Life is all About Timing:
An Examination of Differences in Treatment Quality for Trauma Patients Based on Hospital Arrival Time

Abstract

This paper examines one important factor that drives the differences in the treatment quality of trauma patients: the time of day that they arrive at the hospital. Using data from the National Trauma Data Bank, we find that patients arriving at the hospital during the off-hours (6pm – 6am) receive significantly worse care than those who arrive during the daytime. Quality of care is measured by patient mortality rates, length of ICU stays, number of recorded surgical complications, and the percent of patients requiring multiple surgeries. The differences in care quality between day and off-hours are the most pronounced at smaller, less sophisticated hospitals. Our results are consistent with a pattern of having more limited resources available during the off-hours than during the day.

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1. Introduction

The ability of hospitals to consistently deliver high quality care is a matter of significant concern. At hospitals in the United States, patients receive only about 54% of recommended care (McGlynn et al. 2003), and service quality varies considerably (Vandamme and Leunis 1993, Lam 2010). Finding ways to improve the quality and consistency of care delivered by health care systems is an important mission facing the medical community. Toward that goal, one critical step is to identify factors that lead to variations in care quality.

Until now, most studies have been devoted to the differences in quality of care across hospitals (e.g., academic hospitals and larger hospitals with higher volume tend to provide better quality service (Theokary and Ren 2011)). Most hospital quality measures are aggregated at the hospital-year level, such as the HospitalCompare program by the US HHS or the hospital rankings published by the US News and World Report. While these quality rankings are useful in highlighting cross-hospital quality variation, one underexplored, yet critical, topic is within-hospital quality variation. For any hospital that aims at providing consistent high-quality care, within-hospital variation in quality is an important concern. Within-hospital variation also sends a clear managerial challenge to hospitals. More specifically, systematic variations in quality indicate opportunities for a hospital to improve its quality of service.

In this paper, we study the differences in treatment quality that trauma patients receive based on their arrival time at the emergency department. Trauma from unintentional injury is the number one cause of death among Americans 1-44 years old, and the fifth leading cause of death overall, with 121,902 deaths in 2008 (CDC 2008). Therefore, improving the quality and efficiency of trauma care is of national importance. Additionally, trauma care has a relatively short treatment cycle and clear quality metrics, making it ideal to examine quality variation and consequences by focusing on quantifiable clinical outcomes.

Based on a large national dataset of almost 2 million admissions over 5 years, we examine how service quality varies with patient arrival time. We find that there is a substantial difference, and an interesting tradeoff, in quality of care between day and night among trauma patients. Specifically, patients arriving during the off-hours have shorter waiting time to receive an initial surgery, which is beneficial. On the other hand, these patients experience a higher risk of complications. This can lead to a longer length of stay and higher mortality rates than patients who arrive during the day. Furthermore, we identify the characteristics of hospitals that experience the largest differences in patient outcomes. We find that smaller (fewer beds), less sophisticated (lower level trauma centers) hospitals, and hospitals with more resource stress (higher patient/surgeon ratio) have significantly larger variation in quality of care between daytime and the "off-hours" than their larger, more sophisticated counterparts. The insights generated from this study should be valuable to hospitals as they seek to reduce the variations in care delivery and to improve service quality.

2. Literature Review and Hypothesis Development

2.1 Variations in the Quality of Care

The healthcare industry has been striving to consistently deliver quality care. Hospitals have tried many initiatives to increase the quality of health care, such as implementing checklists and guidelines for care (Downs and Black 1998, Gawande 2009). These efforts yield mixed results. Checklists have been shown to significantly lower the rates of preventable errors and to improve the quality of care delivered in hospitals. There are also nationwide quality transparency programs from both government agencies and practitioners, such as CMS's hospital compare, US News ranking of best hospitals, and the Leap Frog Group. These quality measures are often constructed based on annually aggregated data and do not reflect how service quality varies within a hospital. Consequently, most of the existing academic research based on these quality measures has tried to examine cross-hospital quality variation using fixed characteristics of the hospitals, such as size, volume, ownership, or teaching status, with the goal of improving the performance of low-quality hospitals. For example, Keeler et al. (1992) and Hughes et al. (1987) show that larger, urban hospitals deliver higher quality care than their smaller, rural counterparts. McClellan and Staiger (2000) show that not-for-profit hospitals deliver a slightly higher quality of care than do for-profit hospitals.

Our study, on the other hand, examines a systematic variation in quality over which hospitals have control, namely the differences in hospital staffing and resource availability between night and day. We contribute to an emerging stream of research which has focused on within-hospital quality variation. For example, Kc and Terwiesch (2009) examines how the variation of workload affects service rates in cardiothoracic surgery and the resulting outcome. Several studies have brought up the issue of treatment quality variation at hospitals based on the time of day and the day of the week. These studies (e.g., Magid et al. (2005), Saposnik et al. (2007), Bell and Redelmeier (2001), Reeves et al. (2009)) have shown that patients outside of the emergency department have worse outcomes when they arrive "off-hours", either at night or on the weekends. Specifically, Bell and Redelmeier (2001) found that risk-adjusted mortality rates for patients who arrive at the hospital on the weekends have significantly higher mortality rates. Saposnik et al. (2007) also found increased risk of mortality among patients who had a stroke on the weekend, compared to those having a stroke on a weekday. Most relevant to our work is Egol et al. (2011), which found that mortality rates were higher for trauma patients during the night and that the differences were larger at lower level trauma centers.

In our review of existing studies, we identified gaps in the literature. First, most of the studies only focus on one measure of quality, which makes it hard to understand the full picture of quality difference between day and night. Second, these studies stop at reporting the difference in care quality and fail to reveal what causes the variation in quality of care. In this study, we present a comprehensive examination of how the timing of patient arrival affects the quality of care received and the outcome of treatment. More importantly, we try to uncover the mechanisms driving the quality variation. We root our analysis in the literature of how resource availability affects quality of care and develop testable hypotheses for the causes of the quality variation. Empirically, we advance the existing studies by using a fixed effects model to control for unobserved hospital-specific heterogeneity, which allows for more rigorous estimation of within-hospital quality variation. By filling in the above gaps in the literature, this study contributes to a more comprehensive and fundamental understanding of the time effect in care quality variation.

Below we provide a theoretical foundation and an explanation as to why there might exist a difference in quality of care between day and night from a resource management perspective and derive testable hypotheses.

2.2 Possible Causes of the Variation in Care Quality between Day and Night

Previous studies have identified factors that lead to quality variation in hospitals. This variation can be caused by many factors, such as differences in resource availability (beds, operating rooms, diagnostic equipment). Kc and Terwiesch (2011) show how bed availability in a cardiac ICU affects the treatment quality of patients. Specifically, they show that patients are discharged at a higher rate when the ICU is full, and that these patients are readmitted at a higher rate. The same findings are shown by Anderson et al. (2011, 2012), when studying post-operative discharge and readmission rates. Cardoen et al. (2009) provide a summary of the effects that operating room availability can have on patient care. Having too few staffed ORs can lead to long patient waiting times, and to poorer outcomes. Miro et al (1999) show that overcrowding in emergency departments decreased the quality of care delivered. Trzeciak and Rivers (2003) discuss how overcrowded emergency departments offer lower quality care. As there is more strain on the resources of a hospital (doctors, nurses, operating rooms), the quality of the treatment provided declines. Differences in the quality of the staff at the hospital can also cause variation in the quality of care delivered. Diette et al. (2001) show that patients treated by specialist doctors are more likely to receive high quality care than those treated by general practitioners. In this paper, we study how the availability and quality of resources in the hospital affect the quality of care delivered.

Overall, resource availability has been identified as a dominant factor in determining the quality of care. To deliver consistent, high quality care, it is critical for hospitals to manage their medical resources effectively. Roth et al. (1995) discuss a framework for hospitals to manage their resources. Dobson et al. (2011) show how reserving capacity for urgent patients can help providers deliver higher quality of care to their patient population. Other work has shown that how resources are managed at hospitals affects the quality of care that patients receive.

Hospitals require appropriate staffing levels, both of doctors and support staff. Resource constraints also can adversely impact the quality of care at hospitals. For instance, a shortage of

ICU beds can have a negative impact on patients who are denied an ICU bed (Chan et al. 2012). Other work in the operations management literature has shown a relationship between resource availability and patient care. Price et al. (2011) show that shortages in downstream bed availability can affect post-operative care. Using a health care delivery system as their motivating example, Soteriou et al. (2009) present a method to optimally allocate resources to increase the perceived, and actual, quality of a service system. McManus et al. (2003) show that the primary bottleneck in the care for emergency patients is operating rooms and that the bottleneck is caused more by scheduled elective surgery than by (unscheduled) emergency surgery. Because elective surgeries are typically not scheduled overnight, it might be that resources (e.g., an available surgeon and operating room) are more available during off-hours and patients have shorter waiting times to surgery. The following hypothesis, therefore, emerges:

H1: Patients arriving at night, other things being equal, experience shorter waiting time to surgery than those arriving during the day.

However, operating room availability and the waiting time until surgery are not the only factors in the quality of care that a patient receives. Degree of specialization also matters. The question of how to staff service systems with varying arrival rates and different classes of patients has been well studied in the queueing theory literature. Trauma wards fit this description; arrival rates vary throughout the day and night, and there are many different classes of injury that are treated in the trauma ward. Pinker and Shumsky (2000) claim that "it is a well-known fact from the study of queues that, all things being equal, staffing flexible servers is more efficient than using specialists when customers are heterogeneous in the skills they require." This claim is further examined by Chevalier and Tabrodon (2003). Shumsky and Pinker (2003) study the optimal number of specialists and generalists to have on staff at a call center, based on the arrival rate of patients and the difference in quality of service offered by specialists and generalists. They find that as volume decreases, the optimal percentage of generalists increases. This means that, during the off-hours, when arrival rates are lower, we would expect to see fewer specialty surgeons and fewer specialized resources available in a trauma ward. We expect that the lack of specialized workers (e.g., surgeons and nurses) will lead to a lower quality of care being delivered during off-hours and a higher rate of complications during surgery. This leads us to a second hypothesis:

H2: Other things being equal, surgeries performed on patients arriving during the night will have a higher complication rate.

Combining H1 and H2 provides a more complete picture of the impact of night vs. day on health outcomes. Shorter waiting times typically lead to shorter length of stay and lower mortality (Casaletto and Gatt 2003), while more complications typically lead to longer length of stay and higher mortality (Haynes et al. 2009), so there is a conflict. It is not clear which effect will dominate. Nevertheless, we propose the following two hypotheses:

H3: Other things being equal, patients arriving during off-hours will have longer lengths of stay.

H4: Other things being equal, patients arriving during off-hours will have higher mortality.

We hypothesize that a lack of specialized resources will cause hospitals to deliver lower quality care during off-hours. Because volume goes down during off-hours, we expect the availability of specialized surgeons, nurses, and other resources to decrease as well. This should result in lower quality service. Because it is a lack of specialized resources that leads to the difference in quality of care, we would expect hospitals that are more resource-constrained to have greater differences between night and day (Keeler et al. 1992). Specifically, we expect to see greater increases (from day to night) in complication rates, length of stay, and mortality at the hospitals that are smaller (measured by number of beds) and less sophisticated (lower trauma center level). We also construct a more direct measure of resource strain, the number of visits to the hospital per surgeon employed. This measure provides a good proxy for the workload of surgeons at a hospital. This suggests the hypothesis below:

H5: Hospitals that have fewer beds, a lower trauma level, and have more visits per surgeon will experience greater differences between day and night.

3. Data

We use data from the National Trauma Data Bank (NTDB) version 7.2. The NTDB is the largest aggregation of US trauma data. The research dataset we use includes all patients treated at 570 trauma centers between 2002 and 2007 nationwide. It includes treatment and outcome measures on over 1.5 million patients. The database contains demographic information on the patients, details of their treatment, injury type and severity, and payment, as well as information on the size, type, region, and trauma level of the hospital where the patient was treated. We restrict our focus to only those patients where we have complete information on their age, arrival time to the emergency department (ED), injury severity score (ISS), mortality, and length of ICU stay. After excluding patients with significant missing data, we are left with a sample of 683 thousand patients from 477 different hospitals. The major variables that we use in the study are defined in Table 1.

Corresponding to the first four hypotheses, we choose four measures of the quality of care delivered by a hospital: time to surgery, complication rate, length of stay, and mortality. These quality metrics have been justified in the literature (Thomas et al. 1997; Dimick et al. 2003; and Thomas et al. 1993). They all have been shown to be key measures of the quality of care that a hospital provides. Time to surgery (*Hours to Procedure*) is measured as the number of hours between the patient's arrival at the emergency department and the first surgery that the patient receives. Occurrence of a recorded complication (*Complication*) is a dichotomous variable; if a patient has a complication recorded during his/her surgery, the variable is 1, and it is 0 otherwise. We measure length of stay (*ICU LOS*) as the number of days that the patient spends in the ICU. Lastly, *mortality* is recorded as a 1 if the patient dies in the hospital, and a 0 if the patient is discharged alive.

We next compare descriptive statistics of the populations of patients that arrived at each time of day. Table 2 provides a summary of the three different patient populations and their outcomes. As can be seen, the patient mix is different, highlighting the importance to control for confounding factors. Patients arriving off-hours tend to be younger and have higher ISS scores. We also see that they have higher mortality rates, longer ICU stays, and a higher complication rate during surgery.

4. Empirical Analysis

4.1 Empirical Models

Since our goal is to examine the difference in quality of care between day and night, we adopt the following model to test H1-H4:

$$Q_{ik} = \beta_0 + \beta_1 * T1_{ik} + \beta_2 * T2_{ik} + \gamma * Z_{ik} + \varepsilon_{ik}\ , \tag{1}$$

where i is the trauma center index and k is the patient index. Q is the quality measure, which varies depending on the specific hypothesis we test (e.g., length of stay, mortality). We measure the night effect in two time slots. $T1$ is the time dummy for late night (6:00 pm to 12:00 am), and $T2$ is the time dummy for early morning (12:00 am to 6 am). Z represents a group of control variables to control for the heterogeneity in patient mix. Specifically, we use the injury severity scale (*ISS*) score of the patient, as well as the patient's age, race, and gender.

To further control for the unobserved heterogeneity across the trauma centers, we further include the fixed effect, D, for each trauma center (the fixed effect for the first trauma center is omitted to avoid perfect multicollinearity):

$$Q_{ik} = \beta_0 + \beta_1 * T1_{ik} + \beta_2 * T2_{ik} + \gamma * Z_{ik} + \sum_{i=2}^{570} \theta_i * \mathrm{D_i} + \varepsilon_{ik}\ . \tag{2}$$

4.2 Findings

4.2.1 Waiting Time to Initial Surgery

For Hypothesis 1, the regression model that we test is:

$$\textit{Hours to Procedure}_{ik} = \beta_0 + \beta_1 * \textit{Morning}_{ik} + \beta_2 * \textit{Night}_{ik} + \beta_3 * \textit{Age}_{ik} + B_4 * \textit{Gender}_{ik} + \beta_5 * \ . \\ \textit{Race}_{ik} + \beta_6 * \log(\textit{ISS})_{ik} + \beta_7 * \textit{Trauma Level}_{ik} + \beta_8 * \textit{Facility}_{ik} + \varepsilon_{ik}. \tag{3}$$

The results are shown in Table 3. Column 2 reports the baseline model. We see that the coefficients for the two night dummy variables are negative and significant at $p<0.001$ level. This means that patients arriving during the night and early morning have shorter waiting times for surgery than during day time. Specifically, if a patient arrives between 6 pm and 12 am, the expected waiting time is 16 minutes shorter (-.262 * 60 = -16) than for similar patients who arrive during the day, and 6 minutes shorter (-.098 * 60 = -6) for patients who arrive in the early morning, according to the fixed effects model. Column three of Table 3 reports the model with fixed effect dummies added for each individual hospital.

As an alternative measure, we test the probability that the patient receives surgery within one hour of arriving at the hospital. We see that the odds that a patient arriving at night (or during the early morning) will have surgery in the first hour after arriving at a hospital are on average 17.5% (or 16.9%) higher than for patients arriving during the day (note that (exp(.156) = 1.169 and exp(.161) = 1.175), after controlling for patient and hospital characteristics (shown in Table 13, column 3). Finally, we see that the odds that a patient who arrives during the day will have any surgery at all are 3.0% lower than for those arriving at night or in the early morning (shown in Table 13, column 2). Taken together, these results show that the promptness of care received by patients is actually better at night and during the early morning than it is for a comparable patient during the day.

4.2.2 Quality of Surgery

To test Hypothesis 2, we regress whether or not patients had a complication during surgery on their arrival time and demographic characteristics. The results are given in Table 4. After controlling for severity and demographics, we find that the odds of a patient arriving at night (or the early morning) having a complication during surgery are respectively 5.0% (or 9.5%) higher than for patients arriving during the daytime. After including the fixed effect dummies in column 2, the above findings are essentially the same.

As another measure of surgery quality, we examine whether patients would require multiple surgeries, which usually result from an incomplete or unsuccessful initial surgery. These results are shown in column 4 in Table 13. We find that odds that a patient arriving during the early morning will require multiple surgeries are 13.2% higher than for patients arriving during the day. Taken together, the higher complication rate during off-hours and the lower percentage of daytime surgeries that require no further operations imply that the quality of treatment, especially surgery, is lower off-hours than during the day.

4.2.3 Length of Stay

We next examine the relationship between arrival time and the length of time a patient spends in the ICU, to test Hypothesis 3. These results are shown in Table 5. The data show that patients who arrive at the ED in the early morning or at night have ICU stays that are 8.5% and 5.5% longer (exp(.815) = 1.085, exp(.0537) = 1.055), respectively, than patients who arrive during the day, after controlling for demographics, hospital characteristics, and the patient's severity. This means that not only do patients who arrive at the ED at night or in the early morning have higher mortality rates, they also have longer recovery times after their treatment, after controlling for the severity of their injuries. This implies the care these patients have received is of lower quality than the care delivered during the day.

4.2.4 Mortality

We use the following logistic regression model to examine the effect of patient arrival time on mortality:

$$logit(Mortality_{ik}) = \beta_0 + \beta_1 * Morning_{ik} + \beta_2 * Night_{ik} + \beta_3 * Age_{ik} + B_4 * Gender_{ik} + \beta_5 * Race_{ik} + \beta_6 * log(ISS)_{ik} + \beta_7 * Trauma\ Level_{ik} + \beta_8 * Facility_{ik} + \varepsilon_{ik}. \quad (4)$$

where *Early AM* and *Night* are dummy variables indicating if the patient arrived during the early morning or night, *Severity* is the patient's ISS score, and *Trauma Level* is a categorical variable indicating the level of trauma center at which the patient was treated.

The regression results are reported in Table 6. Using the fixed effects model (column 3), we find that the coefficients of *Night* and *Early AM* are .117 and .109, respectively. They are both statistically significant at the .001 level. These coefficients imply that after controlling for patient characteristics, the odds of death for patients who arrive between 6 pm and midnight and those who arrive between midnight and 6 am increase by 12.6% and 11.2% respectively (exp (.117) = 1.126, exp(.109) = 1.112), when compared to those arriving between 6 am and 6 pm. These results are consistent with the baseline model, in column 2.

4.3 Further Analysis

In the above analysis, we find a significant difference in the quality of care between day and night, which supports H1-H4. As discussed in Section 2, we suspect that one main cause of the lower treatment quality during off-hours is a reduced breadth of resources available. In this section, we further examine whether the difference is intensified by resource availability across hospitals (H5). To examine this, we utilize several proxies for the resource variable across hospitals.

First, we stratify our sample based on the level of the trauma center at which the patient was treated. Level I trauma centers are defined to have a full range of specialists and equipment available 24 hours a day. Level II centers are required to have all essential personnel available

24 hours a day, but not require to have every specialty staffed at all times. Level III centers are not required to have full availability of specialists. Because of these restrictions, we expect the differences in outcomes to be larger at lower-level trauma centers, as they are the most resource-constrained.

We find that the increase in off-hours mortality is larger at lower level trauma centers. Table 7 shows the differences in mortality by trauma level. The detailed results are given in Table 12. These findings are qualitatively consistent with Egol et al. (2011), although there are differences in the magnitude of the effect due to our use of a more recent dataset (version 7.2, instead of version 7.0) and slightly different inclusion criteria. A Chow test shows that the coefficients are significantly different at the 1% level between the different trauma center levels (Chow 1960).

Second, we suspect that the difference in resources available during the day compared to off-hours would be greater at smaller, less sophisticated hospitals. To test this, we looked at subsets of the data to see at which hospitals the differences in mortality were the largest and where they were the smallest. We studied the differences in mortality between early morning/night and day based on the size and sophistication of the hospital. Table 8 shows that large hospitals tend to have smaller differences in patient mortality than their smaller counterparts. We also find that hospitals with more beds and more surgeons have smaller differences in mortality rate, as reflected in Table 9.

Lastly, we examined the differences in the mortality rates based on the number of visits to the hospital per number of trauma surgeons employed by the hospital. This measures the relative load that the surgeons and hospital face and the strain that the patient flow puts on their resources. Again, we see that the difference is greatest at the hospitals with the most visits per surgeon and smallest at the hospitals with the fewest visits per surgeon. The summary statistics are provided in Table 10, and supported by regression analysis in Table 14.

In addition to studying which types of hospitals tend to have the biggest difference in mortality rates between daytime and off-hours, we also examined how complication rates changed over the level of trauma center. We found that lower level trauma centers also have a greater difference in the surgery complication rate. This means that the difference in surgical quality is greater at smaller, less sophisticated hospitals than it is at large trauma centers. Table 11 shows the increases in complication rates between day and off-hours for each level trauma center. The regressions are shown in Table 15. All these findings are consistent with our conjecture that resource-constrained trauma centers experience a quality drop-off at night.

5. Discussion

In this study, we find that there is a significant difference in medical outcomes between trauma patients who arrive at the hospital during the day and those who arrive at night or in the early morning.

Mortality rates are significantly higher, ICU stays are longer, surgery complication rates are higher, and the risk of needing multiple surgeries is higher for those who do not arrive during the day. These differences in mortality rates are much larger at smaller hospitals and at lower level trauma centers. However, patients are treated more promptly during off-hours than during the day. These results suggest that patients arriving during the day have better outcomes not because more care is available, but because the quality of care that they receive is better.

Based on discussions with medical professionals from major hospitals, we believe that these differences are consistent with hospitals having access to higher quality resources (surgeons, nursing staff, lab availability, etc.) during the day than during the night or early morning. Take, for example, a patient who comes to the hospital off-hours needing a specialized surgery. At a large, sophisticated hospital, this patient is likely to be seen by a specialized surgeon, an operating room is likely to be available, and the patient should receive the appropriate level of care. If the patient requires specialized lab tests, or especially intensive care, there is a higher chance that the required resources are available during the day than off-hours. During the day, there will likely be an appropriately specialized surgeon on duty, as well. On the other hand, if the patient arrived during the day, the likelihood that all of the operating rooms are full is higher, thus increasing the average wait time for the patient.

Now consider this same patient arriving at a smaller, lower level trauma center. If he arrives at night, there might only be a general trauma surgeon available. He can perform the surgery, but the likelihood that he will make a mistake, resulting in a complication, rises. He also might perform a temporary "patch" surgery, trying to stabilize the patient until a specialist is available. In this case, the patient will be more likely to require an extra surgery; he will have received inferior care so he will have a higher mortality rate and will spend more time in the ICU recovering. He also will be more likely to need multiple operations, either to fix problems arising from the complications or because the first surgery did not address all of his needs.

We find an interesting tradeoff between day and off-hours. If the patient arrived during the day, the likelihood that all of the operating rooms are full will be higher, thus increasing the average waiting time for the patient. Still, our results on clinical outcome clearly suggest that it is worth the potential extra waiting in exchange for higher quality care.

We believe that the differences in promptness and quality of care can be explained by the fact that while the hospital is less busy off-hours, the quality and variety of resources available during the day is much greater. A patient arriving at night or in the early morning will get prompter treatment, but will get less specialized and sometimes lower quality service. These differences are sufficient to explain the differences that we see in the promptness of care that patients receive, as well as the differences that we see in patient outcomes.

Our findings are consistent with work in the service operations management literature regarding the tradeoffs between hiring generalist and specialist workers. During the off-hours, when arrival rates are lower, we see less specialized work done than during the daytime. We believe this is, in part, because there are fewer specialized resources available during the off-hours, as would be predicted by the queueing literature.

This work highlights one important source of within-hospital variation in the quality of care offered by hospitals. We show that there are systematic ways in which hospital quality of care decreases. The drop-off in quality at night and in the early morning could be mitigated by increasing staffing levels during the off-hours and making an effort to have specialized resources available around the clock at trauma centers. In the future, we hope to examine other factors that cause within-hospital quality variation, such as how daily changes in hospital volume affect treatment quality.

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Table 1: Summary of the variables used in the study

Variable	Description
Age	The patient's age, in years
Gender	The patient's gender
ISS	The injury severity score of the patient
Trauma Level	The level of the trauma center at which the patient was treated, used as a categorical variable
Early AM	A dummy variable that is 1 if the patient arrived between midnight and 6 am, and 0 otherwise
Night	A dummy variable that is 1 if the patient arrived between 6 pm and midnight, and 0 otherwise
Mortality	A dummy variable that is 1 if the patient died, and 0 otherwise
ICU LOS	The number of days the patient spent in the Intensive Care Unit
Complication	A dummy variable that is 1 if the patient had a recorded complication during surgery
Hours To Procedure	The number of hours the patient had to wait until surgery
Facility	The identification key for the hospital at which the patient was treated, used as a categorical variable.
Procedure	A dummy variable that is 1 if the patient had a surgery, and 0 otherwise
Multiple	A dummy variable that is 1 if the patient required multiple surgical procedures, and 0 otherwise
Prompt	A dummy variable that is 1 if the patient received treatment within 1 hour of arrival, and 0 otherwise

Table 2: Summary statistics by arrival time (Early AM: midnight – 6am; Daytime: 6 am – 6 pm; Night: 6pm – midnight)

Time of Day	Avg ISS	Mortality	Avg. Days in ICU	Percent Having Surgery	Avg. Age	Avg. Hours to Surgery	# of Patients	Percent Surgery within 1 hr.	Percent with ICU stays	Percent of Surgeries with Complications
Early AM	10.72	5.377%	1.41	71.4%	36.1	3.44	138304	20.9%	26.0%	5.6%
Daytime	9.92	4.917%	1.27	70.2%	48.7	4.09	384550	17.0%	21.2%	5.4%
Night	10.25	5.389%	1.36	69.7%	43.4	3.67	221487	20.0%	23.6%	5.6%

Table 3: Waiting time for surgery

VARIABLES	Baseline Model	Fixed Effects Model
Early AM	-0.117***	-0.0982***
	(0.0102)	(0.00849)
Night	-0.243***	-0.262***
	(0.00838)	(0.00698)
Age	0.0169***	0.0146***
	(0.000194)	(0.000166)
Male	-0.284***	-0.241***
	(0.00796)	(0.00665)
Black	0.00388	0.0904***
	(0.0338)	(0.0286)
Hispanic	0.910***	0.0832***
	(0.0352)	(0.0299)
Native American	-0.170***	-0.0236
	(0.0641)	(0.0550)
Other	-0.442***	0.122***
	(0.0368)	(0.0323)
White	0.00989	0.161***
	(0.0328)	(0.0278)
Log(ISS)	0.0337***	-0.0459***
	(0.00382)	(0.00332)
Trauma Level II	0.0877***	-0.923***
	(0.00779)	(0.109)
Trauma Level III	0.281***	-1.121***
	(0.0206)	(0.105)
Trauma Level IV	1.262***	-2.058***
	(0.0952)	(0.613)
Trauma Level NA	0.674***	-1.103***
	(0.0219)	(0.0913)
Constant	2.701***	4.840***
	(0.0356)	(0.0583)
Observations	371,262	371,262
R-squared	0.050	0.344

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Surgery complications

VARIABLES	Baseline Model	Fixed Effects Model
Early AM	0.0906***	0.0984***
	(0.0173)	(0.0178)
Night	0.0492***	0.0359**
	(0.0143)	(0.0148)
Age	0.0128***	0.0146***
	(0.000329)	(0.000348)
Male	0.114***	0.111***
	(0.0139)	(0.0143)
Black	0.135**	0.154***
	(0.0562)	(0.0592)
Hispanic	0.172***	0.0474
	(0.0585)	(0.0618)
Native American	-0.419***	0.164
	(0.129)	(0.138)
Other	-0.0837	-0.110
	(0.0629)	(0.0689)
White	0.0186	0.0712
	(0.0544)	(0.0572)
Log(ISS)	1.304***	1.308***
	(0.00922)	(0.00979)
Trauma Level II	-0.275***	-2.110***
	(0.0138)	(0.461)
Trauma Level III	-0.191***	-0.721***
	(0.0411)	(0.260)
Trauma Level IV	0.0414	-0.00626
	(0.171)	(0.193)
Trauma Level NA	-0.0447	0.117
	(0.0378)	(0.168)
Constant	-6.286***	-6.217***
	(0.0645)	(0.108)
Observations	371,262	348,598

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Logged length of ICU stay

VARIABLES	Baseline model	Fixed effects model
Early AM	0.0815***	0.0867***
	(0.00474)	(0.00463)
Night	0.0537***	0.0517***
	(0.00395)	(0.00384)
Age	-0.000211**	0.000768***
	(9.17e-05)	(9.15e-05)
Log(ISS)	0.569***	0.563***
	(0.00159)	(0.00161)
Male	0.159***	0.141***
	(0.00372)	(0.00363)
Black	-0.0492***	-0.0911***
	(0.0134)	(0.0134)
Hispanic	-0.0852***	-0.0748***
	(0.0137)	(0.0137)
Native American	0.118***	0.0660**
	(0.0284)	(0.0285)
Other	-0.0990***	-0.113***
	(0.0153)	(0.0159)
White	-0.0281**	-0.0453***
	(0.0128)	(0.0128)
Trauma Level II	-0.123***	-0.526***
	(0.00369)	(0.0617)
Trauma Level III	-0.358***	-0.615***
	(0.00940)	(0.0603)
Trauma Level IV	-0.704***	-0.194
	(0.0346)	(0.160)
Trauma Level NA	-0.450***	-0.538***
	(0.00847)	(0.0471)
Constant	-2.557***	-2.547***
	(0.0140)	(0.0282)
Observations	681,651	681,651
R-squared	0.173	0.219

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Mortality

VARIABLES	Baseline Model	Fixed Effects Model
Early AM	0.111***	0.117***
	(0.0165)	(0.0168)
Night	0.111***	0.109***
	(0.0137)	(0.0139)
Age	0.0194***	0.0206***
	(0.000317)	(0.000327)
Log(ISS)	1.823***	1.858***
	(0.00933)	(0.00970)
Black	0.313***	0.256***
	(0.0454)	(0.0475)
Hispanic	0.0527	-0.000842
	(0.0473)	(0.0492)
Native American	-0.0339	0.000643
	(0.100)	(0.105)
Other	-0.127**	-0.0704
	(0.0533)	(0.0571)
White	-0.201***	-0.0847*
	(0.0437)	(0.0456)
Male	0.274***	0.257***
	(0.0136)	(0.0138)
Trauma Level II	-0.0329**	-0.799***
	(0.0130)	(0.302)
Trauma Level III	-0.213***	-1.737***
	(0.0405)	(0.422)
Trauma Level IV	-0.685***	1.297*
	(0.168)	(0.706)
Trauma Level NA	-0.305***	-0.161
	(0.0349)	(0.189)
Constant	-8.539***	-8.546***
	(0.0567)	(0.0935)
Observations	681,651	678,762

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Increase in mortality at different level trauma centers compared to daytime (* $p > .05$)

	Level 1	Level 2	Level 3-4
Early AM	11.0%	14.3%	30.6%
Night	10.1%	13.1%	18.9%*

Table 8: Increase in mortality rate by number of beds

Time	Bottom Quartile	2nd Quartile	3rd Quartile	Top Quartile
Early AM	18.8%	17.1%	6.5%	10.6%
Night	11.3%	10.0%	14.7%	9.1%

Table 9: Increase in mortality rate by number of surgeons (* $p > .05$)

	Bottom Quartile	2nd Quartile	3rd Quartile	Top Quartile
Early AM	19.2%	12.7%	11.7%	7.8%
Night	5.8%*	12.9%	10.3%	11.4%

Table 10: Increase in mortality rate by number of visits per surgeon (* $p > .05$)

	Bottom Quartile	2nd Quartile	3rd Quartile	Top Quartile
Early AM	4.7%*	14.0%	8.4%	11.5%
Night	4.7%*	7.4%	9.7%	11.6%

Table 11: Increase in surgery complication rate by trauma center level (* $p > .05$)

	Level 1	Level 2	Level 3-4
Early AM	9.2%	10.8%	31.9%
Night	4.6%	4.7%*	8.2%*

Table 12: Mortality regressions by level of trauma center

VARIABLES	Mortality Level 1 TC	Mortality Level 2 TC	Mortality Level 3-4 TC
Early AM	0.0991***	0.127***	0.219**
	(0.0206)	(0.0302)	(0.109)
Night	0.106***	0.123***	0.167*
	(0.0175)	(0.0238)	(0.0870)
Age	0.0194***	0.0197***	0.0134***
	(0.000407)	(0.000546)	(0.00195)
Log(ISS)	1.821***	1.817***	1.363***
	(0.0120)	(0.0163)	(0.0521)
Black	0.350***	0.211***	0.250
	(0.0559)	(0.0818)	(0.413)
Hispanic	0.0920	-0.00803	0.296
	(0.0588)	(0.0824)	(0.423)
Native American	-0.0291	-0.0413	0.387
	(0.122)	(0.189)	(0.591)
Other	-0.00779	-0.250***	-0.531
	(0.0674)	(0.0909)	(0.516)
White	-0.207***	-0.183**	-0.219
	(0.0542)	(0.0765)	(0.402)
Male	0.250***	0.301***	0.340***
	(0.0175)	(0.0235)	(0.0844)
Constant	-8.524***	-8.588***	-7.310***
	(0.0709)	(0.0987)	(0.444)
Observations	385,446	240,908	25,489

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Procedure and Complication regressions

VARIABLES	PROCEDURE	PROMPT	COMPLICATION	MULTIPLE
Daytime	-0.0305***			
	(0.00575)			
Early AM		0.156***	0.0906***	0.124***
		(0.00966)	(0.0173)	(0.0131)
Night		0.161***	0.0492***	-0.00579
		(0.00807)	(0.0143)	(0.0101)
Age	0.000419***	-0.0132***	0.0128***	-0.0121***
	(0.000152)	(0.000192)	(0.000329)	(0.000232)
Log(ISS)	0.458***	0.0151***	1.304***	0.427***
	(0.00267)	(0.00366)	(0.00922)	(0.00458)
Black	1.093***	0.0229	0.135**	0.166***
	(0.0201)	(0.0319)	(0.0562)	(0.0431)
Hispanic	0.192***	-0.833***	0.172***	-0.576***
	(0.0202)	(0.0339)	(0.0585)	(0.0439)
Native American	0.905***	0.0407	-0.419***	-0.110
	(0.0453)	(0.0598)	(0.129)	(0.0795)
Other	1.368***	0.382***	-0.0837	0.344***
	(0.0242)	(0.0346)	(0.0629)	(0.0476)
White	1.003***	-0.0484	0.0186	-0.0534
	(0.0190)	(0.0310)	(0.0544)	(0.0416)
Male	-0.00380	0.242***	0.114***	0.259***
	(0.00614)	(0.00777)	(0.0139)	(0.00942)
Trauma Level II	-0.161***	-0.110***	-0.275***	-0.290***
	(0.00602)	(0.00752)	(0.0138)	(0.00941)
Trauma Level III	0.0331**	-0.470***	-0.191***	-1.031***
	(0.0155)	(0.0215)	(0.0411)	(0.0204)
Trauma Level IV	-1.030***	-1.103***	0.0414	-0.569***
	(0.0505)	(0.127)	(0.171)	(0.0965)
Trauma Level NA	0.229***	-0.802***	-0.0447	-0.740***
	(0.0148)			(0.0229)
Constant	-0.703***	-0.124***	-6.286***	1.299***
	(0.0209)	(0.0337)	(0.0645)	(0.0445)
Observations	683,324	371,262	371,262	371,262

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Mortality by number of visits per surgeon

VARIABLES	Visits per surgeon Lowest 25%	Visits per surgeon 2nd Quartile	Visits per surgeon 3rd Quartile	Visits per surgeon Highest 25%
Early AM	0.0370	0.127***	0.0621	0.0754**
	(0.0428)	(0.0404)	(0.0387)	(0.0296)
Night	0.0425	0.0761**	0.0991***	0.0912***
	(0.0344)	(0.0329)	(0.0313)	(0.0250)
Age	0.0199***	0.0235***	0.0208***	0.0185***
	(0.000700)	(0.000707)	(0.000669)	(0.000538)
Log(ISS)	1.856***	2.054***	2.006***	1.888***
	(0.0245)	(0.0247)	(0.0236)	(0.0178)
Black	0.200	0.500***	0.205*	0.373***
	(0.129)	(0.157)	(0.111)	(0.0711)
Hispanic	-0.104	-0.0311	-0.196*	0.00267
	(0.135)	(0.165)	(0.119)	(0.0747)
Native American	-0.146	0.0573	-0.186	0.159
	(0.225)	(0.413)	(0.567)	(0.137)
Other	-0.319**	0.0974	0.0295	-0.00558
	(0.148)	(0.169)	(0.124)	(0.0923)
White	-0.271**	-0.0542	-0.258**	-0.155**
	(0.125)	(0.154)	(0.107)	(0.0681)
Male	0.221***	0.152***	0.308***	0.296***
	(0.0335)	(0.0316)	(0.0311)	(0.0253)
Trauma Level II	-0.0644**	-0.222***	0.0264	-0.0818***
	(0.0326)	(0.0327)	(0.0301)	(0.0257)
Trauma Level III	-0.215***	-0.328***	0.122	-0.140
	(0.0795)	(0.0934)	(0.372)	(0.111)
Trauma Level IV	1.351*			0.532**
	(0.756)			(0.223)
Trauma Level NA	-0.0455		0.0326	-0.349***
	(0.0712)		(0.137)	(0.0449)
Constant	-8.514***	-9.475***	-9.137***	-8.800***
	(0.154)	(0.179)	(0.139)	(0.0954)
Observations	107,652	117,463	113,086	204,663

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Complications by level of trauma center

VARIABLES	Complication Level 1 TC	Complication Level 2 TC	Complication Level 3-4 TC
Early AM	0.0876***	0.0989***	0.339***
	(0.0212)	(0.0325)	(0.114)
Night	0.0444**	0.0473*	0.168*
	(0.0178)	(0.0262)	(0.0908)
Age	0.0145***	0.0104***	0.0186***
	(0.000412)	(0.000593)	(0.00204)
Log(ISS)	1.260***	1.364***	1.294***
	(0.0114)	(0.0170)	(0.0574)
Black	0.205***	0.120	-0.580
	(0.0713)	(0.0967)	(0.369)
Hispanic	0.253***	0.0878	-0.843**
	(0.0746)	(0.0986)	(0.400)
Native American	-0.532***	-0.237	-0.903
	(0.176)	(0.200)	(0.836)
Other	-0.107	-0.152	-0.727
	(0.0828)	(0.103)	(0.468)
White	0.197***	-0.267***	-0.899**
	(0.0695)	(0.0919)	(0.353)
Male	0.101***	0.113***	0.173**
	(0.0173)	(0.0252)	(0.0852)
Constant	-6.375***	-6.377***	-5.978***
	(0.0814)	(0.111)	(0.407)
Observations	213,812	134,108	12,710

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1