

Trauma Center Efficacy: Certification Status and its Effect on Traffic Fatalities at Varying Radii

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I. Abstract

This paper seeks to determine the optimal placement of emergency trauma center facilities in order to better inform policy makers and improve urban and emergency planning. I examine the effect of emergency department trauma center certification status and of distance from crash site to medical facility on all traffic fatalities for 2002 to 2008 in California. This method of measuring hospital efficacy circumvents issues with selection bias and coding error that may mar more traditional approaches. Hospital addresses are geocoded and compared to the geographic coordinates of fatal car accidents provided through USDOT in order to create a dependent fatality density variable for every hospital at different radii. Demographic controls for different radii are constructed using ArcGIS to serve as a model for traffic fatalities.

JEL classification: **I1; I10; I18**

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II. Introduction

Healthcare costs in the United States have surged in the last 3 decades, increasing tenfold since 1980 (Centers for Medicare and Medicaid Services, 2012). Today, expenditure in the healthcare system stands at \$2.6 trillion and accounts for roughly 17% of total US GDP. Startlingly, 47% of that expenditure is fronted by the US government (OECD, 2011). Given the alarming size and growth of healthcare expenditure and the reality of the US debt situation, economists have increasingly turned their scrutinizing focus upon our medical institutions and systems in search of inefficiency. Today, the field of health economics is a flourishing subset of the dismal science and its study has profound implications in public policy.

A component of health economics research can be qualified as cost-benefit or cost-effectiveness analysis of medical procedures or technology. This is mostly provided as a service to policy makers or healthcare providers who use the analysis in order to decide what medicines, procedures or technologies to cover or provide. This type of research can invoke some interesting methods; a health economist may attempt to determine the value of a statistical life (Sloan, 2012) by examining choices consumers make towards serious healthcare decisions. Additionally, the health economist must take a very wide-scoped approach, valuing secondary as well as primary consequences to the procedure of interest. Another aspect of health economics relates to behavior and analyzing why individuals make the health related decisions they do. This type of analysis is not limited to the consumer of healthcare, the patient. Healthcare providers or institutions can also be analyzed using econometric methods. Topics can range from obesity (Baum, et al, 2009) to surgical outcomes (Courtemanche, 2009) to physician response to financial incentives (Darren, 2009). One aspect of the medical industry that has recently attracted media attention, and that represents a potential target for public policy measures, are emergency departments that have been certified as trauma centers.

A trauma center is a hospital emergency department that provides trauma surgeons, neurosurgeons, other non-surgical and surgical specialists and medical

personnel, equipment and facilities for immediate or follow-up treatment for severely injured patients, 24 hours-a-day, seven-days-a-week (Florida Department of Health). More simplistically, think of a trauma center as a buffed up emergency department inside a hospital. Although laws and regulations differ state to state, standard emergency departments are not required to offer the same level of care as certified trauma centers; the federal Emergency Medical Treatment and Labor Act (EMTALA) only requires that an emergency services provider has “appropriate medical screening examination to anyone who comes to its emergency department asking for treatment and [offer] necessary stabilizing treatment or transfer to another medical facility if the examination reveals an emergency medical condition”. (Spigel, 2003) On the other hand, trauma centers are highly regulated in the types of care that must be available and in the professional and managerial staff on call; consequently, these facilities offer the most advanced level of care available for trauma patients. (California, 2001)

There are some 1300 certified trauma centers in the United States. Hospitals with a trauma center are on average larger, more likely to be a teaching hospital and are more likely to offer specialized services (MacKenzie, 2006). Patients typically are victims of car accidents, gun and knife violence, or falls. Sizes vary, but required facilities, staff and technology are standardized by a national certification body called The American College of Surgeons. The ACS is a scientific and educational association of surgeons that was founded in 1913 to improve the quality of care for the surgical patient by setting high standards for surgical education and practice (Hoyt, 2012). A division of the College is their committee on trauma. This group is responsible for the examination and certification of hospital emergency departments as trauma centers. They provided standardized guidelines that classify trauma programs as either level 1, 2 or 3 with level 1 providing the highest level of care. Criteria are outlined in the ACS publication “Resources for Optimal Care of the Injured Patient” and include requirements for managerial staff, professional staff, technology and services available (American College of Surgeons, 2006). Additionally, some states choose to certify their hospitals independently of the ACS. The departments of health in both Florida and California review emergency department annually and issue their own certification.

Historically, trauma centers have been money-losers for hospitals. To be a certified trauma center, the ACS requires 24 hour staffing of several specialized departments like neurosurgery and thoracic surgery; this requires highly paid, specialized staff and leads to high fixed operating costs. Additionally, government regulation requires that all patients in need must be treated, regardless of their ability to pay. Passed in 1986, The Emergency Medical Treatment and Active Labor Act (EMTALA) guaranteed nondiscriminatory access to emergency medical care. The bill sought to prevent “patient dumping”, the practice in which uninsured patients are transferred from private to public hospitals without consideration of their medical condition because of financial reasons (Zibulewsky, 2001). The bill dictates that all patients, even those without a means to pay, have a right to emergency treatment. The bill does not include provisions regarding reimbursement, however, and hospitals sometimes find themselves covering the cost of patients without insurance. Thus, high costs and unreliable revenue streams have traditionally made trauma centers a risky investment.

Today however, trauma centers are becoming regarded as profitable components of a large hospital. Trauma center hospitals typically offer services that are unavailable at other hospitals in their market, and thus can demand higher reimbursements for rendering trauma services (Galewitz, 2012). On a more structural level, trauma center hospitals have also begun to charge a “trauma activation fee” in the last decade, which is incurred whenever an ambulance arrives with a patient believed to have traumatic injuries to cover the high operating costs associated with their care; these types of fees have contributed to the profitability of a trauma center department. Strategic placement has also played a role in changing the financial viability of trauma centers: trauma center growth has been particularly robust in suburban settings where patients are more likely to be car crash victims and have either auto or health insurance (Galewitz, 2012). Additionally, having a certified trauma center has a “halo effect” on other hospital departments; consumers may perceive that a certified institution offers better care in other departments, driving increased demand (Karkaria, 2011). These combined factors have made a trauma department more attractive to a hospital’s residual claimants.

Given the improved profitability of trauma centers, the last 3 years have consequently seen extensive trauma center growth; since 2009, more than 200 trauma centers have been certified in the US. Most of these new certifications have been at for-profit hospitals (Galewitz, 2012). This proliferation has raised concerns about the optimal number of trauma centers and their efficacy and cost-effectiveness in competitive environments. Some hospitals have started to complain of over competition. The ACS generally recommends having one high-level trauma center for every 1 million people, but need can vary based on distance to the next trauma center, the presence of accident prone industries such as mining or logging, standard emergency department facilities already in place, local driving habits and population demographics. Additionally, larger trauma centers have been proven to generate better health outcomes as surgeons and specialists are exposed to more patients (Nathans et al., 2001; Galewitz, 2012). This makes for a murky picture of the optimal number of high level trauma centers in a market. The fact that some trauma centers receive direct assistance from taxpayers further highlights the need for additional research on the profitability and competitiveness of these institutions in order to guide policy decisions. My thesis will seek to fulfill this need by determining a radius of efficacy of a trauma center.

By examining panel data from the United States Department of Transportation and hospital information from the California Office of Statewide Planning and Development, I am able to examine the number of driving related fatalities around different emergency departments in order to gauge the effect of trauma center certification, and the associated higher levels of staffing, technology and care, at different radii. This would represent an innovative way to examine efficacy of trauma centers. By integrating data on geographical coordinates of vehicular crashes, a radius of effectiveness of a certified emergency department and for different levels of certification (level 1, 2, 3 or 4) can be determined. These conclusions could have policy implications given the recent proliferation of trauma centers and cries of suboptimal levels of competition.

III. Literature Review

Health economics has a strong focus on cost-effectiveness analysis and trauma centers have not escaped the attention of researchers. Some of this research is summarized in this section. However, no study has sought to determine the radius of efficacy of a trauma center. This type of research would prove helpful for policy makers, hospital residual claimants or Certificate of Need boards when making decisions related to trauma center construction or certification. In this way, my research both adds to the body of knowledge on trauma centers and has policy implications.

Several studies have been published on the improved outcomes of trauma centers when compared to traditional emergency departments. The National Study on the Costs and Outcomes of Trauma (NSCOT) was started in order to evaluate mortality of trauma victims. (MacKenzie, 2004) Their approach was to use patient discharge data at selected emergency departments and trauma centers and look for significant differences in mortality and outcome. The authors identified 68 trauma centers in metropolitan areas of varying size and enrolled 18 centers in their study, although their criteria for selection are ambiguous. The study also enrolled 51 standard emergency departments in the same cities as the trauma centers as their control group. Next, the authors selected 5100 patients at trauma and non-trauma emergency departments. All patients were between the age of 18 and 84, were victims of a traumatic injury and had arrived at the hospital alive. Outcomes of interest were death in the hospital, and death within 30, 60, 90 and 365 days after injury.

In their analysis, MacKenzie et al. controlled for injury type, injury severity, vitals and hospital fixed effects. They used a propensity score matching technique to adjust for difference between patient characteristics at the different types of hospitals and then analyzed the differences in mortality. After adjusting for difference in the case mix, the risk of death within one year of injury was significantly lower when care was provided in a trauma center than when care was provided in a non-trauma center. Difference in mortality risk was significantly related to injury severity, meaning that the beneficial effect of a trauma center versus a standard emergency department is more profound for more serious injuries. Age also played a role: although overall risk of

mortality was lower for younger patients, the benefit provided to that group through treatment in a trauma center was greater than for older patients. On average, the authors found roughly a 25% improvement in mortality for patients who were admitted to a trauma center vs. a standard emergency department. MacKenzie et al. close by noting the significance of their publication and its limitations. Previous studies on the efficacy of trauma centers have been inconclusive due to “limitations in study design [due to referral bias] and reliance on in-hospital mortality as a measure”. MacKenzie et al. use a propensity score matching method to control for hospital selection bias and generated data that look beyond hospital mortality. They conclude noting that the results of their study should not be generalized to rural localities due to the scope of the hospitals they studied. The authors also draw attention to the presence of designated trauma response teams and “trauma directors” who operate inside of standard emergency departments; this is not controlled for in their study. They hope to follow up with a more specific examination of intermediate levels of trauma care: levels 2, 3 and 4 as certified by the ACS.

MacKenzie et al. followed up in 2010 with a study that examined the mortality benefits of trauma centers within the context of their cost. As discussed above, trauma centers are expensive to operate because of their round the clock hours and expensive on-call staff. This raises questions as to whether the benefit is worth the higher cost. In their article, MacKenzie et al. underwent a cost-effectiveness analysis of trauma centers compared to standard emergency departments. The study included 5000 patients from 69 participating hospitals, 19 of which had certified trauma centers. Costs per patient were measured by examining everything from treatment and rehospitalization expenses to transportation costs to and from facilities. These costs were derived from hospital bills and self-reported figures. The authors also assumed an increase in lifetime healthcare expenditure costs for patients with spinal cord injury, brain trauma and other severe injuries and included this in their cost estimate. MacKenzie et al. measured effectiveness of treatment by examining incremental lives saved, incremental life years gained and incremental QALYs (Quality Adjusted Life Year) gained due to care in a trauma center versus in a standard emergency department. Baseline life expectancy was

determined by assuming trauma center care did not confer survival benefit beyond one year and that life expectancy should be the same as the average US population. A standard gamble approach with utility scores from 0.00 to 1.00 was used to determine QALYs. The authors discounted measured benefits by costs to produce three metrics to evaluate trauma centers: cost per life saved, cost per life-year gained, and cost per quality-adjusted life year gained. MacKenzie concluded that the cost for each additional QALY associated with treatment at a trauma center is less than \$37,000. On average, cost-effectiveness was more favorable for patients with severe injuries, which may indicate that there are high fixed costs associated with treating patients. For comparison, incremental cost effective ratios for implantable cardiovascular defibrillators (pacemakers) range between \$24,000 and \$50,000 per life-year gained. Given that the traditionally acceptable threshold is roughly \$100,000/QALY, MacKenzie's analysis indicates that trauma centers are an excellent investment given current assumptions about the value of a standard year of life.

Another relevant study related to emergency department usage is "Utilization of the emergency room: impact of geographic distance" by Lee et al.. In their article, the authors seek to quantify the effect of distance on emergency department usage. Their study focuses on emergency departments in Mississippi, the state with the 3rd highest ED department usage rates at 528.10 visits per 1,000 people per year. Lee et al. geocoded the address of 89 hospitals in Mississippi. Geocoding "is a process in which data elements are imported and assigned geographic coordinates (latitude and longitude)" that can later be used to calculate distances between points using geospatial analysis methods. Patients were assigned to one of 2000 block groups based on the location of their residence, each with a geographical center and with demographic characteristics available through census data. Lee et al. assume that patients will choose the emergency department closest to their residence and assign each block group to a service area (SA) associated with a single hospital/emergency department. On average, each SA had 24 block groups, covered 527 square miles of land and contained 31,000 people. Using the 2003 Mississippi State Department's ER visitor database, Lee et al. estimated the utilization ratio for each hospital and compared it to a theoretical utilization ratio based

upon population in a region. Their analysis concluded that geographical distance has a strong negative impact on ER utilization. Less mileage was significantly correlated with higher utilization of emergency department services. This is consistent with economic theory: it implies that time costs are a component of total cost of visiting the ER. The study reveals that an emergency department has a radius of utilization; my paper would expand on this finding to analyze efficacy at different radii.

Given the rate of trauma center growth in the last two years, another relevant research topic is determining the optimal number or density of trauma centers. Some 200 facilities have been constructed in the last three years and some hospital administrators are beginning to voice concerns about their profitability given increased competition (Galewitz, 2012). Trauma center competition has largely not been studied empirically, partially because it is new phenomenon and also because victims of traumatic accidents infrequently elect the hospital they wish to attend. Some studies have attempted to examine the benefits of large, regional trauma centers versus smaller community trauma centers. In one such 2008 study, author Kim looks for economies of scale in trauma centers. The study examines the short-run cost function of hospitals in order to determine marginal cost per patient. Kim used publically available data from the Medicare Cost Reports (MCR) and focused on Texas, a state with a very large number of hospitals. In 2004, 10% of all domestic acute care facilities and 25% of all trauma centers were in Texas. In order to determine marginal cost, Kim used a regression model with total ED costs as the dependent variable and number of ED patient visits as the key independent variable. A variety of additional variables were considered in order to control for the heterogeneity of hospitals. Kim determined that for trauma centers, average cost per patient is greater than marginal cost per patient, indicating the presence of economies of scale. In terms of policy, this conclusion implies that the proliferation of hospital trauma centers may be inefficient from the societal perspective.

In addition to the presence of economies of scale, another article by Nathans et al. concludes that larger trauma centers statistically produce better outcomes. The authors of this article examined outcomes for specific and serious traumatic injuries using a

linear regression model. They controlled for patient characteristics and injury severity as measured at time of admission to the hospital. Their dependent variables were length of stay and inpatient mortality and their key independent variable was trauma volume per year. Nathans concluded that there exists a strong correlation between trauma center volume and outcomes, particularly in more severe cases (Nathans, 2009). This too is a case for fewer, larger regional trauma centers, but no conclusions related to placement or spacing of these facilities are drawn.

Trauma center benefits and efficacy have been measured and documented but, considering recent complaints of increased competition in the wake of trauma center proliferation, radius of benefit is an important consideration that has not yet been studied. Given the increased debate about increased competition due to proliferation of trauma centers, empirical conclusions about the radius of effectiveness of trauma centers could have useful policy implications. In order to study this question, I will enlist panel data on fatal motor accidents from FARS and compare statistics before and after the introduction of a trauma center in the area. Data from OSHPD will be used to control for hospital and patient characteristics and census data can be incorporated to control for regional trends. I will also attempt to investigate the difference in effects for different level of trauma center.

IV. Empirical Framework

In her papers, MacKenzie has demonstrated the efficacy and efficiency of trauma centers through an examination of patient mortality in emergency departments and trauma centers. Additionally, Lee et al. highlight that distance plays a role in emergency department usage. An unaddressed question relates to the radius of efficacy associated with a trauma center. How do outcomes change at different distances when a trauma center enters the market? This is relevant to the recent debate on hospital competition from the increase in number of certified trauma centers. Given the findings of MacKenzie et al. and Lee et al., there should theoretically be a decrease in mortality within a radius of the hospital, but the benefit will diminish as that radius increases. This will be the focus of my research.

Up unto this point, empirical research on trauma center efficacy has been founded upon hospital outpatient data. Hospital emergency departments have been evaluated based on patient health outcomes within one year of injury and subsequent treatment. This is a limiting feature of past studies; certified trauma centers will attract the most serious cases, potentially biasing data. Researchers rely on controls for case mix and scores for injury severity in order to limit this bias. However, this methodology is dubious and there is ongoing debate within the research community about its validity. One study found that case mix insufficiently indicated comorbidities between surgeons. Additionally, the paper noted concerns about the reliability of coding for case mix variables. (Shahian, 2001) Other studies noted the unethical practice of altering classification of surgical procedure for high risk patients in order to maintain better outcome statistics for physicians. (Birkmeyer, 2003) These findings indicate that bias may be present in hospital outcome studies that employ case mix controls to compensate for patient selection.

The methodology employed in my analysis avoids these types of concerns. Efficacy will be judged by using number of vehicular fatalities within a given radius per year. Fatal automobile crashes, as recorded by the local police department and aggregated by the United States Department of Transportation, occur in a specific location with geographical coordinates allowing for analysis of distance to nearest hospital to be used in my analysis. The presence of a trauma center, in theory, improves the mortality statistics in its market; even if it draws more serious cases from other hospitals and its mortality statistics are poor as a result, the odds of dying in a fatal car accident within a given distance of that hospital are presumably decreased. Since I am measuring that decrease and not mortality statistics at individual hospitals, I do not need to control for case mix and sidestep the selection bias issue. This represents an innovative approach to measuring efficacy and allows for analysis of impact at different distances.

In addition to the use of potentially inadequate patient selection bias controls, MacKenzie also raises other important concerns when she discusses the weaknesses of her analysis. She notes that some of the standard emergency departments in her study have designated staff for trauma, even though the hospital is not certified as a trauma

center. This may improve outcomes at those facilities and mask the benefit to mortality provided by a certified trauma center. It is these types of hospital characteristics for which I would like to control; however, data is sparse. When choosing other hospital control variables, it will be important to not include characteristics that factor into certification status of a trauma center. Inclusion of a control which determines the level of certification would lead to instances of multicollinearity with certification status.

Additionally, Lee et al. also raised important points that warrant consideration in my analysis. Local demographic and driving characteristics that correspond to the geographic location of a hospital and a crash site may influence the number of vehicular fatalities. Variables which control for these factors must be included in an analysis. I need to construct a solid model that predicts vehicular fatalities in a region. Miles of road, population, per capita income and weather are variables which might have an effect on car accidents.

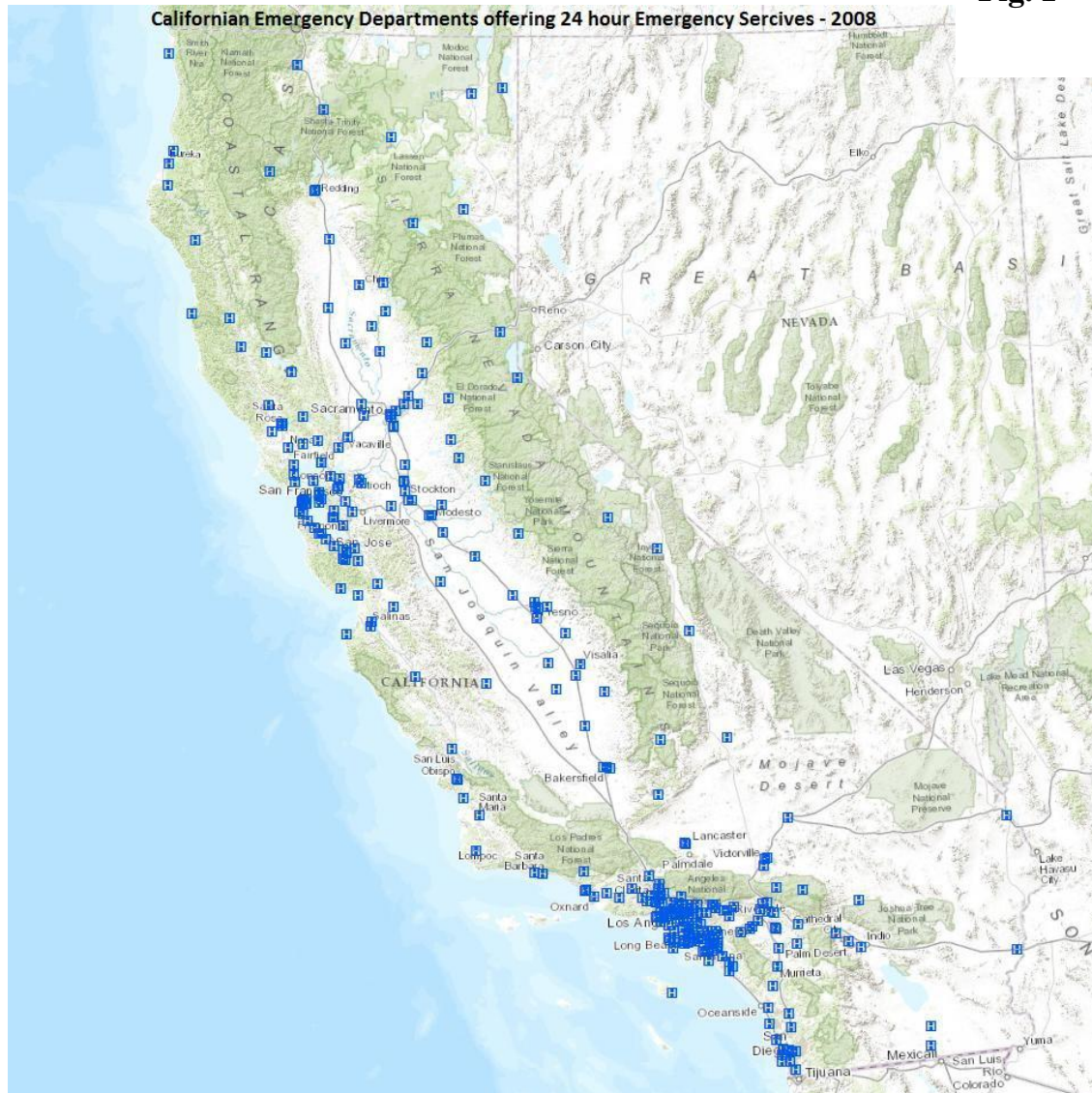
Upon controlling for variables which might influence the number of vehicular fatalities in a given area, for variables independent of trauma center certification that may affect a hospital's ability to save the life of a trauma patient and for time fixed effects, I am able to isolate the effect of trauma center certification (and the associated medical staff/technologies) on vehicular fatalities at different radii. Based on the current body of research related to trauma centers and emergency departments, I hypothesize that certification will be associated with a decrease in road fatalities at most distances, but the significance and coefficient will fall to zero at greater and greater radii. Additionally, I expect level 1 centers to have a greater negative effect on fatalities than institutions with lower level of certifications. I anticipate that these Level 1 centers will also have a larger radius of efficacy than standard emergency departments. In order to test this hypothesis, I draw and merge data from a number of sources.

V. Data

The core of my data comes from the Office of Statewide Health Planning and Development (OSHPD) in California. Finding comprehensive, specific and consistent information on hospitals across the country proved to be somewhat daunting. Fortunately,

OSHPD has extensive annual information on all California hospitals. However, it limits my study to the state of California. It is a large state with some 300 general hospitals with emergency departments in a variety of demographic markets and should prove adequate for analysis of trauma center efficacy. Key components for my analysis are hospital address which can be geocoded into geographical coordinates and trauma center certification level at the time of reporting. OSHPD data goes back to 1999 and represents a comprehensive aggregate set of hospital data for all institutions in the state. The OSHPD hospital financial dataset is publicly available for no charge from the state website. I use data from their annual financial reports in order to construct my hospital control variables. Figure 1 represents the distribution of hospitals with a dedicated emergency department, both those certified as trauma center and those not, in the year 2008. Hospital summary statistics from OSHPD data are included below in Table 1.

Fig. 1



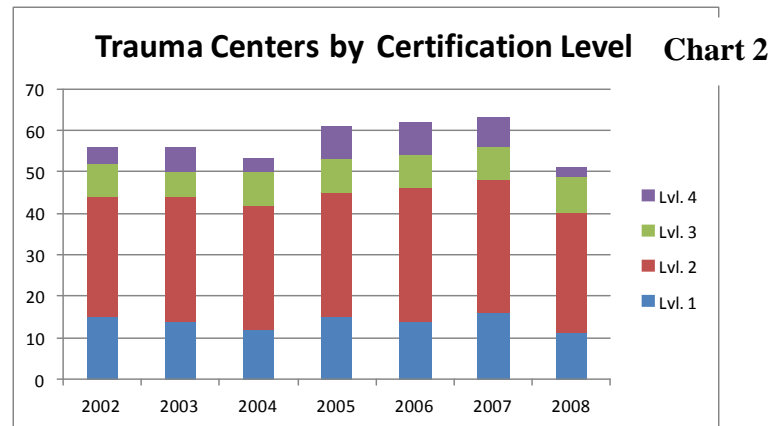
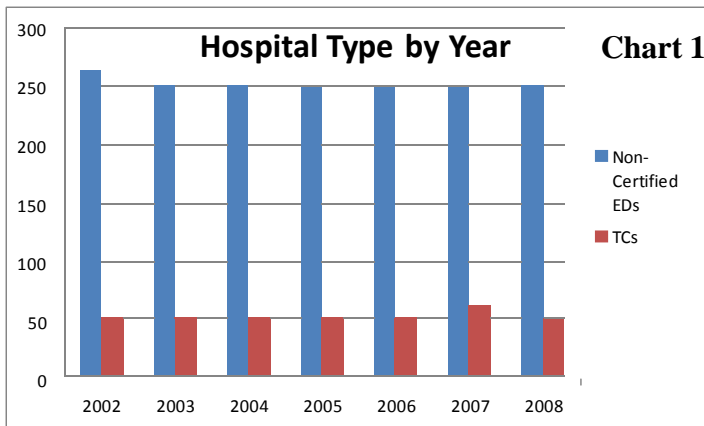


Figure 1 reveals the skewed distribution of hospitals in California; San Diego, Los Angeles and the San Francisco Bay Area have a high concentration of facilities, while hospitals in less populated areas are predictably fewer and farther between. Charts 1 and 2 summarize the number of trauma centers in California. In 2008, which is a reasonably representative year for the entire dataset, trauma centers make up only 57 of all emergency departments in California; this low sample size necessitates the use of panel data in order to increase the power of my regression model. However, even after including several years of data, my number of samples is still rather low; it sits just in the mid thousands for the full regression. Number of samples may represent a shortcoming of my model, especially when analysis is broken down to examine hospitals by certification level. It is also worth noting that the count for Level 3 and 4 centers is very low. In my regression model, I combine these two groups to account for this.

Fatality information comes from The Fatality Analysis Report System (FARS). FARS is a free and public database provided by the United States Department of Transportation and is available online. It includes more than 5 million police-reported motor vehicle crashes each year and provides geographical coordinates of each crash.

Additionally, other information from the USDOT will be important in controlling for driving habits of a region. Miles of major roads, population and income are all important time variant factors that might affect that might influence driving fatalities. Geographical information through FARS is available for years 1999 and onwards. It is

worth noting that California is in some ways exceptional in the driving habits of its residents. The state was one of the first to pass legislation banning cell phone use while driving and penalties for speeding are higher on average. (Steinhauer, 2008) Californian gas prices, a variable that certainly affects driving habits, are typically the highest in the continental United States. This is worth considering before applying the results of my findings to other states.

Control variables related to radii buffers surrounding hospitals will come from Geolytics annual demographic data. This resource is available through Professor Frank Sloan's office and includes indicators like education, income, population density, etc. for each zip code in America. Originally, census data was to be used for this purpose. However, given the once-every-four-years nature of the survey, it was ill suited to the role. The advantage of Geolytics is that the information is provided yearly. Unfortunately, Geolytics data is only available for 2002 to 2008. This severely limits the scope of my model.

VI. Empirical Specification

This section discusses the regression model I will employ in my analysis. I conclude with a discussion of the variables and strengths and weaknesses of the model. My regressions will examine the relationship between number of vehicular fatalities within different radii of an emergency department inside a hospital and the trauma center certification status of that emergency department. Intuitively, at least some fatalities should be a function of the availability of nearby emergency care. Yes, some victims will never make it to the hospital and their deaths will be exogenous of nearby care, but there is a causal relationship for others. Trauma centers provide better care according to research, so the assumption is that fatalities should be lower in a market with a trauma center after controlling for other region/hospital specific characteristics. That decrease should be measurable by using a regression model with adequate controls. I propose the following model:

$$Fatal_{th} = \alpha(TC\ Cert.)_{th} + \beta(LocalChars)_{th} + \gamma(HospChars)_{th} + FE_t + \epsilon$$

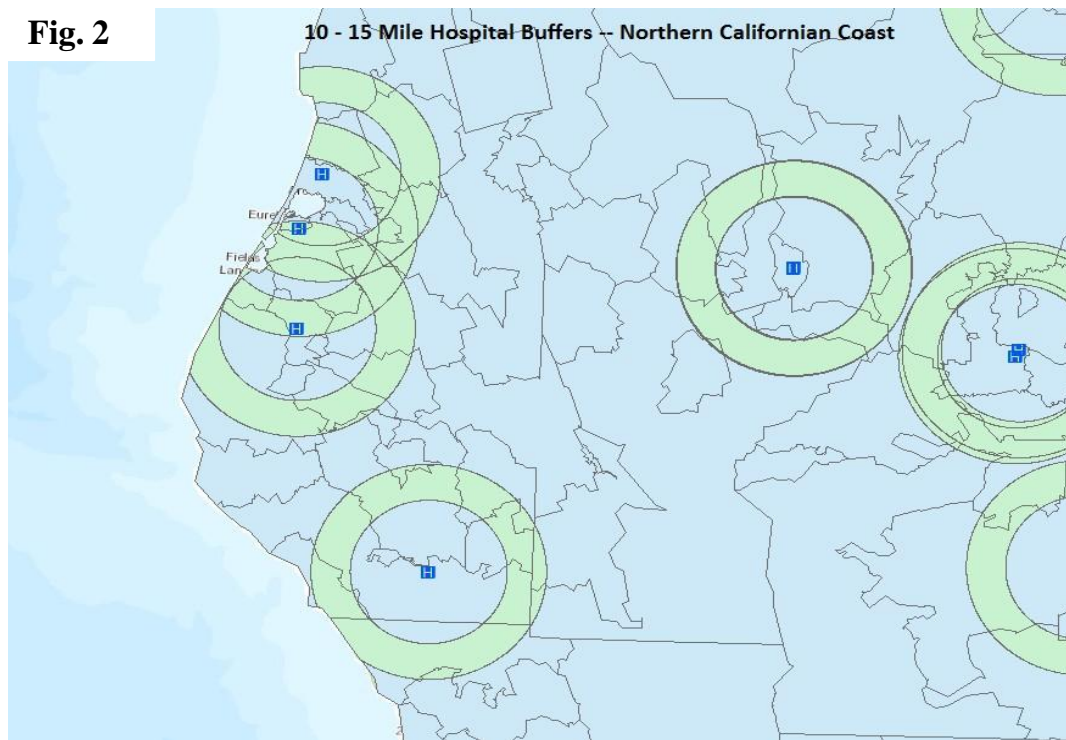
$Fatal_{th}$ represents the density of road traffic fatalities within some radius of each

hospital in a given year. Density is employed in order to allow comparison of coefficients between regressions on different radii. It is calculated simply by dividing the number of fatalities within the given distance and dividing by the area of the donut sized zone. The result is a parameter with units as deaths per square mile per year. Buffer area over water or in other states was not counted, compensating for hospitals on or near the coast.

$TC Cert._{th}$ represents a binary variable that indicates whether a given emergency department is certified by the California Department of Health as a trauma center in a given year. In my second regression, three additional dummy variables are included in order to discriminate between trauma certification levels. I hypothesize that the coefficient α on $TC Cert._{th}$ will be negative, indicating that a trauma center decreases the number of vehicular fatalities within a given a radius, but also that the magnitude of α will decrease at greater radii, indicating that the effect of a trauma center on a given accident decreases with distance. In my analysis I run eight regressions, each examining a different radius: fatalities within 5 miles, at a distance between 5 and 10 miles, between 10 and 15 miles, between 15 and 20, etc., stopping at radius of 40 miles where I anticipate no effect by the trauma center. Intuitively, 40 miles seems like a safe number to use as the furthest radius to analyze; at that distance, there is a higher likelihood that a hospital will not affect the outcome of a victim of a car crash. A 42 mile radius was determined to contain 90% of patient admissions for all Californian hospitals in the year 1989 in a study on hospital market size using OSHPD data; this supports the use of 40 miles as a maximum distance. (Phibbs, 1993)

As discussed above, it is important to create a reliable model to predict traffic fatalities at different radii. In order to accomplish this, circular buffer rings were drawn around each hospital in the dataset. These buffers, represented below in Figure 2, each have 5 miles between their inner and outer radius. They were superimposed on a map containing Californian zip codes, creating many oddly-shaped, intersecting polygons.

The area of each polygon was recorded and used to discount the demographics of each associated zip code. This methodology assumes that demographic characteristics are uniform throughout the entire area of the zip code. Demographics were prepared differently depending on what kind of statistic they represented. If the demographic variable was a total, such as population or number of households, the statistic was



of people or households inside the polygon. The discounted value for each polygon in a buffer was summed in order to determine the total value for the entire ring. Alternatively, if a demographic statistic represented a generalization for the entire zip code, such as population density or median income, each value was multiplied by the ratio of polygon area to ring buffer area; each of these values were summed for all the polygons in a ring in order to produce a weighted average variable. This methodology is particularly useful because it allows for comparison of all hospitals, even those on the coast with buffer areas in the ocean. Correlation between population density and population after this transformation was 1, implying that the methodology was both well devised and correctly executed. These constructed values constitute the *LocalChars* variables in my model. Before listing and discussing the variables prepared, it is worth noting that ideally these controls would be indicative of the demographics of the people driving through the region, rather than of the people living in the area. Presumably, these characteristics are related and thus the variables I have constructed are decent proxies.

With this in mind, *LocalChars_{th}* are used in order to construct a model for number of fatal accidents at different radii. Research indicates that income can play a role in number of traffic fatalities (Maureen et al., 2004), as well as factors like age demographics (Bédard, 2008; Reason et. al., 2010). Unemployment has been observed to

a have negative and significant effect on fatalities, implying that commuter volume is an important component of accidents. (Levine, 2006) These types of controls were incorporated from the Geolytics database. Major road length was derived using ArcMap 10.1 and map layer from ESRI. Proxies were employed in order to get at other significant variables. Research indicates that seatbelt use is related to vehicular fatalities (Bédard, 2008). Although seatbelt usage might vary from hospital market to hospital market, there is no database with usage statistics on such a granular level as it is a somewhat latent variable. Educational attainment is related to seatbelt use and is used as a proxy. Alcohol abuse is also relatively unobservable and is linked to car accidents (Bédard, 2008); a proxy related to household expenditure on alcoholic beverages is included in some models below.

In addition to controls variables that influence the number of vehicular accidents within a hospital market, controls for variables that might affect a hospital's ability to save an accident victim's life must also be implemented. *HospChars_{it}* represents these factors that relate to hospitals in a given year. The key will be choosing variable which are informative/significant but are exogenous of my variable of interest, trauma center certification. This avoids instances of multicollinearity. This proved to be difficult. Certification by the state covers a vast array of services that must be required, and even includes requisite patient volume levels and dedicated trauma managerial staff. (California, 2001) Transportation services to the hospital might play a role but are also certification criterion. Additionally, trauma centers are more likely to be teaching hospitals, ruling out that variable. Ultimately, these variables were excluded from my final model.

Finally, FE_t represents fixed effects control for each year. For this analysis, panel data is employed and a time fixed effect variable will control for latent or unobservable changes felt throughout the state in a given year. This variable will control for components like vehicle safety and changes in laws and enforcement. This is important because legislation did change during my study; in 2006, California banned the use of handheld phones while driving. In addition to a time fixed effect, I also considered including a hospital fixed effect. However, after further examination of my data, there is insufficient variation of hospital certification status across my 7 year data period. Including a hospital FE would likely lead to issues with multicollinearity

VII. Results

Regression results are summarized below in Tables 2, 3 and 4. In each set of regressions, the dependent variable, $Fatal_{it}$, is measured in consistent units throughout: deaths per square meter per year within the given radius.¹ The use of a density variable allows for coefficient comparison between regressions, even when different sized areas are being compared. However, it also makes the coefficients on controls less tangible and incomparable to other studies. Each regression analyzes traffic fatality density and demographic characteristics at a different donut-shaped, ring buffers around a unique hospital-year. In Table 1, each ring buffer is 10-miles wide, from inner radius to outer radius. Variables of interest are listed underneath the Trauma Center Certification header and represent dummy variables with a value of (1) if a hospital is a certified at a specified level by the California Department of Health in a given year. Control variables are listed and include three variables relating to education, population and road mileage. These variables are different for each radius for each hospital for each year. For time fixed effects, 2002 is omitted as the baseline year.

In other iterations of my model, many other controls related to hospital and demographic characteristics are also regressed; these models are discussed in the next section. In Table 2 and in this section however, only three control variables are included

Table 1

Fatality Summary Statistics within variable radii of CA Hospitals in 2008				
Number of Fatalities	Mean	St. Dev.	Min	Max
Within 5	25.74	19.93	0	102
Within 10	77.54	64.77	0	287
Within 15	145.05	119.93	0	466
Within 20	220.50	177.91	0	645
Within 25	297.29	230.53	0	779
Within 30	372.38	278.73	0	919
Within 35	444.10	321.76	6	1092
Within 40	514.39	357.72	8	1253

¹ Each death density dependent variable is multiplied by 10^8 so that coefficients on dependent variables are more easily understood.

in each regression: Major Road Density, Percentage Population with Higher Education, and Population Density. These controls were the most significant and consistent throughout my experimentation and represent the best model for traffic fatality density. In Table 2, Adjusted R-squared values are all above 0.94, a very high value for a sample size of just 2175. With 6 additional control variables related to demographics included, these R-squared values barely increased, budging upwards by less than 0.002 in each regression. Additionally, including additional controls beyond the three in Table 1 actually decreased the F statistic for significance of the regression. Omitted variable bias also does not seem to be present in this three control model as coefficients on the control variables and variables of interest are consistent with other models where all variables are included. For these reasons, I believe that this is my best model for traffic fatalities.

California Trauma Center Certification and Fatality Density at Variable 10 Mile Radii **Table 2**
2002 - 2008

	Radius (mi):								n=2175
	0 to 10	10 to 20	20 to 30	30 to 40	0 to 10	10 to 20	20 to 30	30 to 40	
Trauma Center Certification									
All Levels	0.051608 0.46	0.008856 0.11	0.036123 0.79	-0.11166 -3.07	-	-	-	-	
Level 1	-	-	-	-	0.309448 1.43	-0.04247 -0.27	0.116212 1.35	-0.07671 -1.12	
Level 2	-	-	-	-	0.318875 2.15	0.248872 2.26	0.168413 2.82	-0.03003 -0.63	
Level 3,4	-	-	-	-	-0.77782 -3.52	-0.48785 -2.97	-0.35487 -3.99	-0.34017 -4.8	***
Controls									
Major Road Density	3061.665 44.14	3959.923 49.88	3771.702 53.26	4351.853 54.53	3013.206 42.9	3938.24 49.44	3746.83 53.06	4335.842 54.25	***
Pct w/ higher education	-10.5137 -21.71	-13.6193 -30.1	-11.5449 -35.98	-10.2374 -33.69	-10.8198 -22.2	-13.8322 -30.35	-11.69 -36.48	-10.2595 -33.85	***
Population Density	0.001698 62.77	0.001572 37.69	0.001872 42.46	0.001935 31.73	0.001704 63.15	0.001576 37.85	0.001876 42.77	0.00193 31.67	***
Year									
2003	0.553518 3.42	0.535115 4.43	0.372288 5.67	0.237979 4.54	0.553106 3.43	0.534352 4.44	0.372029 5.7	0.237692 4.55	***
2004	-0.13765 -0.85	0.134191 1.11	0.189748 2.89	0.160413 3.06	-0.13592 -0.84	0.132161 1.1	0.189154 2.89	0.159786 3.05	**
2005	0.045279 0.28	0.117121 0.97	0.256922 3.91	0.908724 16.41	0.058112 0.36	0.123708 1.03	0.261854 4.01	0.909966 16.47	***
2006	0.552555 3.41	0.678799 5.61	0.432373 6.57	0.343324 6.54	0.563311 3.49	0.683481 5.67	0.43655 6.67	0.345601 6.6	***
2007	0.229386 1.42	0.361689 3	0.311283 4.74	0.102892 1.96	0.235772 1.46	0.364986 3.03	0.313611 4.8	0.10428 1.99	*
2008	-0.86977 -5.35	-0.33612 -2.77	-0.38687 -5.87	-0.37744 -7.17	-0.86808 -5.36	-0.33777 -2.79	-0.3868 -5.9	-0.37754 -7.19	***
Adjusted R-squared:	0.9486	0.9474	0.9495	0.9406	0.949	0.9477	0.9598	0.941	
0.0062939	Coefficient	***	p-value < .001						
4.18	t-value	**	p-value < .01						
		*	p-value < .1						

Coefficients on each of my three control variables conform to expectation. Major Road Density is a linear density variable that is indicative of interstates, state highways and major thoroughfares as determined by ESRI, a GIS software company. The coefficient is positive and highly significant in all regressions with a t-statistic of at least 44.0 at each distance. This makes intuitive sense; the more roads, the more possibility for traffic accidents. Additionally, the variable probably represents a good proxy for commuter volume and total traffic volume in the buffer area, both of which would be positively correlated with traffic deaths. It is worth noting that the large coefficient on this control is reflective of the low magnitude of major road density variable in the data.

Likewise, the education variable conforms to expectation with a significant and negative coefficient. The control represents the percentage of the population living in the ring area that has a bachelor's or more advanced degree. The literature indicates that seatbelt use is correlated with education which in turn is related to a decrease in fatalities. Additionally, individuals with more educational attainment may be safer or smarter drivers. They may also drive safer, more expensive cars which would also decrease traffic fatalities in a region. The coefficient is strongly negative with t-values consistently less than -20.

The third control, Population Density, is strongly significant with positive coefficients across all regressions. This is intuitive as more people in an area will likely mean more traffic deaths. The t-value for the 0 to 10 mile radius buffer is as high as 62, indicating a high level of significance. All in all, the coefficients and significance levels on the controls coupled with the high adjusted R-squared values imply that this is an effective model for predicting traffic fatalities at all radii from a given hospital. With this in mind, we turn to look at the results on the trauma center dummy variables of interest.

The strongest support for my hypothesis comes from the regressions that break trauma center certification down by level. Level 3 and 4 trauma centers had a significant and negative impact on traffic fatalities at all distances. The effect is strongest at the 0 to 10 mile radius, as predicted, and then drops by about 60% for larger radii. The coefficients were still significant at the 30 to 40 mile radius, so I saw neither a decrease in significance as distance increased nor a consistent decrease in coefficient magnitude. In general though, the results on the Level 3 certification dummy match my

own predication and the findings of the literature on trauma center efficacy. Unfortunately, coefficients on other trauma center certification dummy variables were largely insignificant and did not support my initial hypothesis. The coefficients on the All Levels of certification dummy were only negative and weakly significant on fatality density at the 30 to 40 radius. For the 0 to 10 mile buffer, the sign on the coefficient was negative, but not significant. At the 10 to 20 and 20 to 30 mile radius, the coefficient was neither the predicted sign nor significant. Breaking certification down by level in the four rightmost regressions yielded more interesting results, however. Results on Level 1 and Level 2 centers also do not support my hypothesis. Signs on coefficients varied at different distances and results indicate a significant, positive relationship between Level 2 trauma centers and fatalities between 0 and 30 miles of each hospital. Level 1 trauma center coefficients were both positive and negative across regressions and were not significant at any distance. These results do not conform to my hypothesis and contradict findings in the literature.

**California Trauma Center Certification and Fatality Density at Variable 5 Mile Radii
2002 - 2008**

Table 3

	n = 2175							
Radii (mi):	0 to 5	5 to 10	10 to 15	15 to 20	20 to 25	25 to 30	30 to 35	35 to 40
Trauma Center Certification								
TC-0	0.448118 * 2.1	-0.05999 -0.5	0.147252 1.36	-0.07344 -0.85	0.114226 * 1.86	-0.02584 -0.51	-0.04446 -1.01	-0.18999 *** -4.32
Controls								
Major Road Density	2779.805 *** 24.06	3257.296 *** 46.17	3521.825 *** 43.78	4146.819 *** 44.93	3811.973 *** 46.28	3664.638 *** 45.32	4169.739 *** 46.74	5062.708 *** 62.07
Pct w/ Higher Education	-15.6725 *** -20.27	-9.54558 *** -18.49	-14.7832 *** -28.47	-13.1284 *** -27.42	-11.571 *** -29.66	-11.6989 *** -32.05	-10.593 *** -31.15	-9.42712 *** -24.87
Population Density	0.001777 *** 45.08	0.001644 *** 56.35	0.001745 *** 45.71	0.001497 *** 28.22	0.001729 *** 34.3	0.00204 *** 39.84	0.001873 *** 30.38	0.001404 *** 21.39
Year								
2003	0.877402 ** 2.87	0.448676 ** 2.6	0.541362 ** 3.47	0.526667 *** 4.22	0.431857 *** 4.89	0.324131 *** 4.44	0.264384 *** 4.2	0.216295 ** 3.41
2004	-0.1625 -0.53	-0.12295 -0.71	0.106591 0.68	0.156994 1.26	0.232425 ** 2.63	0.155045 * 2.12	0.215354 ** 3.42	0.120166 * 1.89
2005	0.018198 0.06	0.062087 0.36	-0.04488 -0.29	0.235543 * 1.89	0.287152 ** 3.25	0.232368 ** 3.18	0.321707 *** 5.11	1.121452 *** 15.3
2006	0.345529 1.13	0.635479 *** 3.68	0.743836 *** 4.76	0.631395 *** 5.06	0.531806 *** 6.01	0.350318 *** 4.8	0.413681 *** 6.56	0.295258 *** 4.65
2007	0.035003 0.11	0.307079 * 1.78	0.334234 * 2.14	0.383782 ** 3.08	0.446568 *** 5.06	0.198721 ** 2.72	0.139928 * 2.22	0.092585 1.46
2008	-1.43719 *** -4.69	-0.66531 *** -3.84	-0.36269 * -2.32	-0.31849 * -2.55	-0.37454 *** -4.22	-0.3983 *** -5.44	-0.34869 *** -5.51	-0.37688 *** -5.92
Adjusted R-Squared	0.8777	0.9387	0.9322	0.9363	0.945	0.9404	0.9345	0.8968
0.0062939 4.18	Coefficient t-value	*** ** *	p-value < .001 p-value < .01 p-value < .1					

In an attempt to improve my results, I ran regressions on smaller 5 mile ring buffers around each hospital. The results are summarized in Tables 3 and 4, below. In Table 3, a single dummy variable is used for trauma center certification, while Table 4 breaks down certification by level.

The results on the controls in both Table 3 and Table 4 conform to expectation and match what was represented in Table 2. An increase in Population Density and Major Road Density both are significantly associated with an increase fatality density in all regressions. Conversely, an increase in the percentage of individuals with a bachelor's degree or better decreases it. t-values range from the mid 20s to low 50s, indicating that these coefficients are strongly significant. Additionally, the high adjusted R-squared values indicate that this is a good model for traffic fatality density.

Also similar to Table 1, the results for the trauma center certification dummy

**California Trauma Center Certification and Fatality Density at Variable 5 Mile Radii
2002 - 2008**

Table 4

		n=2175							
	Radii(mi):	0 to 5	5 to 10	10 to 15	15 to 20	20 to 25	25 to 30	30 to 35	35 to 40
Trauma Center Certification									
Level 1	0.955639 *	0.101919	0.371613 *	-0.25986	0.143977	0.118346	0.085049	-0.26138 **	
	2.32	0.44	1.81	-1.59	1.25	1.24	1.04	-3.15	
Level 2	0.955031 **	0.120938	0.352223 *	0.196887 *	0.298495 ***	0.068513	0.056961	-0.10743 *	
	3.41	0.76	2.47	1.73	3.71	1.03	1	-1.86	
Levels 3,4	-1.10919 **	-0.61563 **	-0.54654 *	-0.50234 **	-0.3435 **	-0.39679 ***	-0.42297 ***	-0.30555 ***	
	-2.67	-2.61	-2.57	-2.96	-2.87	-4.02	-4.98	-3.56	
Controls									
Major Road Density	2702.345 ***	3225.787 ***	3487.113 ***	4130.914 ***	3783.706 ***	3639.336 ***	4153.598 ***	5055.271 ***	
	23.15	45	43.07	44.71	46.01	45.04	46.71	61.59	
Pct w/ Higher Education	-15.9551 ***	-9.78015 ***	-15.1063 ***	-13.2608 ***	-11.7371 ***	-11.8273 ***	-10.6634 ***	-9.42765 ***	
	-20.64	-18.72	-28.78	-27.58	-30.06	-32.43	-31.51	-24.89	
Population Density	0.001779 ***	0.001649 ***	0.001751 ***	0.001499 ***	0.001734 ***	0.002042 ***	0.001864 ***	0.001399 ***	
	45.31	56.47	45.93	28.32	34.55	40.03	30.33	21.29	
Year									
2003	0.877039 **	0.448352 **	0.541554 **	0.525364 ***	0.431341 ***	0.324104 ***	0.264343 ***	0.215734 **	
	2.88	2.6	3.48	4.23	4.9	4.46	4.22	3.41	
2004	-0.15817	-0.12209	0.107173	0.153427	0.231176 **	0.155102 *	0.215134 **	0.118914 *	
	-0.52	-0.71	0.69	1.23	2.63	2.13	3.43	1.88	
2005	0.043361	0.070419	-0.03502	0.240765 *	0.292983 **	0.236995 **	0.326383 ***	1.11979 ***	
	0.14	0.41	-0.23	1.94	3.33	3.26	5.21	15.28	
2006	0.366778	0.64241 ***	0.752647 ***	0.634153 ***	0.536267 ***	0.354695 ***	0.418186 ***	0.295763 ***	
	1.2	3.72	4.83	5.09	6.09	4.87	6.67	4.66	
2007	0.047681	0.311166 *	0.339325 *	0.386237 **	0.449266 ***	0.20093 **	0.142478 *	0.093258	
	0.16	1.81	2.18	3.11	5.11	2.77	2.28	1.47	
2008	-1.43259 ***	-0.66454 ***	-0.36123 *	-0.32189 *	-0.37527 ***	-0.39744 ***	-0.34778 ***	-0.37798 ***	
	-4.69	-3.84	-2.31	-2.58	-4.25	-5.45	-5.53	-5.94	
Adj. R-squared:	0.8787	0.9389	0.9326	0.9366	0.9455	0.9409	0.9352	0.8968	
0.0062939	Coefficient	***	p-value < .001						
4.18	t-value	**	p-value < .01						
		*	p-value < .1						

variables are inconsistent with my hypothesis. In Table 3, the coefficient on certification status is only negative and significant at the 35 to 40 miles radius. I had hypothesized that measurable impact would have diminished at this radius. Certification effect is also weakly significant at the 0 to 5 and 20 to 25 mile radius, but the sign is positive indicating that trauma centers were associated with an increase in traffic fatality density. In general, these results contradict my hypothesis and literature on trauma center efficacy.

Table 4 yields similar results to those in Table 2 broken down by trauma center certification level. The dummy variable for Level 3 and 4 hospitals is significant and negative across all 8 rings buffers. The magnitude of effect is highest at the closet, 0 to 5 mile radius and then has a general decreasing trend as distance increases, the exception being at 25 to 30 and 30 to 35 radii where magnitudes edges up slightly. On Level 1 and Level 2 institutions, results do not support my hypothesis. Coefficients on Level 1 institutions are positive and significant for the 0 to 5 mile and 10 to 15 mile regressions. A coefficient is only negative and significant at a radius of 35 to 40 miles. Coefficients on Level 2 institutions are at least weakly significant for 5 of the 8 regressions, but the sign on the coefficient is positive for all of those regressions, except for the 35 to 40 mile regression. This inconsistency is troubling as it contradicts both my hypothesis and the larger body of trauma center research which indicates that certified centers improve mortality outcomes.

Given that my results generally run counter to intuition and the greater body of literature on trauma center efficacy, it is worth discussing my preliminary regressions and thought process behind selecting the three controls employed in my final model. My initial empirical specification made use of many control variables. The results for this regression are summarized below in Table 5. Nine control variables were used in this model, including the 3 that were used in the final regressions in the previous section. Trauma center coefficients were almost unchanged from the results above in Table 3.

California Trauma Center Certification and Fatality Density at Variable 5 Mile Radii

Table 5

2002 - 2008

n = 2175

Radii (mi):	0 to 5	5 to 10	10 to 15	15 to 20	20 to 25	25 to 30	30 to 35	35 to 40
Trauma Center Certification								
Any Level	1.17E-10 0.06	-2E-09 -1.64	1.42E-09 1.31	-8.7E-10 -1.02	1.16E-09 * 1.93	-4.9E-10 -1	-7E-10 -1.64	-1.7E-09 *** -4.29
Controls								
Unemployment	-8.1E-08 *** -4	-2.3E-08 ** -2.69	-1.4E-08 * -2.25	-2.5E-08 *** -4.15	-2.9E-08 *** -7.11	-1.1E-08 *** -4.05	-1.9E-08 *** -5.63	5.74E-12 *** 16.05
Pct Public Transit Users	1.24E-06 *** 7.28	1.07E-07 0.98	2.28E-07 * 2.31	8.1E-08 1.12	6.95E-08 1.3	6.29E-08 * 1.7	-5.7E-08 -1.63	-7.7E-13 *** -3.93
Median Income	-2E-14 -0.1	-5E-13 ** -3.4	1.79E-13 1.24	-1.3E-14 -0.1	-6.9E-13 *** -6.67	-9.4E-13 *** -9.66	-7.3E-13 *** -7.47	-1.2E-13 ** -2.62
Rate Pop. Chng	4.05E-10 *** 3.85	2.73E-10 ** 3.4	1.35E-11 0.16	-2.8E-11 -0.37	-2.4E-11 -0.4	1.07E-10 * 2.12	1.21E-10 * 2.46	2.73E-11 0.6
Population Density	1.74E-11 *** 41.91	1.62E-11 *** 44.5	1.72E-11 *** 36.22	1.42E-11 *** 22.12	1.6E-11 *** 25.88	1.77E-11 *** 29.56	1.74E-11 *** 25.48	1.88E-11 *** 25.77
Major Road Density	2.56E-05 *** 21.2	3.27E-05 *** 35.81	3.61E-05 *** 33.58	4.35E-05 *** 37.03	4.12E-05 *** 38.44	4.29E-05 *** 41.26	4.43E-05 *** 41.74	4.43E-05 *** 43.88
Pct Pop. aged 15 - 24	1.63E-07 ** 3.43	6.62E-08 * 1.84	4.72E-09 0.12	2.16E-08 0.63	-7.8E-08 ** -2.96	-1.2E-07 *** -5.03	-1E-07 *** -4.33	3.83E-08 * 1.84
Pct. w/ Bac or better	-4.8E-08 ** -3.39	-8.6E-09 -0.66	-1.9E-07 *** -11.31	-1.7E-07 *** -11.71	-1.4E-07 *** -12.51	-1.3E-07 *** -11.99	-1.1E-07 *** -10.98	-8.9E-08 *** -8.87
Mean HH EtOH Spending	-1.6E-10 *** -4.52	-1E-11 -0.43	4.27E-12 0.18	3.06E-11 1.43	1.21E-10 *** 7.1	1.52E-10 *** 9.66	1.12E-10 *** 7.01	-5.3E-13 -0.05
Year								
2003	9.19E-09 ** 3.14	4.07E-09 * 2.38	5.35E-09 ** 3.43	5.04E-09 *** 4.09	3.73E-09 *** 4.34	2.5E-09 *** 3.56	2.12E-09 ** 3.44	2.01E-09 *** 3.53
2004	-7.2E-10 -0.24	-1.9E-09 -1.12	9.3E-10 0.59	1.16E-09 0.93	1.08E-09 1.24	-2.2E-11 -0.03	1.01E-09 1.62	9.47E-10 1.64
2005	1.84E-09 0.61	-3.6E-10 -0.2	-6.1E-10 -0.38	1.75E-09 1.36	9.3E-10 1.03	-1.6E-10 -0.22	1.43E-09 * 2.22	-3.9E-09 * -2.36
2006	6.02E-09 * 1.94	5.23E-09 ** 2.87	7.23E-09 *** 4.33	5.46E-09 *** 4.1	2.56E-09 ** 2.72	-2.3E-11 -0.03	1.61E-09 * 2.38	2.53E-09 *** 4.22
2007	3.79E-09 1.18	1.72E-09 0.9	3.06E-09 * 1.75	2.75E-09 * 1.97	8.63E-10 0.86	-2.6E-09 ** -3.22	-2E-09 ** -2.71	3.77E-10 0.6
2008	-1E-08 ** -3.03	-8.3E-09 *** -4.11	-4E-09 * -2.14	-4.6E-09 ** -3.04	-8.3E-09 *** -7.7	-9.8E-09 *** -11.13	-7.8E-09 *** -9.8	-4.4E-09 *** -6.59
Adj. R^2:	0.8886	0.9494	0.9328	0.9381	0.9482	0.9452	0.938	0.9166
0.0062939	Coefficient	***	p-value < .001					
4.18	t-value	**	p-value < .01					
		*	p-value < .1					

In another set of regressions, I removed all the insignificant variables from the regressions in Table 5. This created a model with different controls at different radii. Trauma center coefficients were largely the same: still insignificant and lacking a consistent sign throughout. Ultimately, I did not present this model because it was inconsistent in the variables used as controls across regressions.

I settled on my three variable control model because it offered the highest values for the F-statistics across all regressions and did not reveal evidence of omitted variable bias when compared to regressions with additional variables included.

VIII. Conclusion

At face value, my results imply that only Level 3 trauma centers provide a consistent benefit throughout their market, while Level 1 and Level 2 institutions actually increase death rates. My regressions are somewhat innovative and largely get around methodological weaknesses persistent in other trauma center research; because I am looking at deaths in a radius of each hospital I do not need to use potentially flawed controls like patient comorbidities or severity scores which can be influenced by patient selection bias and doctor mislabeling. It is possible that my model is a better approximation of the effects of trauma centers. However, there are several other possibilities that might explain the discrepancy between my results and those found in the literature.

When building or upgrading an emergency department to a certifiable trauma center, presumably executives and policy makers consider an array of variables, profitability and potential societal benefit being among them. It is possible and likely that high level trauma centers are placed where accidents are most common, where access to the hospital is easiest and, possibly, where patients are more likely to be able to pay. If my controls do not adequately account for this selection bias, my model may not be able to distinguish the benefit of trauma centers.

Additionally, my model is somewhat limited in scope. Trauma centers serve a wide patient base with a variety of ailments from heart attack to gunshot wound. My

model only examines deaths in car accidents; this allows for geospatial analysis, but limits the wider applicability of my results. It is possible that if my research had included other additional types of injury, as most published papers have, I would find significant and beneficial results to fatalities. It is also possible that the effects of trauma centers go beyond the simple binary of survival and death. The benefits of trauma centers may be realized in decreased recovery times or fewer adverse health events during treatment. Current research suggests that this is the case; trauma centers save QALYs in a cost effective manner (MacKenzie, 2010). My model only looks at deaths, not at improved health or other beneficial outcomes.

An alternative issue may be that my model is not powerful enough to pick up the impact of trauma centers on traffic fatalities. It is the sad reality of car accidents that many victims will die at the scene or on the way to the hospital. A hospital's emergency department may have no influence on the health outcomes of these individuals. Given that the impact of EDs on these types of accidents can be limited, a greater sample size may be necessary in order to elucidate the beneficial effect of trauma centers. This could be accomplished by incorporating hospital information from additional states. Unfortunately, such data is not readily accessible outside of California. Increasing the number of years in my sample would have also increased power, had demographic data been available for 2009 onwards.

It is also possible that trauma certification does not fully represent every emergency department equipped with enhanced, life-saving facilities for trauma patients. As noted in the literature review, some standard EDs have advanced trauma care/staff available but are not certified. A department might meet all but one of the state's criteria and thus not be listed as a trauma center. If some standard, non-certified emergency departments have similar life saving capabilities as trauma centers, the significance of the certification status dummy variables would be diminished.

In summary, the variables assembled in the results section constitute a good model for traffic fatalities at different distances from a hospital. Unfortunately, results on variable of interest trauma center certification were inconsistent in significance and sign. I was unable to find support for my hypothesis that trauma centers would have a

significant and negative impact on traffic fatalities relative to traditional emergency rooms. Additionally, there was no evidence that impact of the trauma center diminished as distance from the hospital increased for Level 1 or Level 2 facilities. There was some evidence suggesting that Level 3 centers decrease fatalities significantly and that their beneficial effect decreases as distance from the hospital increases. However, this contradicts my hypothesis and intuition that Level 1 and Level 2 facilities would have a greater beneficial effect than Level 3 EDs. In addition to not supporting my hypothesis, my results largely contradict the findings in trauma center literature. Although my model measures efficacy in an innovative way that avoids some traditional problems encountered when examining hospital outcomes, there are several potential weaknesses in my methodology that may be responsible for my lack of significant findings.

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