regressions for various demographic groups separately. In Table 7, I include regression results from separate regressions for men and women, and for major age categories ($<$15, 15-25, 25-65, and over 65). I find little difference in results between men and women, but great variation by age; very young and middle-aged patients appear to benefit substantially less from response time improvements than do young adults and older people.[23] Because Utah's population is more than 89% non-Hispanic white, there

[22] Almost 80 percent of transfers and transports are to hospitals. More than one third of these transfers to hospitals are between hospitals. These transfers are almost entirely from urban hospitals with less beds and lower case mix indices, which are less likely to be teaching, hospitals to more sophisticated urban hospitals. The remaining transfers to hospitals are from long term care facilities, mental health facilities, airports, the scene, homes, and other locations.

[23] Base mortality rates for men and women are similar, but average mortality rates differ considerably

are not enough calls by nonwhites to estimate treatment effects separately by race (U.S. Census Bureau Census 2000).

7 THE MECHANISM

There are several potential mechanisms through which EMS response times could affect patient outcomes.

One is that earlier EMS arrivals stop the deterioration and limit the extent of damage to patients' internal organs. The sooner the paramedics arrive, the less the damage, and the smaller the later chance of death. This explanation is consistent with the finding that the probability of death is increasing over longer time periods. 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.[24] 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).

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." But they should have higher hospital admission rates, and should

by age: over 39 percent of those over 65 who call EMS die within one year, but less than 7 percent of those between 25 and 65, less than 2 percent of those between 15 and 25 and less than 2 percent of those under age 15.

[24] By contrast, a review of 13 randomized controlled or cohort studies examining the impact of pharmacological interventions by paramedics found "no evidence that any medication given by the prehospital care provider is beneficial or cannot safely be delayed until arrival at hospital" (Shuster and Chong 1989).

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.[25] 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, since 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.

In Table 8, I look at how response times affect 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, the distance from the incident address to the hospital (for admitted patients), health index 1, health index 2, which are measured at the scene, and time at scene.[26] 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 result in lower costs because they are more likely to die (Dier, Yanez, Ash, Hornbrook, and Lin, 1999).[27]

[25] 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. The Utah Department of Health is in the process of providing me with additional data including ambulatory surgery and hospital discharge records which I will use to evaluate this claim.

[26] I also regressed indicators for individual hospitals on response times. The response time to the scene does also seem to affect the choice of hospital by the EMS personnel. I do not look at the impact of response time on individual health status measures (blood pressure indicators, pulse, Glasgow coma score, or respiration) because individually these do not provide a reliable picture of the patient's condition at the scene.

[27] According to Dier et al, because laboratory procedures and emergency department expenditures are distributions with many zeros and/or long right tails it is typical to transform them into the log scale. This "shortens the long right tail, lessens heteroscedasticity, and decreases the influence of outliers" and in practice, makes the distribution close to normal (Dier et al. 1999). If the dataset is sufficiently large, "OLS regression on the untransformed data ... will provide unbiased estimates of the regression

Table 8 follows the same format as Table 7. 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. 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 regression includes the entire regression sample, but columns 2 through 6 only include patients admitted to the hospital. Columns 7 through 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 health care 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.[28] 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 show. 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, while 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

parameters" (Dier et al. 1999). In this project, I treat each patient incident as largely independent. I used the natural log of ED expenditures and the untransformed number of ED procedures as measures of health care utilization.

[28] Unfortunately, I do not have a measure of each facility's "cost to charge" ratio. This ratio, produced by the Healthcare Cost and Utilization Project, allows researchers to convert hospital charges into actual hospital costs. Then, they can identify when providers are actually treating patients equally and "providing the same relative value," but have a different cost structure, and when, instead, discrepancies in charges truly represent differences in care (Dier et al. 1999).

that response times do not significantly affect either health index – suggesting that these health indices may not capture long-term "damage." Response times also do not affect the time that EMTs and paramedics spend at the incident scene. In regressions not reported here, I 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 Table 8.[29]

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. I 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, rather than constant.

I provide evidence to evaluate these claims. First, I created individual identifiers for each person who ever appears in the prehospital data set (an individual could appear as a patient multiple times). Then, I calculated the average number of EMS calls following the initial call. I find that this number is 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,

[29] Given that outcomes for a given individual may be correlated, it is possible that by treating each regression as an independent test that I may over reject the null hypothesis. Kling and Liebman have suggested several options for overcoming this problem, including an adjusted Bonferroni procedure, a Westfall-Young procedure, or running seeming unrelated regressions which allow for errors between regressions to be correlated (Kling and Liebman 2004).

impact of longer response times on mortality.[30] For example, The IV estimate for the hazard of mortality in day 2 conditional on survival to day 1 is .1803 (with standard errors of .0906). The hazard of mortality by day 30 conditional on survival to day two is .4236 (.1288), while the hazard of mortality by day 90 conditional on survival to day 30 is .3375 (.0952).[31] 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 I find.

8 COST BENEFIT ANALYSIS AND ONE POTENTIAL EXPLANATION FOR UNDERPROVISION

In this section, I provide a cost-benefit analysis for reducing response times in the Salt Lake City metropolitan area.

While there are clear advantages to reducing average response time, there are also costs. Unfortunately, I do not have cost data for the ambulance agencies within the Salt Lake City metropolitan area. Even if I did have such data, it is likely that differences in accounting and budgetary practices would make it very difficult for me to accurately determine per-agency ambulance costs (Peter Buchard, Naperville, IL, City Manager, personal communication, August 2006). The marginal cost of reducing response times between communities is likely to vary with a number of characteristics, including density, area, traffic, geography, weather and demographic characteristics.[32] Lacking the actual cost data, I assume a constant marginal cost for ambulances within the Salt Lake City metropolitan area. I use $450,000 as the estimated cost per additional ambulance,

[30] What I 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.

[31] The hazard of mortality by day 365 conditional on survival to day 90 is .3320 (.1175) and the hazard of mortality by day 1460 conditional on survival to day 354 is 1.2389 (.2230).

[32] These differences in marginal costs (and response times) could also be used to estimate the value placed on life in different communities (as in Felder and Brinkmann, 2002). That is not the intent of this paper, however.

including crew. In the U.S., Pons estimates the cost of 24-hour staffing for an additional ambulance at $400,000 to $500,000 per year (Pons and Markovchick, 2002, Pons at al. 2005).[33]

I am interested in approximating the basic cost of adding additional ambulances that would be used to reduce the use of mutual aid by agencies. Mutual aid calls are common in Utah. The mutual aid system works as follows: when a provider runs out of ambulance units, that provider contacts a neighbor to answer the call, according to a previously-defined agreement. In 2001, the year for which I have data, I identified 10,887 mutual aid calls out of a total of 109,789 geocoded calls. Most mutual aid calls occurred in more densely populated parts of Utah around Salt Lake City and Washington County. Agencies with more ambulances were less likely to use mutual aid (Figures 2 and 3), and the proportion and number of mutual aid calls decrease in tandem with the number of ambulances.

The response-time penalty for mutual aid calls is substantial. Mutual aid providers are much farther away from incidents. In Table 9, I provide summary statistics for the distribution of response times and distance for mutual aid and non-mutual aid calls. The average response time for mutual aid calls is 10.5 minutes, but it is only 8.9 minutes for non-mutual aid calls. The distance between the provider and the incident for mutual aid calls is also much greater than for non-mutual aid calls. In Figure 4, I show the distribution of response times for mutual aid calls and for non-mutual aid calls; the distribution of response times for mutual aid calls is clearly shifted to the right. Figure 5 also shows the distribution of distance between each incident and the provider answering the call, for both mutual aid calls and non-mutual aid calls. Again,

[33] Fischer estimates the cost of an additional ambulance in Surrey to be £250,000 at 1999 levels, which in 2007 dollars is approximately $635,000 assuming a 2.061-dollars-per-pound exchange rate and a Consumer Price Index of 202.4 in 2007 and 164.3 in 1999. In an interesting cost-benefit analysis using data from Ontario, Canada, Nichol et al, used an alternate approach, estimating the impact of increasing unit hours, rather than the addition of an ambulance. Those results, unfortunately, were specific to either a one-tier or two-tier system and so are not relevant to my analysis (Nichol et al 1996b).

the distribution of distances is shifted substantially to the right for mutual aid calls. This is consistent with longer response times.

I assumed that by increasing the total number of ambulances in Utah by approximately 10% (because mutual aid calls constitute 10% of all calls) or 34 ambulances, I eliminated all mutual aid calls. Average response times can be expected to decrease by 9.5 seconds (10% of the difference in average response times between mutual aid and non mutual aid calls), at a total cost of $15,300,000 (34 * $450,000).

Now, I directly estimate the survival benefit in years of a minute decrease in response times.[34] I assume that there are no benefits to survival beyond four years after the initial incident and I decompose the impact of response time on survival into four different components. That is,

$$E(S) = E(S|S < 4)P(S < 4) + E(S|S > 4)P(S > 4)$$

which suggests that

$$\begin{aligned}\frac{\partial E(S)}{\partial RT} &= \frac{\partial E(S|S<4)}{\partial RT}P(S<4) + E(S|S<4)\frac{\partial P(S<4)}{\partial RT} \\ +\frac{\partial E(S|S>4)}{\partial RT}P(S &> 4) + E(S|S>4)\frac{\partial P(S>4)}{\partial RT}\end{aligned}$$

I estimate $\frac{\partial E(S|S<4)}{\partial RT}$ by regressing survival on response time instrumented with distance

[34] Ideally, I would measure the benefit of reduced response times by gauging their impact on mortality, emergency department utilization, and morbidity. In particular, I would track the resulting reductions in later hospitalizations; days of restricted activity; lost days of productive work or productive life years; and overall patient and customer satisfaction (Pons and Markovchick 2002, Mann, Mullins, MacKenzie, Jurkovich, and Mock 1999, Bailey and Sweeney 2003). It is possible that reducing response time, and the total time before patients receive definitive care, might have additional effects which I have not captured here, such as reductions in the within-hospital death rate, rather than simply the overall death rate. Also, by preventing the "deterioration of condition of the patient," the reduced time-to-treatment may limit later complications, reduce temporary disability, prevent permanent disability, cut down on psychological trauma at the scene, and improve the chances of a full recovery. Unfortunately, these measures are not currently available. (Riediger and Fleischmann-Sperber 1990). In later analyses, I will incorporate inpatient hospital visits, ambulatory surgery and hospital discharge records. Following Cutler, Landrum, and Steward (2006), I will use medical utilization after an initial incident as an indicator for later disability. Unfortunately, I do not have access to subjective patient measures of pain and suffering, life satisfaction, or disability.

where survival is measured in years from the initial incident and the sample is restricted to those who survive less than four years after the initial incident.[35] I estimate $\frac{\partial P(S<4)}{\partial RT}$ and $\frac{\partial P(S>4)}{\partial RT}$ by regressing an indicator for mortality at 4 years on response time instrumented with distance. I observe $P(S<4), E(S|S<4)$ and $P(S>4)$ directly in the data. I assume that a change in response time does not affect the length of survival conditional on surviving to four years. Finally, because I cannot directly estimate $E(S|S>4)$ for my sample, I use life tables produced by the Utah Governor's Office of Planning and Budget to estimate future life expectancies for those patients who survive more than four years from the initial incident (for whom I have gender and age information) (State of Utah 2005). Table 10 presents my results.

I find that if I assume conservatively that those who survive "beyond" four years live for exactly 4 years (the minimum possible), an increase in response time of one minute reduces survival by 23.7 days (.065 years), and an increase in response times of 9.5 seconds reduces total survival by 3.8 days. This corresponds to a change of 758.8 life years, given a sample of over 70,000 patients. This suggests that the per life year cost of a 9.5 second reduction in response time is ($15,300,000/758.8) $20,169, which is far less than even the most conservative estimates of the value of a year of life.[36] A less conservative estimate, that is one that assumes the average length of survival for those who live beyond four years is 43.7 years (based on Utah life tables), suggests a per life year cost of a 9.5 second reduction in response time of less than $1,390 (almost $20,000 less than the previous estimate). Either estimate of the benefit of reducing response times seem to suggest that ambulances are significantly underprovided within Utah.

EMS agencies in Utah may underprovide ambulances for many reasons. I focus on

[35] The reliability of this estimate depends on the assumption that the error terms from this regression are nicely behaved. I estimate this regression using three different approaches (a regular instrumental variables regression which assumes normally distributed standard errors), an instrumented censored regression, and an instrumented tobit regression. For ease of presentation, I only present the first results here. However, there were no significant differences between the results for the three methods.

[36] Even assigning different values for a year of life for those above 65 and below 25, (approximately 52% of the sample), does not fundamentally affect this conclusion.

one potential explanation here. In Utah, as in many other states, EMS providers are required to provide mutual aid to other agencies (personal conversations with agency directors and Utah Bureau of EMS, 2006). Communities with available resources must answer mutual aid calls, regardless of the number and extent of these calls. This may lead to a free-rider problem. If the costs of using mutual aid (higher response times) are less than the benefits (lower costs), then providers will systematically underprovide ambulances.

In a work in progress, I model the decision of communities to purchase ambulances. In that paper, I show that providers that behave strategically will choose to buy fewer ambulances than if mutual aid were not available. They will also choose to buy fewer ambulances than the socially efficient number of ambulances. Empirically, I cannot reject the hypotheses that communities behave strategically , and therefore underprovide ambulances.

This finding has significant policy implications. It suggests that central planning of ambulance purchasing may produce welfare improvements, that state governments may want to subsidize the cost of ambulances, and also that Utah and other states may want to discourage mutual aid. The assumed value of mutual aid agreements, which are common in other local public-good contexts such as police and fire services, should be carefully reconsidered. Given the size of state and local expenditures on police, fire and Emergency Medical Services (over $105 billion in 2004-5), the financial significance of these mutual aid resource flows between communities is clearly sizable. The potential for underprovision is significant (Annual Survey of Government Finances, 2004-5). This issue warrants additional study.

9 CONCLUSION

In this paper I have resolved an empirical puzzle within the previous literature, which found only mixed and limited evidence that shorter response times improve outcomes, despite policy-makers' long-held assumption that this was true. This is the first paper to clearly demonstrate the importance of response times for patients suffering from non-cardiac conditions, as well as for any demographic subgroups. I propose several mechanisms through which response times may affect outcomes. I find that a mechanism in which response times determine the extent of damage to the internal organs, increasing the hazard of death, best explains the data. I provide a cost-benefit analysis for an estimated 9.5-second decrease in response times – and I find that the anticipated benefits far exceed the costs. Finally, I suggest one potential explanation for this underprovision – strategic behavior by communities in the presence of mandatory mutual aid agreements.

10 APPENDIX

10.1 APPENDIX A: CONSTRUCTION OF THE DATA

Figure 3A summarizes the relevant data connections.

I standardized prehospital incident address, city, and name records according to U.S. census conventions (Utah Prehospital Incident Data, 1999-2005). I used ArcMap 9.1 with the StreetMap USA (SDC) address locator, GCS North American 1983 Coordinate System, and default matching options to identify the latitude and longitude, census block group, tract, and census place for each incident, EMS agency, and hospital.

To match prehospital incident reports to emergency department reports using probabilistic matching methods (Link Plus), I used these variables: sex, first name, last name, complete name, incident date, hospital number, race, sex, and birth date. I used the following elements to match prehospital incident reports to mortality records: sex, birth date, complete name, first name, last name, race, sex, injury county, and hospital. In a few cases, I filled in data which was missing from a prehospital report with emergency department or mortality data.

The mortality data includes all deaths in the state of Utah between 1999 and 2005 by residents of Utah. Because of agreements with other states, deaths by non Utah residents within the state of Utah, and deaths by Utah residents outside the state of Utah cannot be disclosed to outside researchers (Utah Death data, 1999-2005). In appendix C, I explore the impact of this potential underreporting of deaths on my results.

For the small proportion of prehospital incident reports for which patient zip code is included, I identify out-of-state residents. I also used the emergency room data which includes patient zip code to identify patients from outside of Utah (Utah Emergency Department Encounter Data, 1999-2005).

The emergency room data includes a small number of patients who were subsequently admitted to the hospital as inpatients (15% of all emergency department admissions).

My traffic data includes hourly vehicle counts from 97 automatic traffic counters located throughout Utah (Utah Automatic Traffic Counter Data, 1990-2005). Each traffic counter identifies the total vehicle flow every hour in two directions. To get an average measure of congestion, I combined traffic counts from both directions and calculated and means by counter-day-hour unit. A more precise measure of traffic would have identified the actual route of each ambulance, and the traffic counters which were along this route in the appropriate direction; however, without knowing the starting location of each ambulance, this would be impossible to do precisely. Such an analysis would also take me away from the central purpose of this paper. I matched each incident to the traffic counter which was closest in distance, during the hour which corresponded to the time when the call was dispatched. I did not fill in data when no traffic data was available.

I gathered weather data from hourly data collected from 20 weather stations throughout the state of Utah (Integrated Surface Hourly Database, 2001). I collapsed over 100 descriptions of current weather into eight basic categories: rain, fog, snow, ice or hail, mist/haze, drizzle, thunderstorm, or other. I matched each incident to the weather reading which was geographically closest and which was closest in time after the instant of dispatch.

For each of the 29 counties in Utah, I used latitude and longitude coordinates to identify daily sunset and sunrise times in 2001 (Sunrise/Sunset/Sun Angle Calculator, 2007), which I subsequently merged by incident, county and date with the incident data.

Because actual ambulance location prior to dispatch was unavailable, I used the agency address provided by the Bureau of EMS. In cases where the agency address was a post-office box, I used the latitude and longitude of the agency zip code as the agency location. I calculated distance using the spherical law of cosines:

$d = \text{acos}(\sin(\text{lat1}).\sin(\text{lat2})+\cos(\text{lat1}).\cos(\text{lat2}).\cos(\text{long2-long1})).R.$

I identified tourist locations or Olympic locations using Utah Department of Tourism attendance rankings and Olympic information provided by the Utah Tourism Industry (Top 25 Tourist Attractions by Volume 2000, 2002 Winter Olympics 2007).

I geocoded verbal descriptions of the jurisdiction of each valid EMS license as of fall 2006 which were given to me by the Utah Bureau of EMS. An example follows: Beginning at the Carbon/Utah/San Pete County line, south along the Carbon/San Pete County line to the Carbon/San Pete/Emery County line; south along the Carbon/Emery County line, then east along the Carbon/Emery County line to one mile west of Highway 6, then southeast to Woodside Highway 6 at mile marker 279, then northeast two miles; then northwest to one mile east of Highway 6 at the Carbon/Emery County line, then east along the Carbon/Emery County line to the Carbon/Uintah County line, then north two miles to the Carbon/Sunnyside license line, then west to one mile east of Highway 6, then northwest to one mile north of Junction SR 123 and Highway 6, then east to one mile west of East Carbon City limits, then north two miles to one mile northwest of Sunnyside City limits, then east to the Carbon/Uintah County line, then north along the Green River to the northeast corner of Carbon County, then west along the Carbon/Uintah County line and continuing west along the Carbon/Duchesne County line to one mile East of SR 191; then northeast to one mile east of the summit of Indian Canyon SR 191 at mile marker 173; then west 2 miles to one mile west of SR 191, then southwest to Reservation Ridge road, then west along Reservation Ridge Road and White river road to Soldier Summit, then south from Soldier Summit to the Carbon/Utah County line; then west on the Carbon/Utah County line to point of beginning.

According to the Utah Bureau of EMS, no areas should have more than one provider of a given level. Although there were likely to be some changes in agency boundaries between 1999 and 2006, conversations with a random sub-sample of agency directors suggested that agency boundaries were stable.

I excluded prehospital reports from the primary analysis if they lacked patient names, dispatch codes, or addresses, or if they contained variations of **CANCELLED** in the incident addresses, names, or dispatch codes. I also excluded duplicated prehospital reports. Table 9A shows how many observations from the original sample were excluded from the main regression sample and why.

10.2 APPENDIX B: PROBABILISTIC MATCHING

I used the program Link Plus, created by the National Program of Cancer Registries within the Centers for Disease Control and Prevention, to probabilistically match incident reports with mortality and emergency department reports using formal mathematical models based upon the framework of Fellegi and Sunter (Link Plus 2005, Fellegi 1969). Similar software is commonly used within epidemiology and has previously been used in economics to link administrative records (Hellerstein, Neumark, and McInerney 2007, Abowd and Vilhuber 2005).

After I cleaned and standardized the elements in both data sets (first, for prehospital and mortality, and second, for prehospital and emergency department) so that the values of the variables were equivalent, I used the software to match on selected elements. For the match between the mortality and prehospital data set, these elements were: sex, birth date, complete name, first name, last name, race, sex, injury county, and hospital. For the match between the emergency department and prehospital data sets, these elements were: sex, first name, last name, complete name, incident date, hospital number, race, sex, and birth date. I matched the mortality records to the EMS records and the emergency department (ED) records to the EMS records. Appendix Figures 1A and 2A show the distribution of matching scores for the ED and mortality matches; in neither case is there an obvious cut-off point. Therefore, I follow the guidelines recommended by the CDC and choose a minimum match score between 10 and 15. I matched 13,103 of 64, 442 mortality records to EMS records (20%) and 66,556 of 668,888 ED records to EMS records (10%).

The software can account for minor mistypings, misspellings, and even missing names (in the case of maiden versus married names, for example), missing or slightly inaccurate day or month values for dates. It can assign higher weights to matches of rare values and can also match on exact terms, equivalent to deterministic methods. Note that if a patient appeared more than once in the prehospital data, and he or she died, the mortality record would be matched multiple times. The emergency department record that is most relevant to each prehospital incident, according to the matching software, is the one that will be matched. This might mean that a particular emergency department record is matched to more than one prehospital incident, if the prehospital incidents were close enough in time and only one emergency department visit resulted from multiple prehospital incidents. Link Plus allowed me to customize the matching weight on each variable; to choose the number and type of variables for matching; and to set the score above which observational matches would be accepted, based on the strength of all of the variable matches. For a useful introduction and background on probabilistic matching methods, see Winkler 1995 or Winkler 1999. The m and u parameters and the direct link number used in these probabilistic matching procedures are available from the author.

However, there may still be mismatches. Deterministic matching methods reduce the number of Type 1 Errors, or false positives, but these methods increase the number of type 2 errors, or missed matches. Probabilistic matches reverse that pattern: they reduce the number of type 2 errors but increase the number of type 1 errors. I tried to minimize the number of false positives by standardizing the elements to be merged in each dataset. To check the quality of the matching algorithm, I visually inspected a random sample of matches. I refined the algorithm until the matches in this random subsample were satisfactory. I dropped all matched ED reports that bore an admission date more than one day prior to the incident date and also the small number of matched death reports that reported a death date more than one day prior to the incident date; approximately 11 percent of mortality and ED matches. Originally, I checked the number of matched mortality records against the outcomes in the prehospital records that listed them as "dead on arrival." But I later found that prehospital "dead on arrival" reports (which represent less than 1 percent of the sample) were highly inaccurate. In fact, a large proportion of these patients were later found alive in the Emergency Department and also had recorded positive vital signs, both findings highly unlikely in people who were dead before they were brought to the hospital. I also interacted the score which LinkPlus assigned to each match, indicating its strength and reliability, with the mortality indicator variable (Table 7A). In no cases were the results sensitive to the quality of the match. For the sample of patients who were admitted to the hospital, I used the emergency department data match score as a weighting variable. Again, these results were similar to my original specification. Table 8A shows the impact of changing the minimum match score for the mortality records from 15 to 20, which did not affect the results substantially. Finally, I also compared the proportion of prehospital calls which listed a hospital admit as the call outcome and the proportion of calls that I successfully matched to ED records. There are many legitimate reasons why these would differ (for example, if a patient arrived at the hospital and was not admitted to the emergency room, or if a patient decided to go to the emergency room through other means later in the day or the next day). However, these proportions are consistent.[37]

10.3 APPENDIX C: MEASUREMENT ERROR

In this section, I discuss several potential sources of measurement error: mismatches from the probabilistic matching, missing mortality data, censored ED data, missing prehospital reports, missing variables within the prehospital reports, and misreporting.

Utah non-residents who died in Utah were not included in the mortality data. Utah residents who died outside Utah were also excluded. To evaluate the size of the bias this introduced into the mortality outcomes, I estimated the hospital outcomes regressions excluding all patients identified as either being involved in incidents outside of Utah, or whose zip codes came from outside of Utah (less than 3 percent of the sample). The results did not change. Mortality regressions which excluded these same patients (a very small proportion of the total sample) did not differ from the base results, either, indicating that this is not a severe problem. Finally, the CDC reports the total number of deaths by residents of Utah by year; less than 2 percent of deaths by Utah residents in 2004, for example, (approximately 200 deaths) occurred outside the state of Utah (LCWK9 2004, Utah Death Data 2004). Therefore, given that only 20 percent of deaths in Utah are preceded by an EMS call, these missing deaths are unlikely to significantly affect my results.

Current merged ED records only identify the first ED incident associated with each prehospital record (if there is one). I matched only emergency department visits from 2001 to prehospital incidents in 2001. If an incident occurred on December 31st, and the ED visit occurred on January 1st, I will not have records for it within this data set. But the average difference in days between ED admission and incident is less than one,

[37] Note also that John Doe does not appear in mortality records (which only contain actual names) but does appear in ED and prehospital records. When I excluded patients identified as John Doe (and various equivalent anonymized names) from the mortality regressions, however, the main results are unaffected.

and less than 1% of prehospital incidents occurred on December 31st, so I am unlikely to miss many ED reports. The Utah Department of Health is currently constructing linked ED, Ambulatory Surgery, and Hospital Discharge records, which will allow me to identify all ED, AS and HD trips within two years for each prehospital incident. I will use these linked reports to estimate the total charges for all hospital medical care following each prehospital incident.

Although Utah state law requires that all providers submit reports for each call, there is no system which audits agencies; there may be many missing prehospital reports. According to the Bureau of EMS, 2001 was a good reporting year. There is no reason to believe that misreporting or attrition is systematically correlated with incident characteristics, the agency says.

There are also missing variables. In cases where there were multiple reports of the same individual at the same incident, I filled in details that were missing from other reports. In practice, these filled-in variables did not affect the results in any way.

Response time may be measured with error: in some cases, responders will record a 10:57 response time as 10 minutes, and in other cases, 11 minutes. This is likely to be classical measurement error, and will bias the coefficients towards zero; the instrument should correct for this. The potential for incorrectly-measured influential observations is a possible concern; results from regressions which excluded response time outliers more than one standard deviation (or two or three) above the mean had effects stronger and in the same direction as the original specification.

I excluded any reports which are missing values from the regression analysis. Particularly in the case of outcomes measured at the scene, intermediate health status could possibly be missing because patients had already died; however, very few patients were actually dead on arrival. Also, intermediate health indices are available for 83 percent of patients coded as dead on arrival. This proportion is only slightly lower than that for the rest of the sample (92%). Around 15,000 addresses could not be geocoded due to the limited information available in the administrative data. Only a small share of observations were missing weather or traffic station data due to equipment problems. Dispatch code, or the code given by the dispatcher to the paramedic when the call is dispatched, is only available for 50% of the sample. Injury/illness code is available for a much higher proportion of the sample, however. Response time is unavailable for a reasonably high proportion of the sample. Appendix Table 9A shows the impact of these missing values on the construction of the final regression sample.

In addition to matching individual patient-level records, I matched particular incident reports to hourly weather and traffic data, and sunset and sunrise times. It might have been possible to simulate weather and traffic at locations between traffic counters, or to identify the sunset and sunrise time for each day for each precise incident location, rather than for each county. These gains in precision, however, seem marginal and unlikely to affect my results.

In addition, there is no doubt that some of the Utah Bureau of EMS agency boundaries overstate or understate the true territory. But the measurement error in these descriptions is concentrated in the rural parts of Utah, where there are very few residents and few calls, and so the likely impact of this error is minimal for my analysis. Most mutual aid calls are not close to the territory borders, so these slight variances are unlikely to bias my mutual aid estimates significantly.

In the measurement of distance, the assumption of a spherical earth seems to be a reasonable one. Conveniently, Utah is not located at an extreme of the earth, where this approximation is likely to be most inaccurate. As a check on the quality of the distance measures, a small proportion of agencies reported distance from ambulance to incident and incident to hospital. Where the hospital was identified, the distance from incident to hospital measured using GIS technology could be directly compared to the distance measured using the ambulance odometer. This was reasonably accurate. The measure of the distance from the agency to the scene was positively correlated with the change in the odometer of the ambulance that made the trip.

Lastly, in addition to missing dispatch codes, there are a number of dispatch codes which differ from the injury or illness code identified at the scene. While this may be a sign that dispatch codes were improperly assigned, it may also indicate updating by the paramedics or EMTs. There are a number of possible explanations for these discrepancies: the patient or dispatcher may not have initially identified the injury or illness of highest priority (among many); the patient or dispatcher may have imprecisely described the primary injury or illness; the person making the call may not have actually observed the patient's condition (as in a traffic accident); or the patient's condition may have changed between the time of dispatch and moment of the paramedics' arrival at the scene. This may have implications for paramedics and EMTs – if certain dispatch codes are more likely to be recategorized or are consistently misrepresented, then they may need to update their reactions in a Bayesian manner and thereafter respond more appropriately to these dispatch codes.

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Table 1: Utah Prehospital Sample Demographic Characteristics

	Utah 2001 Prehospital Sample* (mean)	Utah Census 2000 (mean)	US Census 2000 (mean)
Age			
Less than 15	0.085	0.266	0.214
15 to 24	0.169	0.198	0.139
25 to 64	0.473	0.451	0.523
65 & over	0.273	0.085	0.124
N=62,982			
Gender			
Female	0.515	0.499	0.509
N=73,556			
Race			
White	0.913	0.892	0.751
Black	0.019	0.008	0.123
Native Am / Alaskan Native	0.009	0.013	0.009
Asian / Pacific Islander	0.023	0.024	0.037
Other	0.056	0.063	0.079
N=45,164			

*Regression sample as defined in Appendix Table 9A.
Sample sizes very because of missing covariates.

Table 2: Distribution of Patient Complaints for 2001 Utah Prehospital Sample

Complaint Category	Proportion of Calls	1 Year Mortality Rate*
Heart, Breathing Problems, Cardiac Arrest	**0.159**	**16.558**
Breathing problems	0.079	16.630
Cardiac, respiratory arrest	0.015	55.121
Chest pain	0.058	7.603
Heart problems	0.007	7.313
Stroke, Falls, Fainting	**0.178**	**10.867**
Convulsions, seizures	0.044	4.571
Falls	0.077	11.647
Stroke	0.014	23.235
Unconsciousness, fainting	0.043	11.887
Traffic Accident	**0.160**	**1.453**
Traffic injury accident	0.160	1.453
Transfer	**0.093**	**15.786**
Transfer	0.093	15.786
Trauma	**0.133**	**4.095**
Animal bites	0.004	7.395
Assault, rape	0.028	1.737
Burns	0.002	4.706
Carbon monoxide poisoning,inhalation	0.002	3.614
Drowning, diving accident	0.001	11.765
Electrocution	0.000	7.692
Hemorrhage	0.021	9.627
Industrial, machinery accidents	0.001	1.149
Overdose, poisoning, ingestion	0.039	2.512
Stab, gun shot wound	0.005	11.976
Traumatic injuries, specific	0.030	2.561
Other Issues	**0.277**	**10.731**
Abdominal pain or problems	0.037	8.960
Allergic reactions, hives,stings	0.006	3.081
Back pain	0.014	7.365
Choking	0.004	5.882
Diabetic problems	0.022	12.024
Eye problems	0.001	4.124
Headache	0.006	2.643
Heat, cold problems	0.001	5.236
Pregnancy, childbirth, miscarriage	0.008	1.040
Psychiatric, behavioral problems	0.038	3.397
Specific diagnosis, chief complaint	0.050	15.194
Unknown problem	0.035	7.668
Diarrhea	0.054	18.843
Ear Problems	0.000	12.500
Fever	0.001	23.077

N=73,706

*Mortality outcomes multiplied by 100.

Table 3: Incident Characteristics

Variable	Mean	Median	Standard Deviation	N
Time from Dispatch to Arrival at Scene (minutes)	8.46	7.00	6.64	73,706
Time from Contact at Scene to Departure from Scene (minutes)	18.27	16.00	11.14	66,813
Time from Departure from Scene to Arrival at Hospital, Home (minutes)	12.86	10.00	11.32	65,231
Time from Call to Dispatch Notified (minutes)	0.00	0.00	0.03	1,174
Time from Dispatch Notified to Ambulance Dispatched (minutes)	26.14	3.00	45.03	259
Time from Arrival at Scene to Arrival at Patient (minutes)	13.85	0.00	38.44	845
Distance to Closest Non Mutual Aid Agency (miles)	3.25	1.78	5.74	73,706
Distance to Closest Hospital with ED (miles)	2.01	1.49	2.40	73,706
Distance from Incident Location to Actual Hospital ED if Admitted (miles)	7.70	3.03	24.77	51,579

Note that the Closest Non Mutual Aid Agency is the closest agency which has territory including the incident.

Table 4: Outcome Summary Statistics

Outcome	Mean	Standard Deviation	N
Mortality			
Death within One Day of Incident*	1.69	12.90	73,706
Death within Two Days of Incident*	1.97	13.91	73,706
Death within 30 Days of Incident*	4.28	20.25	73,706
Death within 90 Days of Incident*	5.95	23.66	73,706
Death within 1 Calendar Year of Incident*	9.77	29.69	73,706
Death within 4 Calendar Years of Incident*	19.01	39.24	73,706
Intermediate Health and Expenditure Measures			
Health Index 1*	98.30	6.44	67,510
Health Index 2*	98.33	6.83	67,510
Number of ED Procedures (For ED Patients)*	33.12	85.90	51,607
Total Hospital Expenses (For ED Patients)	2934.34	9841.07	51,607
Ln (Total Hospital Expenses)	6.83	1.43	51,607
Patient at High Mortality Risk (ED personnel)*	5.97	23.69	50,519
Patient Has Severe Injury or Illness (ED personnel)*	7.13	25.74	50,519

* Scaled by 100 for ease of interpretation.

Sample size varies because not all patients are admitted to the hospital or have recorded vital signs.

Table 5: Main Regression Results

	Dependent	Variable				
	1 day mortality	**2 day mortality**	**30 day mortality**	**90 day mortality**	**1 year mortality**	**4 year mortality**
Reduced Form Regression of Mortality on Distance (Coefficient on Distance)	0.0150	0.0342	0.0780	0.1112	0.1392	0.2443
	(0.0083)	(0.0123)*	(0.0177)*	(0.0200)*	(0.0232)*	(0.0283)*
OLS (Coefficient on RT)	-0.0077	-0.0058	0.0205	0.0276	0.0157	0.0030
	(0.0063)	(0.0069)	(0.0124)	(0.0149)	(0.0176)	(0.0221)
IV (Coefficient on RT)	0.1363	0.3099	0.7080	1.0084	1.2617	2.2151
	(0.0754)	(0.1139)*	(0.1648)*	(0.1854)*	(0.0209)*	(0.2704)*

	Dependent	Variable				
	Response Time	**Response Time**	**Response Time**	**Response Time**	**Response Time**	**Response Time**
1st Stage (Coefficient on Distance)	0.1103	0.1103	0.1103	0.1103	0.1103	0.1103
	(0.0084)*	(0.0084)*	(0.0084)*	(0.0084)*	(0.0084)*	(0.0084)*
N	73, 706	73, 706	73, 706	73, 706	73, 706	73, 706

Note: Sample includes report of 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.Mortality outcomes are multipled by 100 for ease of coefficient interpretation. Robust standard errors in parentheses. See Appendix A for a discussion of the sample.* Indicates significant at 5% level.

Table 6: Heterogenous Treatment Effects (Varying by Condition)

	Dependent Variable					
	1 day mortality	2 day mortality	30 day mortality	90 day mortality	1 year mortality	4 year mortality
Coefficient on Interaction of Transfer and Response Times (IV) (N=6,848)	0.7674	0.3630	1.1501	3.0258	3.0368	6.4979
	(0.5192)	(0.4937)	(0.9575)	(1.4686)*	(1.5861)	(2.7461)*
Coefficient on Interaction of Traffic Accident and Response Times (IV) (N=11,768)	0.1655	0.2075	0.3778	0.5820	0.7231	0.8476
	(0.1386)	(0.1405)	(0.1762)*	(0.2068)*	(0.2262)*	(0.2650)*
Coefficient on Interaction of Stroke, Falls, Fainting and Response Times (IV) (N=13,161)	0.0597	0.2313	0.5723	0.8437	0.9205	1.8545
	(0.1028)	(0.1492)	(0.2226)*	(0.2752)*	(0.3091)*	(0.3963)*
Coefficient on Interaction of Heart Problems, Breathing Problems, Cardiac Arrest, and Response Times (IV) (N=11,779)	0.2238	0.3954	0.8623	1.1369	1.8522	2.1875
	(0.3162)	(0.3198)	(0.3895)*	(0.4077)*	(0.4792)*	(0.5562)*
Coefficient on Interaction of Other Issues and Response Times (IV) (N=20,352)	0.1156	0.5931	1.2905	1.4057	1.7610	3.5234
	(0.1164)	(0.3228)	(0..4600)*	(0.4903)*	(0.5446)*	(0.7089)*
Coefficient on Interaction of Trauma and Response Times (IV) (N=9,798)	-0.1095	-0.0247	-0.0144	0.0648	0.2305	0.2451
	(0.0549)	(0.0981)	(0.1140)	(0.1490)	(0.1987)	(0.2477)
IV (Coefficient on RT for Base Regression (Table 5))	0.1363	0.3099	0.7080	1.0084	1.2617	2.2151
	(0.0754)	(0.1139)*	(0.1648)*	(0.1854)*	(0.0209)*	(0.2704)*
N	73,706	73,706	73,706	73,706	73,706	73,706

Note: Sample includes report of 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.Mortality outcomes are multipled by 100 for ease of coefficient interpretation. Robust standard errors in parentheses. See Appendix A for a discussion of the sample.* Indicates Significant at 5% level. First stage Cragg Donald F value equals 15.46.

Table 7: Heterogenous Treatment Effects (Varying by Gender, Age)

			Dependent Variable			
	1 day mortality	**2 day mortality**	**30 day mortality**	**90 day mortality**	**1 year mortality**	**4 year mortality**
IV (Coefficient on RT) (Men Only)	0.0773	0.3208	0.5080	0.8478	1.0286	1.6626
(N=35,645)	(0.1087)	(0.1893)	(0.2221)*	(0.2499)*	(0.2808)*	(0.3338)*
IV (Coefficient on RT) (Women Only)	0.1797	0.2829	0.8949	1.1610	1.5070	2.8183
(N=37,911)	(0.0993)	(0.1187)*	(0.2416)*	(0.2724)*	(0.3098)*	(0.4318)*
IV (Coefficient on RT) (Age Less Than 15 Only) (N=5,328)	0.0831	0.0566	0.0201	0.1759	0.1528	0.1924
	(0.1015)	(0.1036)	(0.1136)	(0.1769)	(0.1857)	(0.2520)
IV (Coefficient on RT) (Age 15-24 Only) (N=10,670)	0.0167	0.0261	0.1679	0.5778	0.5881	0.8041
	(0.0774)	(0.0759)	(0.1459)	(0.2345)*	(0.2519)*	(0.3112)*
IV (Coefficient on RT) (Age 25-64 Only) (N=29,792)	0.0321	0.2895	0.3657	0.3687	0.4246	0.5579
	(0.1247)	(0.2397)	(0.2648)	(0.2730)	(0.2990)	(0.3356)
IV (Coefficient on RT) (Age Over 65 Only) (N= 17,192)	0.2232	0.4848	1.0470	1.3183	1.2972	2.5113
	(0.2332)	(0.2869)	(0.5421)	(0.6068)*	(0.6666)*	(0.7035)*
IV (Coefficient on RT for Base Regression (Table 5))	0.1363	0.3099	0.7080	1.0084	1.2617	2.2151
	(0.0754)	(0.1139)*	(0.1648)*	(0.1854)*	(0.0209)*	(0.2704)*
N	73,706	73,706	73,706	73,706	73,706	73,706

Note: Sample includes report of 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.Mortality outcomes are multipled by 100
for ease of coefficient interpretation. Robust standard errors in parentheses.
See Appendix A for a discussion of the sample.* Indicates Significant at 5% level.
First stage Cragg Donald F value equals 15.46.

Table 8: Intermediate Outcomes

	Dependent Variable								
	Indicator for Admitted to ED**	Natural Log of Total Hospital Expenditures	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
Reduced Form Regression of Dependent Variable on Distance (Coefficient on Distance)	0.1622	0.0008	0.0217	0.0627	0.0528	-0.1111	0.6973	0.3796	-0.0077
	(0.0358)*	(0.0011)	(0.0672)	(0.0226)*	(0.0239)*	(0.0273)*	(0.4663)	(0.6397)	(0.0102)
OLS (Coefficient on RT)	-0.1568	-0.0027	-0.2332	0.0041	-0.0043	0.0252	0.4957	0.3040	-0.2403
	(0.0274)*	(0.0010)*	(0.0571)*	(0.0166)	(0.0174)	(0.0197)	(0.3027)	(0.3362)	(0.0118)*
IV (Coefficient on RT)	1.4709	0.0067	0.1722	0.4966	0.4182	-0.8843	5.9665	3.2486	-0.0677
	(0.3038)*	(0.0091)	(0.5334)	(0.1816)*	(0.1904)*	(0.2165)*	(3.9095)	(5.4281)	(0.0889)

	Dependent Variable								
	Response Time	Response Time	Response Time	Response Time	Response Time	Response Time	Response Time	Response Time	Response Time
1st Stage (Coefficient on Distance)	0.1103	0.1258	0.1258	0.1263	0.1263	0.1256	0.1169	0.1169	0.1140
	(0.0083)*	(0.0108)*	(0.0108)*	(0.0110)*	(0.0110)*	(0.0108)*	(0.0094)*	(0.0094)*	(0.0088)*
N	73,706	51,607	51,607	50,519	51,607	51,579	67,519	67,519	66,813

Note: Sample includes report of 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 multipled by 100 for ease of coefficient interpretation. Robust standard errors in parentheses. See Appendix A for a discussion of the sample.* Indicates Significant at 5% level.

Table 9: Response Time Statistics

Variable	Mean	Median	Standard Deviation	p10	p90
Average Response Time to Non Mutual Aid Calls	8.9	7.0	8.3	3.0	16.0
Average Response Time to Mutual Aid Calls	10.5	7.0	11.9	3.0	19.0
Average Distance from Incident to Answering Agency for Non Mutual Aid Calls	6.7	2.5	22.8	0.5	8.8
Average Distance from Incident to Answering Agency for Mutual Aid Calls	10.1	4.9	24.0	1.0	14.5

Providers with only 1 Ambulance (N=84). Providers with more than 1 Ambulance (N=53).

Note: All Calculations are made from Utah Prehospital Data (2001) (sample including calls outside of Salt Lake City).Note: There are 10,887 mutual aid calls identified and 98,902 non mutual aid calls out of the 109,789 geocoded calls.

Table 10: Cost Benefit Analysis

dE(S|S<4)/dR	PR(S<4)	E(S|S<4)	dPR(S<4)/dR	dE(S|S>4)/dR	PR(S>4)	E(S|S>4)	dPR(S>4)/dR	dE(S)/dR
-0.025	0.190	1.304	0.022	0.00	0.810	4.0	-0.022	-0.065
-0.025	0.190	1.304	0.022	0.00	0.810	10.0	-0.022	-0.197
-0.025	0.190	1.304	0.022	0.00	0.810	15.0	-0.022	-0.308
-0.025	0.190	1.304	0.022	0.00	0.810	20.0	-0.022	-0.419
-0.025	0.190	1.304	0.022	0.00	0.810	25.0	-0.022	-0.530
-0.025	0.190	1.304	0.022	0.00	0.810	30.0	-0.022	-0.640
-0.025	0.190	1.304	0.022	0.00	0.810	43.7	-0.022	-0.943

Notes: Recall that E(S)=E(S|S<4)(PR(S<4)) + E(S|S>4)PR(S>4). This implies that
dE(S)/dR=dE(S|S<4)/dR(PR(S<4) + E(S|S<4)*dPR(S<4)/dR + dE(S|S>4)/dR(PR(S>4) + E(S|S>4)*dPR(S>4)/dR
I assume that dE(S|S>4)/dR=0. Given that I don't directly observe
E(S|S>4), I show the results for several potential values ranging from 4 (all patients who survive 4 years die at exactly 4.01 years) to the expected life expectancy for the sample of patients who survive 4 years after the initial incident calculated from Utah model life tables (43.66).

Figure 1: Selected EMS License Boundaries and Call Locations

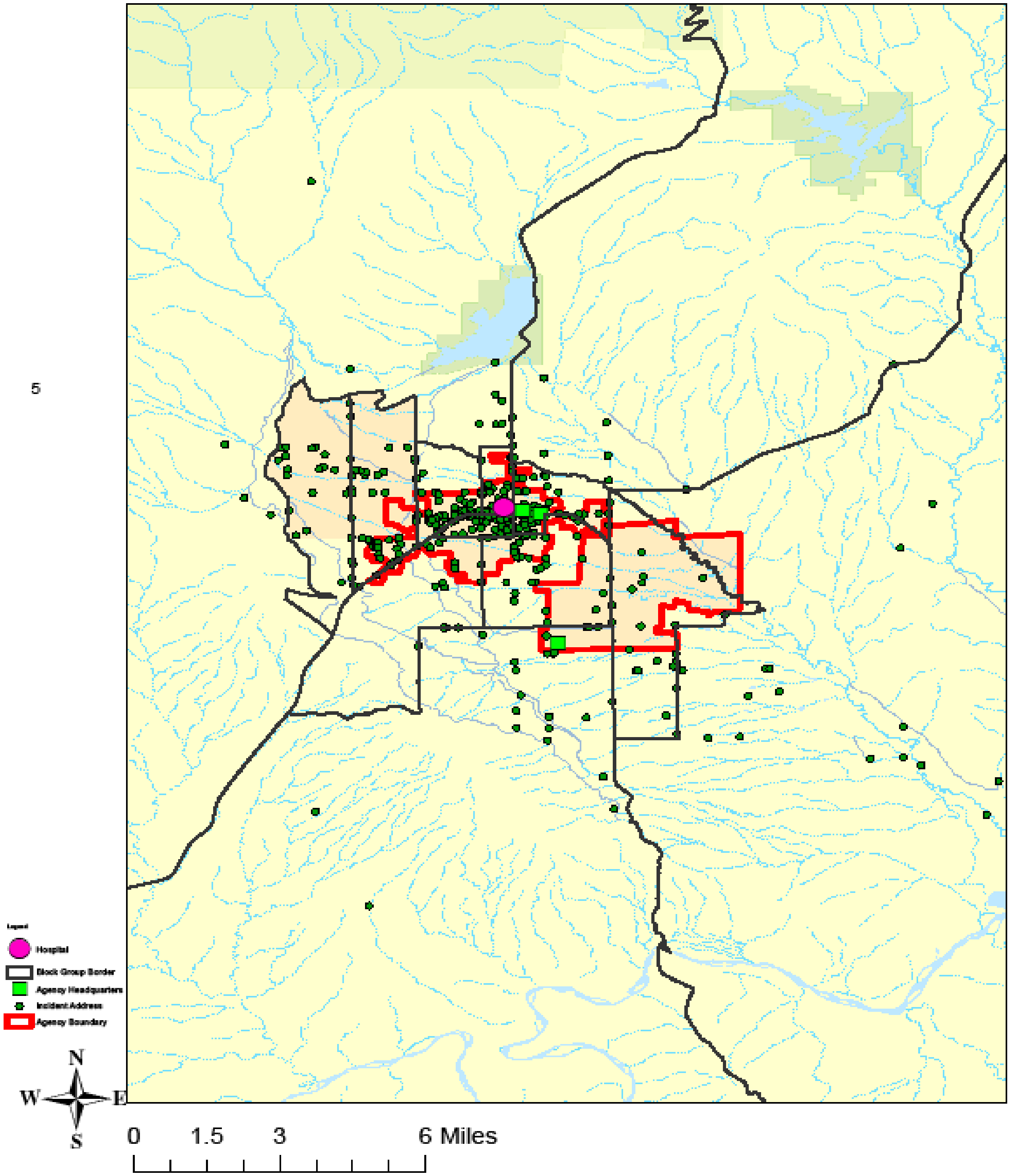


Figure 2:
Probability of Being Stocked Out By Number of Ambulances

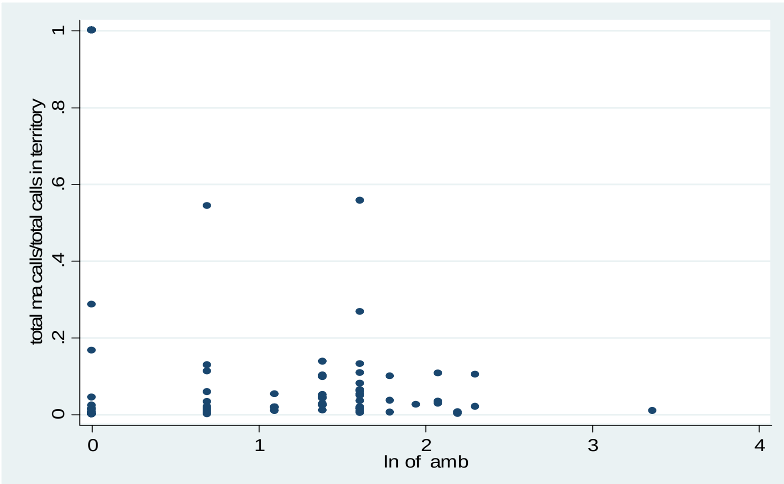


Figure 3:
Total Mutual Aid Calls By Number of Ambulances

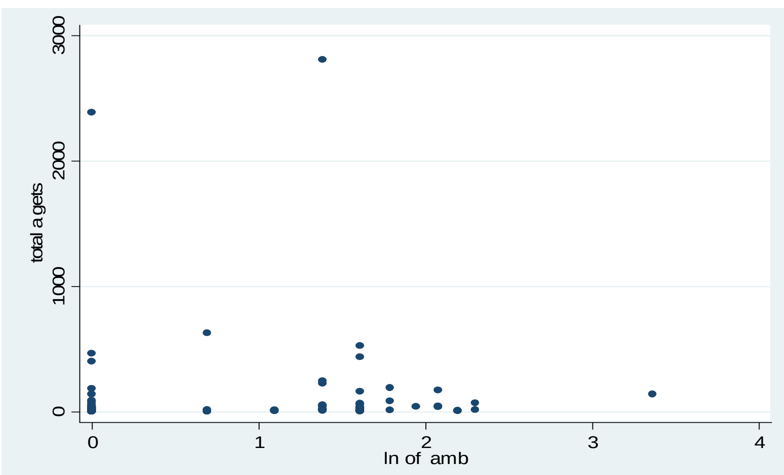


Figure 4:
Distribution of RT For Mutual Aid Calls and
Non Mutual Aid Calls

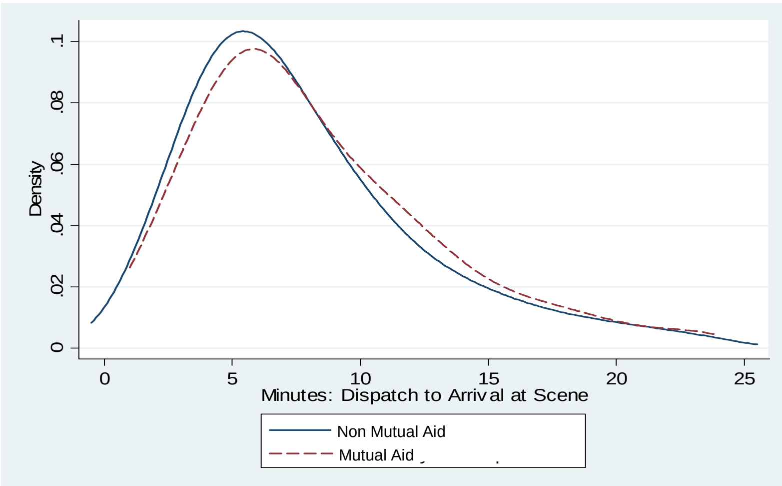
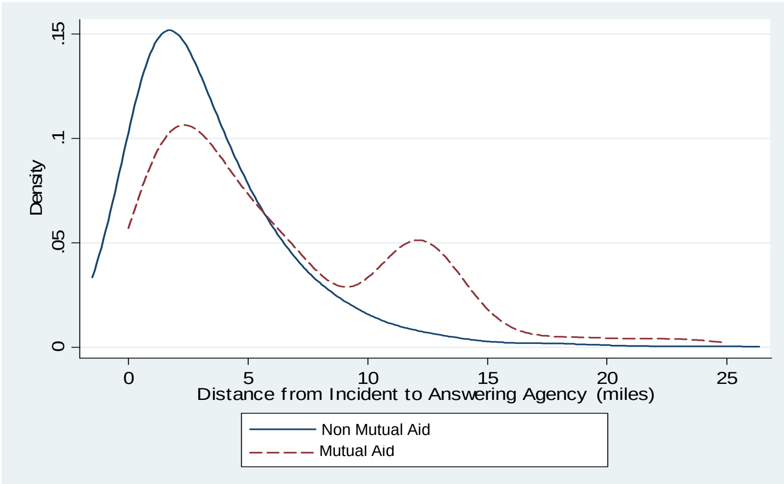


Figure 5:
Distance from Incident to Provider for
Mutual Aid Calls and Non Mutual Aid Calls



Appendix Table 1A: Variable Definitions for Standard Regression Specification

Variable	Definition	Data Source
Outcome Variable		
1 day mortality	Equals 100 if death date- incident date is less than or equal to 1	Death Data
2 day mortality	Equals 100 if death date- incident date is less than or equal to 2	Death Data
30 day mortality	Equals 100 if death date- incident date is less than or equal to 30	Death Data
90 day mortality	Equals 100 if death date- incident date is less than or equal to 90	Death Data
1 year mortality	Equals 100 if death date- incident date is less than or equal to 1 year	Death Data
4 year mortality	Equals 100 if death date- incident date is less than or equal to 4 years	Death Data
Health Index 1*	Intermediate Health Index From Scene: 100 = Good Health	Prehospital Report
Health Index 2*	Intermediate Health Index From Scene: 100 = Good Health	Prehospital Report
Hospital number of procedures*	Total number of procedures multiplied by 100 (from ED)	ED Report
Ln (Total Hospital Expenses)	Natural Log of total Hospital Expenditures (from ED)	ED Report
High Mortality Risk (ED)	Equals 100 if mortality risk by ED assessed at 3 or 4 where 4 is maximum.	ED Report
Severe Injury or Illness (ED)	Equals 100 if ED personnel asssess condition severity as 3 or 4 where 4 is maximum.	ED Report
Weather characteristics		
rain	Indicator for Rain during hour of incident at Weather Station which is closest to incident location	Integrated Surface Hourly Database
fog	Indicator for Fog during hour of incident at Weather Station which is closest to incident location	Integrated Surface Hourly Database
snow	Indicator for Snow during hour of incident at Weather Station which is closest to incident location	Integrated Surface Hourly Database
icehail	Indicator for Ice or Hail during hour of incident at Weather Station which is closest to incident location	Integrated Surface Hourly Database
misthaze	Indicator for Mist or Haze during hour of incident at Weather Station which is closest to incident location	Integrated Surface Hourly Database
drizzle	Indicator for Drizzle during hour of incident at Weather Station which is closest to incident location	Integrated Surface Hourly Database
thunderstorm	Indicator for Thunderstorm during hour of incident at Weather Station which is closest to incident location	Integrated Surface Hourly Database
other	Other Weather at Weather Station during hour of incident which is closest to incident location	Integrated Surface Hourly Database
Block Characteristics		
Percentage of Population without Government Assistance	Census Block Group Characteristics	US Census 2000 Summary File 3
Poverty Rate	Census Block Group Characteristics	US Census 2000 Summary File 3
Total Area	Census Block Group Characteristics	US Census 2000 Summary File 3
Density	Census Block Group Characteristics	US Census 2000 Summary File 3
Total Population	Census Block Group Characteristics	US Census 2000 Summary File 3
Percentage Rural	Census Block Group Characteristics	US Census 2000 Summary File 3
Proportion of Population Less than 5	Census Block Group Characteristics	US Census 2000 Summary File 3
Proportion of Population 16-24	Census Block Group Characteristics	US Census 2000 Summary File 3
Proportion of Population More than 65	Census Block Group Characteristics	US Census 2000 Summary File 3

Incident Characteristics		
Minutes Dispatch to Scene	Minutes from dispatch of ambulance to arrival at scene: response time	Prehospital Report
Distance to Closest Agency	Distance from incident to closest eligible, non mutual aid agency (Miles)	Prehospital Report/Utah Bureau of EMS
Month of year indicators	Month of incident	Prehospital Report
Hour of day indicators	Hour of day of incident	Prehospital Report
Weekend indicator	Equals 1 if incident occurred on weekend	Prehospital Report
Weekend indicator interacted with hour of day	Interaction of hour of day and weekend	Prehospital Report
Injury or Illness Category		
Abdominal pain/problems	Primary Injury Illness as Assessed by EMS	Prehospital Report
Allergies/hives/medicine reactions/stings	Primary Injury Illness as Assessed by EMS	Prehospital Report
Animal bites	Primary Injury Illness as Assessed by EMS	Prehospital Report
Assault/rape	Primary Injury Illness as Assessed by EMS	Prehospital Report
Back pain	Primary Injury Illness as Assessed by EMS	Prehospital Report
Breathing problems	Primary Injury Illness as Assessed by EMS	Prehospital Report
Burns	Primary Injury Illness as Assessed by EMS	Prehospital Report
Carbon monoxide poisoning/inhalation	Primary Injury Illness as Assessed by EMS	Prehospital Report
Cardiac/respiratory arrest	Primary Injury Illness as Assessed by EMS	Prehospital Report
Chest pain	Primary Injury Illness as Assessed by EMS	Prehospital Report
Choking	Primary Injury Illness as Assessed by EMS	Prehospital Report
Convulsions/seizures	Primary Injury Illness as Assessed by EMS	Prehospital Report
Diabetic problems	Primary Injury Illness as Assessed by EMS	Prehospital Report
Drowning/diving accident	Primary Injury Illness as Assessed by EMS	Prehospital Report
Electrocution	Primary Injury Illness as Assessed by EMS	Prehospital Report
Eye problems	Primary Injury Illness as Assessed by EMS	Prehospital Report
Falls	Primary Injury Illness as Assessed by EMS	Prehospital Report
Headache	Primary Injury Illness as Assessed by EMS	Prehospital Report
Heart problems	Primary Injury Illness as Assessed by EMS	Prehospital Report
Heat/cold problems	Primary Injury Illness as Assessed by EMS	Prehospital Report
Hemorrhage	Primary Injury Illness as Assessed by EMS	Prehospital Report
Industrial/machinery accidents	Primary Injury Illness as Assessed by EMS	Prehospital Report
Overdose/poisoning/ingestion	Primary Injury Illness as Assessed by EMS	Prehospital Report
Pregnancy/childbirth/miscarriage	Primary Injury Illness as Assessed by EMS	Prehospital Report
Psychiatric/behavioral problems	Primary Injury Illness as Assessed by EMS	Prehospital Report
Specific diagnosis/chief complaint	Primary Injury Illness as Assessed by EMS	Prehospital Report
Stab/GSW	Primary Injury Illness as Assessed by EMS	Prehospital Report
Stroke/CVA	Primary Injury Illness as Assessed by EMS	Prehospital Report
Traffic injury accident	Primary Injury Illness as Assessed by EMS	Prehospital Report
Traumatic injuries, specific	Primary Injury Illness as Assessed by EMS	Prehospital Report
Unconsciousness/fainting	Primary Injury Illness as Assessed by EMS	Prehospital Report
Unknown problem	Primary Injury Illness as Assessed by EMS	Prehospital Report
Diarrhea	Primary Injury Illness as Assessed by EMS	Prehospital Report
Ear Problems	Primary Injury Illness as Assessed by EMS	Prehospital Report
Fever	Primary Injury Illness as Assessed by EMS	Prehospital Report
Transfer	Primary Injury Illness as Assessed by EMS	Prehospital Report

Appendix Table 2A: Basic Specification Controlling For Block Group Fixed Effects

		Dependent Variable				
	1 day mortality	**2 day mortality**	**30 day mortality**	**90 day mortality**	**1 year mortality**	**4 year mortality**
Reduced Form Regression of Mortality on Distance (Coefficient on Distance)	0.0381	0.0608	0.0942	0.0756	0.0364	0.1228
	(0.0181)*	(0.0281)	(0.0364)*	(0.0409)	(0.0475)	(0.0536)*
OLS (Coefficient on RT)	-0.0026	-0.0022	0.0236	0.0224	0.0126	0.0081
	(0.0072)	(0.0079)	(0.0141)	(0.0166)	(0.0194)	(0.0241)
IV (Coefficient on RT)	0.9719	1.5489	2.4027	1.9262	0.9289	3.1319
	(0.4355)*	(0.7150)*	(0.9283)*	(1.0137)	(1.1740)	(1.4068)*

		Dependent Variable				
	Response Time	**Response Time**	**Response Time**	**Response Time**	**Response Time**	**Response Time**
1st Stage (Coefficient on Distance)	0.0392	0.0392	0.0392	0.0392	0.0392	0.0392
	(0.0097)*	(0.0097)*	(0.0097)*	(0.0097)*	(0.0097)*	(0.0097)*
N	73,706	73,706	73,706	73,706	73,706	73,706

Note: Sample includes report of shortest response time to scene; distance is that of closest non-mutual aid agency. All specifications include block group fixed effects, hour, week, week by hour, month and injury illness fixed effects.Mortality outcomes are multipled by 100 for ease of coefficient interpretation. Robust standard errors in parentheses. See Appendix A for a discussion of the sample.* Indicates significant at 5% level.

Appendix Table 3A: Main Regression Specification - Ln (RT)

	Dependent	Variable				
	1 day mortality	**2 day mortality**	**30 day mortality**	**90 day mortality**	**1 year mortality**	**4 year mortality**
Reduced Form Regression of Mortality on Distance (Coefficient on Distance)	0.0150	0.0342	0.0780	0.1112	0.1392	0.2443
	(0.0083)	(0.0123)*	(0.0177)*	(0.0200)*	(0.0232)*	(0.0284)*
OLS (Coefficient on ln(RT))	-0.0917	-0.0389	0.2465	0.3463	0.4487	0.6812
	(0.0650)	(0.0708)	(0.1086)*	(0.1299)*	(0.1615)*	(0.2130)*
IV (Coefficient on ln(RT))	1.3577	3.0865	7.0474	10.0429	12.5659	22.0616
	(0.7505)	(1.1291)*	(1.6220)*	(1.8129)*	(2.0415)*	(2.5830)*

	Dependent	Variable				
	Response Time	**Response Time**	**Response Time**	**Response Time**	**Response Time**	**Response Time**
1st Stage (Coefficient on Distance)	0.0111	0.0111	0.0111	0.0111	0.0111	0.0111
	(0.0007)*	(0.0007)*	(0.0007)*	(0.0007)*	(0.0007)*	(0.0007)*
N	73,706	73,706	73,706	73,706	73,706	73,706

Note: Sample includes report of 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.Mortality outcomes are multipled by 100
for ease of coefficient interpretation. Robust standard errors in parentheses.
See Appendix A for a discussion of the sample.* Indicates significant at 5% level.

Appendix Table 4A: Basic Regression Specification Controlling for Distance to Closest Hospital

	Dependent Variable					
	1 day mortality	2 day mortality	30 day mortality	90 day mortality	1 year mortality	4 year mortality
Reduced Form Regression of Mortality on Distance (Coefficient on Distance)	0.0146	0.0340	0.0781	0.1106	0.1396	0.2417
	(0.0084)	(0.0125)*	(0.0178)*	(0.0202)*	(0.0234)*	(0.0286)*
OLS (Coefficient on RT)	-0.0080	-0.0061	0.0201	0.0268	0.0152	0.0005
	(0.0063)	(0.0069)	(0.0124)	0.0149	(0.0176)	(0.0222)
IV (Coefficient on RT)	0.1399	0.3249	0.7462	1.0571	1.3345	2.3099
	(0.0801)	(0.1214)*	(0.1756)*	(0.1973)*	(0.2226)*	(0.2885)*

	Dependent Variable					
	Response Time	Response Time	Response Time	Response Time	Response Time	Response Time
1st Stage (Coefficient on Distance)	0.1046	0.1046	0.1046	0.1046	0.1046	0.1046
	(0.0082)*	(0.0082)*	(0.0082)*	(0.0082)*	(0.0082)*	(0.0082)*
N	73,706	73,706	73,706	73,706	73,706	73,706

Note: Sample includes report of 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 as well as distance to closest hospital.Mortality outcomes are multipled by 100 for ease of coefficient interpretation. Robust standard errors in parentheses.
See Appendix A for a discussion of the sample.* Indicates significant at 5% level.

Appendix Table 5A: Basic Regression Specification Excluding Transfers

	Dependent Variable					
	1 day mortality	2 day mortality	30 day mortality	90 day mortality	1 year mortality	4 year mortality
Reduced Form Regression of Mortality on Distance (Coefficient on Distance)	0.0106	0.0375	0.0787	0.0984	0.1262	0.2092
	(0.0092)	(0.0147)*	(0.0201)*	(0.0221)*	(0.0254)*	(0.0308)*
OLS (Coefficient on RT)	-0.0070	-0.0047	0.0012	0.0104	0.0091	-0.0241
	(0.0075)	(0.0080)	(0.0117)	(0.0143)	(0.0176)	(0.0231)
IV (Coefficient on RT)	0.0881	0.3121	0.6560	0.8202	1.0518	1.7438
	(0.0769)	(0.1254)*	(0.1733)*	(0.1882)*	(0.2107)*	(0.2589)*

	Dependent Variable					
	Response Time	Response Time	Response Time	Response Time	Response Time	Response Time
1st Stage (Coefficient on Distance)	0.1200	0.1200	0.1200	0.1200	0.1200	0.1200
	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0103)
N	66,858	66,858	66,858	66,858	66,858	66,858

Note: Sample includes report of 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.Mortality outcomes are multipled by 100 for ease of coefficient interpretation. Robust standard errors in parentheses. Transfers are excluded.* Indicates significant at 5% level.

Appendix Table 6A: Basic Regression Specification - Outcomes Weighted by Quality of Match

		Dependent	Variable			
	1 day mortality	**2 day mortality**	**30 day mortality**	**90 day mortality**	**1 year mortality**	**4 year mortality**
Reduced Form Regression of Mortality on Distance (Coefficient on Distance)	0.0041	0.0102	0.0217	0.0298	0.0331	0.0569
	(0.0032)	(0.0043)*	(0.0061)*	(0.0067)*	(0.0072)*	(0.0089)*
OLS (Coefficient on RT)	-0.0034	-0.0030	0.0039	0.0059	-0.0013	-0.0114
	(0.0021)	(0.0023)	(0.0040)	(0.0049)	(0.0055)	(0.0066)
IV (Coefficient on RT)	0.0370	0.0929	0.1966	0.2703	0.3001	0.5156
	(0.0295)	(0.0401)*	(0.0571)*	(0.0620)*	(0.0662)*	(0.0885)*

		Dependent	Variable			
	Response Time	**Response Time**	**Response Time**	**Response Time**	**Response Time**	**Response Time**
1st Stage (Coefficient on Distance)	0.1103	0.1103	0.1103	0.1103	0.1103	0.1103
	(0.0084)*	(0.0084)*	(0.0084)*	(0.0084)*	(0.0084)*	(0.0084)*
N	73,706	73,706	73,706	73,706	73,706	73,706

Note: Sample includes report of 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.Mortality outcomes are multipled by 100 for ease of coefficient interpretation. Robust standard errors in parentheses. For discussion of the sample, see Appendix A.* Indicates significant at 5% level.

Appendix Table 7A: Basic Regression Specification - Mortality Match Scores Above 20

		Dependent	Variable			
	1 day mortality	**2 day mortality**	**30 day mortality**	**90 day mortality**	**1 year mortality**	**4 year mortality**
Reduced Form Regression of Mortality on Distance (Coefficient on Distance)	0.0154	0.0348	0.0785	0.1134	0.1397	0.2433
	(0.0084)*	(0.0123)*	(0.0177)*	(0.0200)*	(0.0230)*	(0.0283)*
OLS (Coefficient on RT)	-0.0082	-0.0058	0.0217	0.0294	0.0174	0.0044
	(0.0063)	(0.0068)	(0.0123)	(0.0148)*	(0.0175)	(0.0220)
IV (Coefficient on RT)	0.1394	0.3152	0.7115	1.0280	1.2667	2.2058
	(0.0757)	(.1141)*	(0.1646)*	(0.1852)*	(0.2081)*	(0.2694)*

		Dependent	Variable			
	Response Time	**Response Time**	**Response Time**	**Response Time**	**Response Time**	**Response Time**
1st Stage (Coefficient on Distance)	0.1103	0.1103	0.1103	0.1103	0.1103	0.1103
	(0.0084)*	(0.0084)*	(0.0084)*	(0.0084)*	(0.0084)*	(0.0084)*
N	73,706	73,706	73,706	73,706	73,706	73,706

Note: Sample includes report of 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.Mortality outcomes are multipled by 100 for ease of coefficient interpretation. Robust standard errors in parentheses. For discussion of the sample, see Appendix A.* Indicates significant at 5% level.

Appendix Table 8A: Treatments and Medications Provided at the Scene

Treatments:
Airway Inserted
Assisted Ventillation
Bleeding Controlled
Blood Tubes Drawn
Cervical Immobilization
CPR
Defibrillation
Endotracheal Intubation
Esophageal Obturator Airway
Extrication Equipment
Heimlich Maneuver
Intraosseous Infusion
IV
MAST Inflated
MAST Not Inflated
NG Tube
OB Care
Oxygen Mask
Oxygen Cannula
Pneumo Tube
Spinal Immobilization
Splinted
Suctioned
Turned on Side
No Treatment Given
Vitals Assessed Monitored
Vitals Unobtainable
Other Assessment/Monitoring
Other Treatments

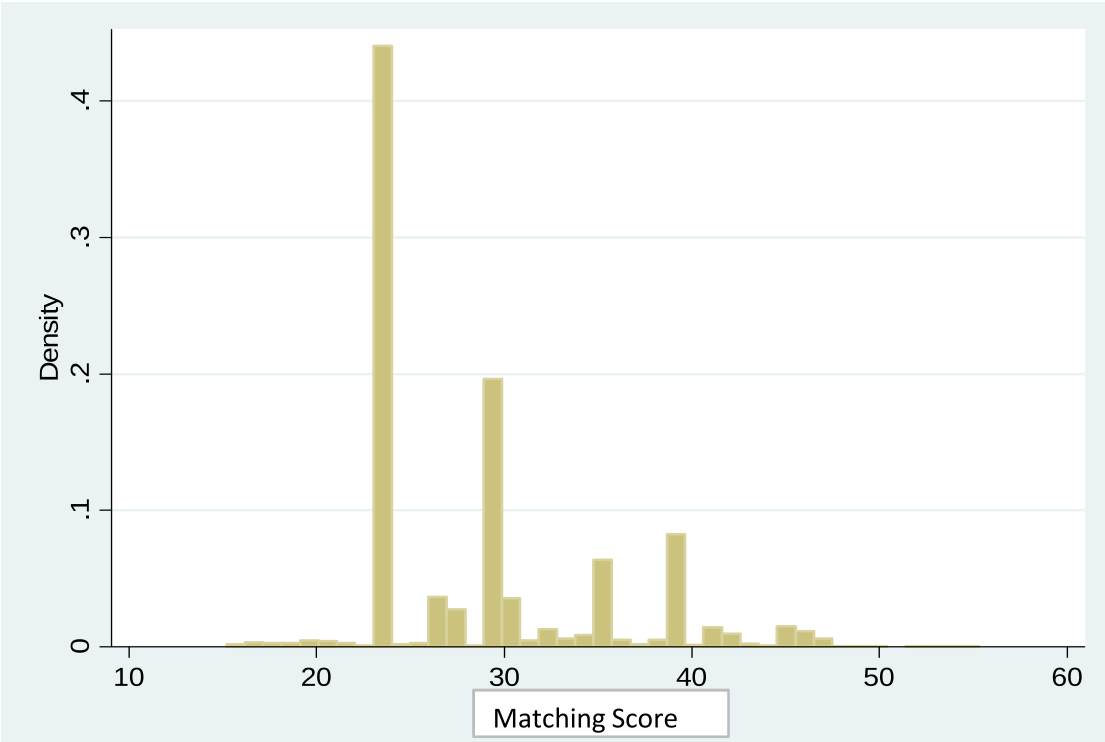
Medications:
Adenosine
Albuterol Sulfate
Aminophylline
Atropine/Atropine sulfate
Baby Aspirin
Benadryl/Diphenhydramine
Bretylol/Bretylium tosylate
Calcium Chloride
Charcoal
Decadron/Hexadrol/Dexamethasone
Demerol/meperidine
Dextrose 5% (D5W)
Dextrose 50%-Glucose (D50W)
Epinephrine 1:1,000/Adrenalin
Epinephrine 1:10,000/Adrenalin
Haloperidol/Haldol
Intropin-Dopamine HCL
Ipecac Syrup
Isuprel HCL - Isoproterenol
Lactated Ringers
Lasix - Furosemide
Luminal - Phenobarbital
Mark I
Midazolam/Versed
Morphine Sulfate
Narcan - Naloxone HCL
Nitrostat - Tri Nitroglycerine
Normal Saline
Nubain
Oral Glucose
Phenergan - Promethazine HCL
Pitocin - Oxytocin
Sodium Bicarbonate
Thiamine
Valium - Diazepam
Xylocaine - Lidocaine - IV Drip
Xylocaine - Lidocaine - Direct IV
Xylocaine 1% - 1% Lidocaine w/o Epinephrineaine
Other Medications

Appendix Table 9A: Sample Construction

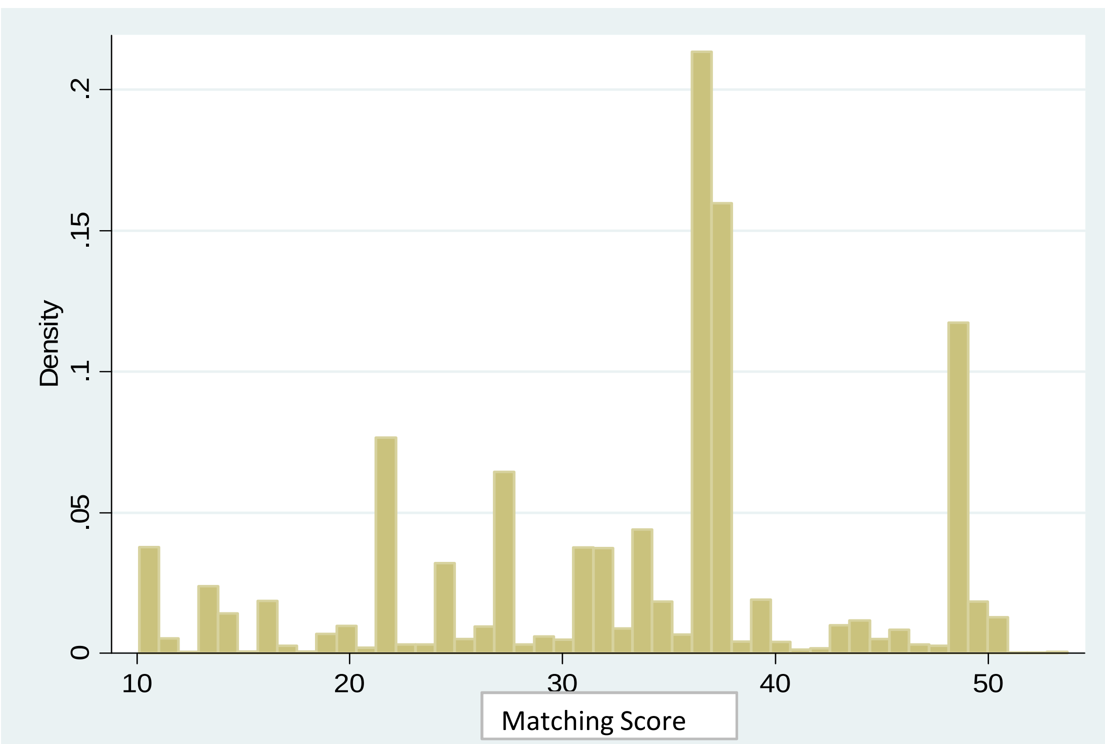
	Number of Observations
Original Sample	145,764
Duplicates	113
Cancelled Calls Or Name Missing	25,546
Response Time Missing	19,294
Injury Illness Code Missing	4,285
Weather Missing	831
Agency Distance Missing	3,888
Not In Salt Lake City Area	11,024
Block group Characteristics Missing	133
Second or Third Etc. on Scene	6,944
Main Regression Sample:	73,706

Note: The final regression sample may differ by one or two observations depending on the specification.

Appendix Figure 1A: Distribution of Matching Scores for Mortality Records



Appendix Figure 2A: Distribution of Matching Scores for ED Records



Appendix Figure 3A: Map of Data Connections