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Do Children's Hospitals Have Lower Mortality Rates? Evidence from the 2003 Kids' Inpatient Database

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Abstract

Objective: To compare mortality rates at children's hospitals and non-children's hospitals.

Data Source: I used the Healthcare Cost and Utilization Project Kids' Inpatient Database (KID) released by the Agency for Healthcare Research and Quality in 2003. Thirty-six states participated in the HCUP in 2003, which included 3,438 hospitals, and 2,984,129 pediatric discharges.

Study Design: I hypothesized that mortality rates at children's hospitals would be lower than mortality rates at non-children's hospital because children's hospitals have more specialized inputs, from the clinical training of sub-specialists and nurses to advanced machines and diagnostic tools, and may use these inputs more productively. To test this hypothesis, I analyzed mortality for seven diagnoses using a logistic regression model. To control for selection bias, I selected diagnoses that were likely to occur at both children's hospitals and non-children's hospitals and controlled for risk of mortality and severity of illness.

I found that mortality rates at children's hospitals were lower, but these lower rates were not statistically significant. Risk of mortality and severity of illness were highly significant in the model. These findings suggest that hospital type does not make a difference in determining medical outcome, but do not diminish the value of children's hospitals because they are important assets in their communities.

Table of Contents

Preface

When I enrolled in the Honors Program nearly four years ago, I had no idea that I was going to graduate with Honors in Economics. In September 2003, the beginning of my sophomore year at SU, two major things happened to me. The first was that I was recruited by Mary Ann Shaw to do some research work for the new Central New York Children's Hospital (now the Golisano Children's Hospital of Central New York) at SUNY Upstate Medical University. The second was that I enrolled in ECN 203: Economic Ideas and Issues with Professor Jerry Evensky, a requirement for the policy studies major. In that course, I fell hard and fast for economics.

I enrolled in the Economics Department's Program of Distinction last fall with Professor Mary Lovely and immediately started looking for a topic. Combining my interests in health policy and hospital administration seemed the logical choice to make. Promotional materials obtained from SUNY Upstate Medical University revealed that Syracuse was one of two cities of comparable size in the nation without a children's hospital, and that the presence of a children's hospital was a symbol for how much a community cared for its children. As a budding economist, I naturally wondered if children's hospitals actually provided better care.

A foray into the literature along with conversations with some experts uncovered that there has been little research performed on this question, and no study has been conducted on the national level. I had no idea what kind of results I would find, though I had a hunch that children's hospitals had lower mortality rates. After all, children's hospitals had highly skilled pediatricians, surgeons, nurses, and use highly specialized equipment.

The first decision I needed to make was to find a dataset. I found the Kids' Inpatient Database (KID) from the U.S. Department of Health and Human Services Agency for Healthcare Research and Quality. The dataset included variables such as whether or not the patient died (Bingo!), if the patient was at a children's hospital or not (Double Bingo!), the patient's diagnosis, and other juicy information such as what kind of admission it was (trauma, emergency, etc.) and how large the hospital was.

Very early in the process, I understood that I needed to address a major problem: Since sicker patients choose go to children's hospitals for care, how in the world was I going to control for hospital choice? I am not going to go into detail here, as I cover my procedures and decisions in the actual thesis. What I will say now is that I quickly learned that missing data is the curse of econometrics. When data we need are missing, we as economists have no other choice but to use what is available to us. In this light, economics is not an exact science, and can be seen as an art, requiring much intuition, skill, and critical thinking.

A major challenge this project presented was managing the KID database. I purchased and began to work with the 2000 edition KID last fall and designed a procedure where I could cut the database down to include only the diagnoses I was interested in analyzing. Shortly after returning to school for the spring semester, I learned that HCUP had recently released the 2003 edition of the KID, and it included additional variables, including controls for risk of mortality and severity of illness. I believed that using these new risk and severity controls would help me deal with my selection bias problem, so I thought it was a wise decision to switch datasets. All the work and procedures I had performed on the 2000 dataset were then replicated on the 2003 database. I spent several weeks executing a method to reduce the dataset and performed additional data preparation. I needed to work very carefully and methodically, because if I were to make a mistake, I would have to start over again. This process required a great deal of skill. While the body of my thesis is rather short (approximately 45 pages) and straightforward, there was much behind the scenes data management work and I estimate that I spent approximately 45 hours on data management alone. I am also happy that I found the new dataset in January as opposed to, well…March.

After my dataset was finished and ready to be analyzed, I began running regressions using Statistical Package for the Social Sciences (SPSS). The results I was getting were not looking right to me. SPSS analysis showed me that even when accounting for risk and severity, mortality at children's hospitals was higher than at non-children's hospitals. Intuitively, I knew these numbers had to be wrong. I soon grew frustrated with not being able to specify additional commands and options within SPSS, and I began searching for other avenues. I do like SPSS and I find it a user-friendly program, but it is not well suited to econometric analysis. Professor Lovely directed me to a PhD student, Beyza Ural, who had a great deal of knowledge about the

STATA analysis package. In mid-April, I found myself converting my dataset to STATA and learning STATA's command syntax on the fly. Luckily, I am a bit of a quick study, and a half-hour tutorial on STATA was enough to get me moving. Although I was facing a deadline crunch, this process was well worth it, because when I ran the regressions in STATA, I was getting the results I thought I would get.

So now I have an Honors Thesis in Economics, a thesis that I am both happy with and proud of. Not bad for a former English major. Not bad at all.

Advice to Future Honors Students

Professor Evensky likes to say, “It’s about an education.” What he means is that you learn something from every aspect of a project. This thesis taught me a lot. Some of the more important ideas I learned included:

Get a topic and get one you are genuinely interested in and have some knowledge about. The sheer volume of work requires that you give up a lot of your time, and you need to spend it on something you enjoy doing. Professor Evensky encourages his students to have fun while working and to enjoy discovering and thinking. If your project does not naturally engage you, it will become a chore and not fun at all, and a chore is no way to finish the academic portion of your undergraduate experience.

As soon as you know what you want to research, find data. You never know how much data preparation you will need to do. Some students use prepared datasets like me, while others work from self-created Excel spreadsheets. Whether you purchase a dataset or create your own, data entry, preparation, and management is tedious and time consuming. You need to do it. Don’t give up. One of Professor Lovely’s professors at the University of Michigan once said to her, “Damnit, Lovely, have a whiskey to get it done...”

I think one of the smarter decisions I made was that I spoke with the real experts: pediatricians. Dr. Thomas Welch, Chair of the Department of Pediatrics at SUNY Upstate, and Dr. Robert Kanter provided advice on choosing diagnoses and additional literature to read. Do not be afraid to talk to the real experts. I realized that as an economist, I have skills in data analysis, but I lack clinical knowledge. Obtaining knowledge from experts provides your project with additional context and meaning.

Admit your weaknesses and deal with them. My first weakness was lack of clinical knowledge, so I spoke with doctors. My other weakness was, and still is, lack of theoretical and mathematical training. I came to SU and English major and had no exposure to math beyond high school precalculus. I never expected to become an economics major, so I never sought mathematics courses in college beyond probability and statistics. Now I regret that. I understand that mathematical skills are required for graduate school, whether I decide to continue my schooling in public policy, public health, or economics. I already have strong writing skills, and I want my quantitative skills to be just as strong. It is not enough for me to just be a strong writer or a deep thinker; being able to derive and understand the numbers and the theory behind the method is just as important. I expect to move to Washington, D.C. after graduating SU, and the U.S. Department of Agriculture General Schedule Graduate School offers courses in math and econometrics. I expect that my first job, combined with taking extra courses in math and econometrics, will help me to decide what graduate degree to pursue.

Be persistent, inquisitive, intuitive, and skeptical. I was skeptical of the initial regression results I obtained through SPSS and intuitively knew that they had to be wrong. I persisted in finding the best method available, even though it meant learning a new data analysis package. Also, push hard and follow through.

Be prepared to give up a Friday night on occasion. This was a hard one for me, especially since I enjoy my beer and my friends. I realized that in order to complete the best thesis possible, I needed to make sacrifices. Sometimes that involved missing out on the activities of a typical second semester senior. But I would not change that for anything. All the hard work was worth it, and I am proud of what I accomplished.

Acknowledgements

There are several people without whom this project could not have been possible. To Professor William Coplin, Mary Ann Shaw, and Patricia Sealing, I thank for the opportunity to do research at Upstate in the first place. To Professor Thomas Kniesner, I thank for agreeing to be my second reader. To Dr. Robert Kanter and to Dr. Thomas Welch, respectively, I thank for speaking with me about selecting diagnoses. To Professor John Moran, I thank for alerting me to the selection bias problem and helping me figure out a way around it. To Beyza Ural, I thank for teaching me STATA less than a week before I was scheduled to present my results to the Economics Department.

To my roommates and closest friends – most notably Lindsay Marlenga, Kat Bice, Mary Palumbo, Jack Romain, Brian Byrnes, Jeff Kaczmarczyk, Kristen Viscera, Rachel Poppe – I thank for putting up with me this year while I was constantly obsessing over this project, almost to the point where they limited the amount of time I could talk about it in a single day. Their encouragement, listening ears (even only when they pretended to listen), and good humor got me through some rough spots.

To Professor Jerry Evensky I thank for his moral support throughout my last semester as I was struggling to meet multiple deadlines. More importantly, I thank him for getting me into economics in the first place.

Most importantly, I owe a huge thanks to Professor Mary Lovely. I took Critical Issues in the United States with her three years ago and after that

course, I thought I would not have any occasion to see her ever again (after all, at the time I was not going to be an economics major). Little did I know that she would become my thesis advisor my senior year. She has all the qualities that I admire in a teacher – high expectations, dedication to students, and knowledge and expertise in her subject. Plus, she's a real hard-ass. The hard-ass quality is what I appreciate most about her, since, like most students, I tend to perform my best when I am challenged and inspired. What I also admire about her is that she balances both her career and her personal life and I hope someday to be able to strike that balance in my own life. While college has taught me much about balance and time management, I still have a lot to learn, and I am grateful to have had the opportunity to work with a woman who embodies so much of what I aspire to.

I. Introduction

In its case to build a children's hospital, SUNY Upstate Medical University said that Syracuse was one of two cities in the United States of comparable size without a children's hospital. Albany has a children's hospital. So do Buffalo and Rochester. Advocates for children's hospitals, such as the National Association of Children's Hospitals and Related Institutions, claim that children's hospitals are indispensable to all children needing health care. Children's hospitals have highly trained staffs, unique medical equipment, and family-friendly environments that make the hospital stay a more comfortable experience. According to the American Hospital Association, there are approximately 250 children's hospitals nationwide, less than 5% of all hospitals.

As the only Level I Trauma Center in Central New York, the Department of Pediatrics at University Hospital is responsible for the intensive and critical care in the 17-county region, and is not a conducive environment for providing family-centered care, which nearly all children's hospitals in the country provide. The department is fragmented, and spread across multiple units with many patients to a ward. In some cases, children must share a room with adult patients. Because of its outdated and deteriorating physical condition, University worries about not being able to recruit talented pediatricians and pediatric surgeons to provide the optimal care that Upstate is known for.

Upstate has spent over 20 years trying to build a children's hospital in Syracuse. In 2003, the New York State Department of Public Health approved a Certificate of Need for a $90 million addition to University Hospital, of which the top two floors will house the Golisano Children's Hospital of Central New York at University Hospital. As of April 2006, the Upstate Medical University Foundation has raised more than $21.5 million towards the addition, which will triple and concentrate the space devoted to pediatric services. The "children's hospital within a hospital" will be able to provide care in an integrated environment that enables more efficient information sharing and service delivery while simultaneously providing family-centered care to help children, and their parents, have a more comfortable hospital experience.

While the nation's hospitals agree that providing family-centered care is an important component of quality at children's hospitals, there have been few studies exploring whether children's hospitals actually do provide higher quality care. After all, parents bring their children to pediatric hospitals because they assume pediatric hospitals provide higher quality care. Quality in medical care is notoriously difficult to define, though is it generally accepted that there are many components of quality, such as family-centered care. NACHRI and a number of other trade groups and advocates are currently working to define quality and measures of quality. According to Phelps (2002), quality assesses how well the medical care produces outcomes of improved health. While most would agree that family-centered care and more efficient information sharing and service delivery are important aspects of quality, they are not measurable and certainly not as important as medical outcome.

Hospital mortality is the generally accepted medical outcome. Mortality is death and is used to describe the relation of deaths to the population in which they occur. The mortality rate (death rate) expresses the number of deaths in a unit of population within a prescribed time and may be expressed as crude death rates or as death rates specific for diseases and sometimes, for age, sex, or other attributes (AcademyHealth, 2004). Outcomes measurement is in some ways the ultimate form of quality measurement because what interests most people is whether care has improved the patient's health (Donaldson, 1999). Reducing mortality is one of the most cherished goals of all who are involved in health care (Schneider, 2002). Particularly when looking at studies of aggregate population data, mortality may be the only measure of health (Phelps) because it can be reliably measured and is difficult to misinterpret or to manipulate the result (Schneider).

This project addresses several questions using data from the 2003 Kids' Inpatient Database released by the Agency for Healthcare Research and Quality. Are mortality rates lower at children's hospitals than at non-children's hospitals? Do larger hospitals have lower mortality rates than smaller hospitals? Do higher income patients have lower mortality rates than lower income patients? Is there a difference in mortality rate between trauma, emergency, and urgent cases? Is there a difference in mortality rate across diagnoses?

In the next section, I describe what children's hospitals are and how there has been little research into medical outcomes at them. In Section III, I theorize that children's hospitals will have significantly lower mortality rates than non-children's hospitals. In Section IV, I describe the 2003 edition of the Kids' Inpatient Database, a 2.9 million record administrative dataset obtained from the Agency for Healthcare Research and Quality. In Section V, I describe my econometric method using logistic regression. In Section VI, I describe and discuss my data analysis, and in Section VII, I present this study's economic relevance and relation to policy.

II. Institutions and Related Research

A children's hospital is a hospital that offers services exclusively to children, usually until the age of 21, and is characterized by greater support for children and their families. Children's hospitals account for nearly 39% of all admissions, 49% of inpatient days and 59% of costs for all children hospitalized in the United States. Because children require more nursing care, children's hospitals have higher nursing staff ratios than do other hospitals, and there have been a number of studies that show that higher nurse to patient ratios leads to a decrease in 30-day mortality and a reduction in adverse events such as pneumonia, shock, cardiac arrest, and urinary tract infection (Stanton, 2004).

NACHRI grants hospitals Institutional Membership if they meet one of the three following conditions: (1) Self-governing, not-for-profit children's hospitals that care for patients with conditions normally requiring a stay of less than 30 days; (2) Self-governing, not-for-profit, independent specialty and psychiatric children's hospitals, including those with clinical specialization in orthopedics, rehabilitation, chronic diseases or mental illness; and (3) Pediatric units of not-for-profit medical institutions caring for patients normally requiring stays of less than 30 days and serving as the primary teaching sites of organized pediatric departments of approved medical schools.

Hospitals may also have Associate or Supporting membership. Associate members are (1) Not-for-profit medical institutions each with a pediatric graduate education program affiliated with a medical school, but not the primary teaching site, and having a minimum daily pediatric census of 45 and recognition as a pediatric referral center and (2) Committees or other entities pursuing the development of not-for-profit children's hospitals. Supporting members are not-for-profit or for-profit organizations not eligible for institutional or associate membership, but wishing to support the NACHRI programs of advocacy for children and child health care[1].

Kanter and Dexter (2005) have set additional criteria for defining a pediatric hospital, which includes that a hospital must be in the top decile for both clinical volume and diversity of diagnostic disorders, as well as having an accredited pediatric residency. Moran and Kanter (2005), in a study of mortality at pediatric and other hospitals, identified 11 hospitals out of 241 hospitals in New York State as children's hospitals. Even with the additional criteria, less than five percent of hospitals in New York are pediatric hospitals. Seven out of the 11 children's hospitals are members of NACHRI at the Institutional, Associate, or Supporter Level.

There has been very little research comparing quality of care at children's hospitals with non-children's hospitals, and no study has been performed at the national level. A 1991 study by Murray Pollack found that critically ill children in Oregon admitted to adult intensive care units had mortality rates 40% greater than expected, compared with kids in pediatric

[1] Membership Criteria. National Association of Children's Hospitals and Related Institutions. http://www.childrenshospitals.net/Content/NavigationMenu/About_Us/Membership_Criteria/Membership_Criteria.htm

units. In New York State, Moran and Kanter (2005) found that mortality at pediatric hospitals was lower than at other hospitals by 4.7 deaths per 1000 patients. There are so few of these studies because limitations in administrative datasets have made controlling for hospital selection a difficult problem.

III. Theory

Production of Quality

The production of quality at children's hospitals is:

Q = f(medical inputs, patient characteristics, intake condition) where the output is the quality of medical care and is the change in condition between intake, or admission to the hospital, and the time of measurement, typically discharge from the hospital or death. The change in condition is unobserved, or latent, meaning that it is not observed until it falls below a certain threshold. When quality falls below this threshold, death is observed. Because quality is unobserved, a logistic regression model is the appropriate econometric method for the production of quality. Specific discussion of the logistic method will be covered in Section IV.

Table 1 shows the inputs of the production of quality. Intake Condition is the most important input because it is unobserved and is correlated with the error term in the regression model. This correlation with error term is also known as selection bias, which will be exposed further in this paper.

Table 1: Inputs of the Production of Quality

Medical Inputs (Hospital Characteristics)	**Patient Characteristics**	**Intake Condition (Patient's Diagnosis)**
Hospital Type - Children's Hospital or Non-Children's Hospital	Age	Severity of Illness
Hospital Bedsize	Race	Risk (Likelihood) of Death
	Gender	
	Socioeconomic Status	
	Admission Source	
	Admission Type	

Hypothesis

Children's hospitals, ceteris paribus, will have lower mortality rates. Thus, patients at children's hospitals will have a lower risk of dying. The process of transforming medical care into health can be thought of as a standard production function….Our underlying desire for health itself leads us to desire medical care to help produce health (Phelps). Inputs of the production function for medical care include physical capital, human capital, and labor. Pediatric hospitals will have lower mortality rates because children's hospitals may use larger amounts of inputs, including physical capital, human capital, and labor. For example, there are higher nursing staff ratios at children's hospitals. Children under two require 40% more nursing care, according to NACHRI, pediatric nurses are highly skilled, and there is much evidence that nursing care influences hospital outcomes. Doctors are also highly skilled in pediatric sub-specialties, which require extended residencies and fellowships. Virtually all children's hospitals are teaching hospitals, which means they have accredited pediatric residency programs.

Children's hospitals also have highly specialized diagnostic equipment and children's hospitals have more resources, including monetary, physical, and technological to devote to children than do other hospitals. Thus, because these inputs of production are higher at children's hospitals, the output, or quality of care, will be higher at children's hospitals as well. Children's hospitals may also be able to use any given quantity of inputs more productively, such as having several highly trained surgeons on one case using specialized machinery.

The literature suggests that a number of characteristics are correlated with mortality. These characteristics include age, race, gender, socioeconomics status, payer type, admission source and admission type, and severity of diagnosis and risk of mortality.

Race and ethnicity, historically viewed as biological, has more recently come to be understood as a social characteristic that varies across cultures. "Racial disparities in health generally do not reflect biologically determined differences in the genome or physiology. Indeed, genetic differences between racial groups are small compared with genetic differences within groups, so racial differences in diseases are, to a significant degree, currently unexplained" (Committee on Pediatric Research). It is difficult to isolate the impact of race on the outcome of a disease or a procedure because race is probably affected by both gender and socioeconomic status. In this paper, race is measured using 2 categories: white and nonwhite, and I expect the sign on the coefficient for race to be negative.

Sex or gender has been incorporated in studies because it is considered important to consider differences between men and women, although many of these differences may be socially driven as opposed to biologically driven and may also be affected by a person's race and socioeconomic status, which are also socially driven. "Given the health correlates of the differences in social roles and behaviors of men and women, any differences found are not inevitable expressions of the biological factor" (Committee on Pediatric Research). However, some studies, such as a study on coronary artery bypass graft (CABG) surgery on children in California between 1995 and 1997 found that "female sex was associated with higher in-hospital mortality among children" and for CABG surgery, "sex appears to be an important determinant of surgical outcome among children" (Chang et al., 2002). I expect the sign on the coefficient for sex to be negative and not statistically significant. In this paper, sex is measured using 2 categories: male and female. I hypothesize that the sign on the coefficient for sex to be negative in general.

Socioeconomic status has long been known as a strong predictor of morbidity and premature mortality. Adults with lower SES suffer disproportionately from many diseases with mortality rates above (Naclerio, et al. 1999). Higher per capita income gives more buying power, which directly increases the amount of medical care used, also improving health outcomes (Phelps, 2002). However, when adjusted for severity, many studies have found no relationship between diagnoses and procedure and mortality. Marcin et al. (2003) find that children from lower socioeconomic status had higher injury hospitalization and mortality rates and presented more frequently with more lethal and fatal mechanisms of injury. However, they did not have higher severity adjusted mortality, suggesting that there was no relationship between income and the quality of care. In this paper, SES is measured as median household income quartile for patient's zip code with 4 categories: 0-25% percentile, 26-50% percentile, 51-75% percentile, and 76-100% percentile. I expect the sign on the coefficient for SES to be negative and not significant.

Previous studies find no relationship between mortality and payer type. Tilford et al. (2005) find that children residing in low-income households and children with public insurance were not at increased risk of in-hospital mortality. Children's hospitals treat a disproportionate number of low-income children – nearly half the care they provide - because Medicaid accounts for more than 45% of the inpatient days at most children's hospitals (NACHRI). In this paper, payer type is measured using the following categories: Medicare, Medicaid, Private Insurance, Self-Pay, No Charge, and Other. I expect the sign on the coefficient for payer type to be positive and not significant. Patients who are admitted to the hospital via the emergency department may have a greater risk of mortality because their diagnoses are more likely to be classified as emergency or trauma. For these cases, the quality of care the hospital provides may be critical to the outcome. Thus, the way the patients were admitted to the hospital, or admission source, and the kinds of diagnoses they have, or admission type, are correlated with the condition presented by the patient. Moreover, severity of diagnosis is significantly correlated with mortality. Patients with more severe diagnoses are more likely to be at greater risk to die. Severity and risk of mortality will be elaborated on further in this paper. In this payer, admission source is measured using the following categories: Emergency Department, Another Hospital, Another Health Care Facility Including Long-Term Care, Court or Law Enforcement, and Routine or Birth or Other. Admission type is measured using the following categories: Emergency, Urgent, Elective, Newborn, Trauma, and Other. I expect the signs on the coefficients for admission source and admission type to be negative and statistically significant.

NACHRI claims research demonstrates significantly better health care outcomes frequently result when a hospital performs a high number of a particular type of procedure, which is known as surgical volume. Birkmeyer (2002) also finds that higher-volume hospitals had lower operative mortality rates for six types of cardiovascular procedures and eight types of major cancer resections. Phelps (2002) mentions that several studies have shown that more surgeries have shown better outcomes. Hannan, et. al. (1998) report similar findings looking at pediatric cardiac care surgery, showing that both hospital volume and surgeon volume are significantly associated with in-hospital mortality, and these differences persist for both high-complexity and low-complexity pediatric cardiac procedures. McClellan and Staiger (1999) found that for specific diagnoses, such as acute myocardial infarction, which is a major heart attack, quality improves with the size of the hospital (Phelps, 2002). In this paper, bedsize is measured using the following categories: large, medium, and small. I expect the sign of the coefficient on bedsize to be negative and significant.

<u>Selection Bias</u>

According to Hartz (1989), outcome, or probability of death, alone cannot be used to measure the quality of care because "patients' characteristics may have more effect on outcome than does the quality of care. Thus, comparisons of outcomes must incorporate adjustments for the characteristics of patients that affect outcome. If the adjustment is not adequate, then the outcome will appear to be worse in hospitals that care for more severely ill patients." Children's hospitals treat more severely ill patients than do non-children's hospitals because they are perceived to deliver higher quality care and patients do not randomly select into hospitals. Patients choose a hospital based on location, ambiance, food, price, and most importantly for this study, quality (Phelps, 2002). Since hospitalwide quality factors are influenced by the case mix of patients (Pollack et al., 1994), including severity of illness and risk of death, without controlling for severity and risk of death through risk adjustment, excess mortality will be observed at children's hospitals (Moran and Kanter, 2005). This problem is known as selection bias. Without controlling for selection, Moran and Kanter observe greater mortality at children's hospitals.

The challenge then is to employ a strategy that mitigates selection bias. Kanter and Moran controlled for selection bias using an instrumental variable (IV) approach. An IV is a variable that does not appear in the regression equation, is uncorrelated with the error in the equation, and is partially correlated with the endogenous explanatory variable (Woolridge, 2006).

Moran and Kanter create an instrument for hospital choice using the differential distance from each patient's residence to the nearest pediatric hospital, relative to the nearest hospital. The IV estimator compares mortality rates among those who live relatively close to pediatric hospitals to those who live relatively far away. Kanter and Moran make two assumptions regarding differential distances: (1) differential distances are a sufficiently strong predictor of hospital choice and (2) differential distances are uncorrelated with the unobservable determinants of mortality, which is severity of illness[2]. Differential distance is correlated with the choice of a pediatric or other hospital but does not directly affect outcome, thus mimicking a randomization to the type of hospital.

It may not be necessary to use an IV approach to mitigate for selection when severity of illness and risk of mortality are observed. Moran and Kanter used data from the New York State Statewide Planning and Research Cooperative System (SPARCS) and the only measure of mortality risk in that dataset is diagnosis. Lack of clinical information, including severity

[2] Severity of illness is a risk prediction system to correlate the "seriousness" of a disease in a particular patient with the statistically "expected" outcome (eg. Mortality). Most effectively, severity is measured at or soon after admission, before therapy is initiated, giving a measure of pretreatment risk (AcademyHealth, 2004).

information and risk of mortality, in administrative datasets such as SPARCS and the Kids' Inpatient Database through the year 2000 has been a major concern among researchers using these datasets to evaluate the quality of health care (Iezzoni, 1997). The 2003 edition of the Kids' Inpatient Database (KID), available through the Agency for Healthcare Research and Quality's Healthcare Cost and Utilization Project, includes information of severity of illness and risk of mortality. Because the KID includes a rich set of controls, using an instrumental variable is unnecessary.

Because this study measures quality using mortality, I restrict my analysis to diagnoses that fit two criteria. These criteria are: (1) mortality risk is non-negligible and (2) quality of care is important to the outcome. These criteria at first appear to be contradictory, but emergency and trauma procedures may qualify. In emergency and trauma-related procedures and diagnoses, if patients do not receive care immediately, they are more likely to die. Quality of care may be important for other diagnoses, a broken arm, for example, but we cannot observe it by analyzing mortality because patients do not die from broken arms. Mortality is observed and quality of care is also important for serious diagnoses such as leukemia or pediatric cardiac heart surgery, but these cases only go to children's hospitals. A major challenge this project presented was choosing diagnoses that would be observed at both children's and non-children's hospitals.

To choose a diagnosis to investigate, I calculated mortality rates by diagnostic related group[3] (DRG) using the Kids' Inpatient Dataset. I selected diagnoses where mortality was observed and then arranged meetings with Dr. Robert Kanter[4] and with Dr. Thomas Welch[5], Chair of the Pediatrics Department at Upstate, to discuss possible procedures. Using my criteria for selecting diagnoses, the doctors recommended the following:

Table 2: Diagnosis (DRG) Groups Selected for Study

Medical/ Surgical	**Diagnosis**	**Died**	**Did Not Die**	**Total**
Surgical	Craniotomy Age >17 Except for Trauma	24 (2.8%)	845 (97.2%)	869
Surgical	Craniotomy for Trauma Age > 17	87 (14.7%)	504 (85.3%)	591
Surgical	Craniotomy Age 0-17	286 (2.4%)	7,324 (97.6%)	7,610
Surgical	Other OR Procedures for Injuries with Complications	70 (3.8%)	1,651 (96.2%)	1,721
Surgical	Craniotomy for Multiple Significant Trauma	173 (29.0%)	423 (71.0%)	596
Surgical	Other OR Procedures for Multiple Significant Trauma	349 (11.3%)	2,753 (88.7%)	3,102
Medical	Other Multiple Significant Trauma	255 (6.7%)	3,547 (93.3%)	3,802
Medical	Other Injury, Poisoning, Toxic Effect Diagnoses with Complications or Comorbidities	194 (16.8%)	963 (83.2%)	1,157
Medical	Other Injury, Poisoning, Toxic Effect Diagnoses Without Complications or Comorbidities	17 (0.9%)	1,936 (99.1%)	1,953

[3] Diagnosis Related Groups (DRG) are groupings of diagnostic categories drawn from the International Classification of Diseases and modified by the presence of a surgical procedure, patient age, presence or absence of significant comorbidities or complications, and other relevant criteria (AcademyHealth, 2004). They were developed by Medicare and are often referred to as Medicare DRGs.

[4] Meeting with Dr. Robert Kanter took place on December 7, 2005.
[5] Meeting with Dr. Thomas Welch took place on December 5, 2005.

Table 2 shows the differences in mortality for the nine DRGs. Procedures and diagnoses that were selected generally involved trauma or injuries where mortality is non-negligible and quality of care critical to outcome. Four of the diagnoses involve craniotomies, which is any procedure that is performed on the head. 1,444 or 6.5% of the 22,088 cases resulted in death. The average mortality rate for the nine selected diagnoses is approximately 9.82%.

A major limitation in using DRGs for severity adjustment is that there is limited adjustment for severity of illness. Principal diagnoses and procedures are stratified into categories based on the presence of a substantial complication or comorbidity (CC) in secondary diagnoses. The CC list includes about 3,000 diagnosis codes for diverse conditions that range from major acute illnesses to less severe chronic conditions. As a result, DRG categories are unable to sufficiently account for the differential effects of these secondary diagnoses on resource use (HCUP, 2005).

> An alternative to the DRG is the All-Patient Refined-DRG (APR-DRG): Developed during the mid to late 1980s, Refined DRGs (R-DRGs) and All-Patient DRGs (AP-DRGs) represented the first modifications of Medicare DRGs that attempted to account for severity of illness. Both systems addressed the limitations of DRGs through refinement of the CC list. AP-DRGs formed the basis of All-Patient Refined DRG, which were developed by 3M Health Information Systems in the early 1990s. APR-DRGs add severity of

illness and risk of mortality subclasses for each base DRG. In determining the severity level, 3M incorporated principal diagnosis, age, interactions with multiple secondary diagnoses, and combinations of non-operating procedures with principal diagnosis. The severity of illness and risk of mortality subclasses have levels of 1 to 4, indicating minor, moderate, major, and extreme, respectively. Based on these enhancements, APR-DRGs represented a significant improvement over both R-DRGs and AP-DRGs, and thus also a significant improvement over the original Medicare DRGs (HCUP, 2005).

Based on these refinements, instead of controlling using DRG, I control for patient's intake condition using APR-DRG, severity of illness, and risk of mortality. I selected a subset of diagnoses for study and matched as close as possible with the original DRG selected. Table 3 gives a breakdown of the APR-DRGs by mortality:

Table 3: APR-DRG Groups Included in Study

Medical/ Surgical	Diagnosis	Died	Did Not Die	Total
Surgical	Craniotomy For Trauma	269 (11.0%)	2,176 (89.0%)	2,455
Surgical	Craniotomy Except for Trauma	144 (2.1%)	6,596 (97.9%)	6,740
Surgical	Craniotomy for Multiple Significant Trauma	288 (29.6%)	685 (70.4%)	973
Surgical	Abdominal/Thoracic Procedures for Multiple Significant Trauma	238 (12.9%)	1,603 (87.1%)	1,841
Surgical	Musculoskeletal Procedures for Multiple Significant Trauma	30 (1.1%)	2,820 (98.9%)	2,850
Medical	Multiple Significant Trauma Without OR Procedure	263 (6.6%)	3,720 (93.4%)	3,983
Medical	Other Injury, Poisoning, Toxic Effect Diagnoses	212 (6.5%)	3,044 (93.5%)	3,256

Table 3 shows the differences in mortality for the seven APR-DRGs. There was a difference in categorizing procedures; the APR-DRGs have separate categories for multiple significant trauma, (1) abdominal and thoracic procedures and (2) musculoskeletal procedures. The Medicare DRGs do not distinguish these two types of multiple significant trauma. The average mortality rate for the seven selected diagnoses is 9.97%, which is 0.15% higher than the mortality rate for the Medicare DRGs.

By narrowing down diagnostic categories and adding controls for severity and risk, I believe I will be able to adequately control for selection bias.

IV. Data Source

The data for this project is from the Healthcare Cost and Utilization Project Kids' Inpatient Database (KID) from the year 2003, released by the Agency for Healthcare Research and Quality (AHRQ) on December 15, 2005. This dataset is publicly available for a nominal fee. The KID was developed to enable analyses of hospital utilizations by children across the United States. The sampling frame is limited to pediatric discharges from community, non-rehabilitation hospitals for which data were provided by HCUP Partner states[6]. Pediatric discharges are defined as all discharges that had an age at admission of 20 years or less (ARHQ, 2005). As defined by the American Hospital Association, community hospitals comprise all non-federal, short-term, general and other specialty hospitals, and include academic medical centers and pediatric hospitals. The KID contains charge information on all patients, regardless of payer, including persons covered by Medicare, Medicaid, private insurance, and the uninsured. The KID's large sample size enables analyses of rare conditions (AHRQ). Thirty-six states participated in the HCUP in 2003, which includes 3,438 hospitals, and 2,984,129 unweighted pediatric discharges. The data was analyzed using SPSS and STATA.

[6] States that participated in the HCUP are Arizona, California, Colorado, Connecticut, Florida, Georgia, Hawaii, Illinois, Indiana, Iowa, Kansas, Kentucky, Maryland, Massachusetts, Michigan, Minnesota, Missouri, Nebraska, Nevada, New Hampshire, New Jersey, New York, North Carolina, Ohio, Oregon, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, and Wisconsin.

V. Method – Logistic Regression

This study uses logistic regression because it is used for regression on a dummy variable, which is death. "Logistic regression can be used to predict a dependent variable on the basis of continuous and/or categorical independents and to determine the percent of variance in the dependent variable explained by the independents and to rank the relative importance of independents" (Garson, 2006).

Logits can be derived from an underlying latent variable, which is unobserved (Woolridge, 2006). In this study, the latent variable is quality. If quality falls below a certain threshold, then mortality is observed. Since this threshold naturally differs by diagnosis, each diagnosis is analyzed separately.

According to Pampel (2000), logits transform the dependent dummy variable and eliminate the floor (0) and ceiling (1) inherent in probabilities. Probabilities and proportions cannot exceed 1 or fall below 0, but regression lines can extend toward positive or negative infinity as the values of the independent and dependent variables can increase or decrease indefinitely. Because a model can give predicted values above 1 and below 0, these values make no sense. The other problem with the floor and ceiling is that it seems likely that the effect of a unit change in the independent variable on the predicted probability would be smaller near the floor or ceiling than near the middle. As values get closer and closer to 0 or 1, the relationship requires a larger and larger change in the independent variable to have the same impact as a smaller change in the independent variable at the middle of the curve.

The general principle is that the same additional input has less impact on the outcome near the ceiling or floor, and that increasingly larger inputs are needed to have the same impact on the outcome near the ceiling or the floor.

Pampel explains that the ceiling and the floor create another problem besides nonlinearity. Regression assumes additivity, which means that the effect of one variable on the dependent is the same, even if the levels of the other independents are different. Binary dependent variable violate this assumption; If the value of one independent variable reaches a sufficiently high level to push the probability of the dependent variable to near 1 (or to near 0), then the effects of other variables cannot have much influence.

Another problem arises because the two observed values of 0 and 1 violate assumptions of normality and homoscedasticity. First of all, distribution of errors for any X value cannot be normal when the distribution has only two values, so this violates normal distribution. The error term violates homoscedasticity because the regression error term varies with the value of X and as a result, the variance of the error terms is not constant. The sample estimates of the standard errors will be biased, making tests of significance invalid. Thus, standard ordinary least squares (OLS) regressions cannot be used.

The first step in logit transformation is transforming probabilities into odds. First, assume that each case has a probability of having a characteristic or experiencing an event, defined as P1. Take the ratio of P1 to 1-P1, or the odds of experiencing the event. Odds express the likelihood of an occurrence relative to the likelihood of a non-occurrence, eliminating the upper bound or ceiling. As a probability gets closer to 1 (so the patient becomes more likely to die), the numerator of the odds becomes larger relative to the denominator and the odds become an increasingly large number. The transformation allows values to extend linearly above the previous upper limit of 1.

The next step is to eliminate the lower bound or the floor. To do this, take the natural log of the odds. For odds above 0 and below 1, the natural log is negative. If odds equal 1, the natural log is 0, and if odds are greater than 1, the natural log is positive. The first property of a logit is that it has no upper or lower boundary. Odds eliminate the upper boundary and the logged odds eliminate the lower boundary. The second property of a logit is that the logit transformation is symmetric around the midpoint probability of 0.5.

Next is to obtain probabilities from logits by taking the exponent to eliminate the logarithm. The linear relationships between the independent variables and the logit dependent variable imply nonlinear relationships with probabilities, which complications in the interpretation of regression coefficients, which will be elaborated on later.

What the logit transformation has done is that it straightens out the nonlinear relationship between X and the original probabilities. Linear relationship between the independent variables and the logit dependent variable imply non-linear relationship with probabilities. What is essentially done is regression on a dependent variable that transforms nonlinear relationships into linear relationships, shifting the interpretation of coefficients from changes in probabilities to changes in logged odds. Logistic regression estimates the probability of an event occurring. In this study, that event is death.

The error term has the standard logistic, or binomial, distribution, which means it is symmetrically distributed around zero. Error terms are assumed to be independent.

VI. Descriptive Statistics

Table 4 gives a list of the independent variables used in this study. All of the independents, with the exception of age, are categorical variables. Also listed are the means, standard deviations, and variances for the variables.

Table 4: Descriptive Statistics for the Independent Variables

Variable Name	Categories	Mean	Standard Deviation	Variance
Age		12.00	6.598	43.540
Sex	0 = Male 1 = Female	.37	.484	.234
Race	0 = Non-White 1 = White	.44	.497	.247
Median Household Income for Zip Code	1 = 0-25th Percentile 2 = 26-95th 3 = 51-75th 4 = 76-100th	2.46	1.104	1.218
Admission Source	1 = Emergency 2 = Another Hospital 3 = Another Health Care Facility 4 = Court/Law Enforcement 5 = Routine/Other	2.18	1.743	3.038
Admission Type	1 = Emergency 2 = Trauma 3 = Urgent 4 = Elective 5 = Other	1.87	1.238	1.532
Risk of Mortality	1 = Extreme Likelihood of Dying 2 = Major 3 = Moderate 4 = Minor	3.29	1.004	1.007
Severity of Illness	1 = Extreme Loss of Function 2 = Major 3 = Moderate 4 = Minor	2.62	1.047	1.096
Bedsize of Hospital	1 = Small 2 = Medium 3 = Large	2.55	.676	.457
Hospital Type	0 = Non-Children's Hospital 1 = Children's Hospital	.53	.499	.249

Table 5 shows the unconditional mortality for APR-DRG, mortality, and hospital type.

Table 5: Deaths in Children's and Non-Children's Hospitals by Diagnosis

Diagnosis	**Died in Children's Hospital**	**Died in Non-Children's Hospital**
Craniotomy For Trauma	10.3%	11.7%
Craniotomy Except for Trauma	2.0%	2.7%
Craniotomy for Multiple Significant Trauma	28.0%	31.0%
Abdominal/Thoracic Procedures for Multiple Significant Trauma	12.0%	13.4%
Musculoskeletal Procedures for Multiple Significant Trauma	1.0%	1.1%
Multiple Significant Trauma Without OR Procedure	7.5%	6.0%
Other Injury, Poisoning, Toxic Effect Diagnoses	9.9%	4.1%

The unconditional mortality shows that lower mortality rates is observed at children's hospitals, except for multiple significant trauma without an operating room procedure and other injury, poisoning, or toxic effect diagnosis. Thus, there is no obvious unconditional relationship between hospital type and mortality. Selection bias may be an important problem.

VII. Regression Results and Discussion

Tables 7-13 show the logistic regression results for each APR-DRG. For each regression, the dependent variable is death and is coded as 0 = Did Not Die and 1 = Died. When automatically assigning dummies for variables with more than two categories in the logistic procedure, STATA assigned the first category as the omitted reference category. Table 6 shows these categories. All coefficients on the dummy variables are relative to the reference category.

Table 6: Omitted Reference Categories

Variable	**Omitted Reference Category**
Income	0-25th Percentile
Admission Source	Emergency Department
Admission Type	Emergency
Risk	Extreme Likelihood of Dying
Severity	Extreme Loss of Function
Bedsize	Small

For dummy variables, STATA calculated the coefficient, standard error, z statistic, significance level, and pseudo R-square.

Table 7: Craniotomy for Trauma

Variable	Coefficient	Standard Error	z Statistic	p value
Children's Hospital	-.1302232	.2199692	-0.59	0.554
Risk (Likelihood of Death)				
Major Likelihood	-2.547792	.2676266	-9.52	*0.000*
Moderate Likelihood	-3.572357	.3203116	-11.15	*0.000*
Minor Likelihood	-5.53556	.583738	-9.48	*0.000*
Severity (Loss of Function)				
Major Loss	.8778432	.2266496	3.87	*0.000*
Moderate Loss	-.2536941	.5062139	-0.50	0.616
Minor	.1568887	.6039005	0.26	0.795
Age	-.0001407	.0160986	-0.01	0.993
Female	-.0045142	.2330323	-0.02	0.985
Race	-.0346996	.0310568	-1.12	0.264
Income				
Income: 26-59th Percentile	-.285633	.2768082	-1.03	0.302
Income: 51-75th Percentile	-.1341763	.277854	-0.48	0.629
Income: 76-100th Percentile	-.4761909	.3022598	-1.58	0.115
Admission Source				
Another Hospital	-.4163498	.3911651	-1.06	0.287
Another Facility	9689107	.948416	1.02	0.307
Routine/Other	-1.070225	.573629	-1.87	0.062
Admission Type				
Trauma	.9426665	.4792701	1.97	*0.049*
Urgent	-.5345449	.3910721	-1.37	0.172
Elective	-1.276158	1.132809	-1.13	0.260
Other	.8586221	1.805211	0.48	0.634
Bedsize				
Medium	.0814353	.4024429	0.20	0.840
Large	.2767483	.3529898	0.78	0.433
Sample Size = 2,047 Pseudo R Square = 0.5343				

Table 8: Craniotomy Except for Trauma

Variable	Coefficient	Standard Error	z Statistic	p value
Children's Hospital	-.1981447	.2411083	-0.82	0.411
Risk (Likelihood of Death)				
Major Likelihood	-.8596557	.2482466	-3.46	*0.001*
Moderate Likelihood	-1.746576	.309016	-5.65	*0.000*
Minor Likelihood	-3.300454	.4258194	-7.75	*0.000*
Severity (Loss of Function)				
Major Loss	-.8702736	.2443915	-3.56	*0.000*
Moderate Loss	-1.472475	.4025457	-3.66	*0.000*
Minor	-.8228636	.4583596	-1.80	0.073
Age	.0424125	.0157874	2.69	*0.007*
Female	-.025523	.2000559	-0.13	0.898
Race	-.0499196	.03135	-1.59	0.111
Income				
Income: 26-59th Percentile	-.5183026	.2887939	-1.79	0.073
Income: 51-75th Percentile	-.2159185	.2661345	-0.81	0.417
Income: 76-100th Percentile	-.3392664	.2847287	-1.19	0.233
Admission Source				
Another Hospital	.1686357	.2749693	0.61	0.540
Another Facility	1.072784	.5237949	2.05	*0.041*
Admission Type				
Urgent	-.4338684	.286182	-1.52	0.130
Elective	-1.208923	.4102701	-2.95	*0.003*
Bedsize				
Medium	-.0025294	.3648785	-0.01	0.994
Large	.1893425	.310598	0.61	0.542
Sample Size = 5,613 Pseudo R Square = 0.3461				

Table 9: Other Injury, Poisoning, or Toxic Effect Diagnoses

Variable	Coefficient	Standard Error	z Statistic	p value
Children’s Hospital	.0898835	.2401315	0.37	0.708
Risk (Likelihood of Death)				
Major Likelihood	-.764496	.2665113	-2.87	*0.004*
Moderate Likelihood	-3.047748	.5359171	-5.69	*0.000*
Minor Likelihood	-4.934195	.8063207	-6.12	*0.000*
Severity (Loss of Function)				
Major Loss	-.6916868	.282309	-2.45	*0.014*
Moderate Loss	-.964086	.6723935	-1.43	0.152
Minor	-1.312594	.8392807	-1.56	0.118
Age	-.0007618	.0163784	-0.05	0.963
Female	-.2407454	.2351993	-1.02	0.306
Race	-.0347876	.0332228	-1.05	0.295
Income				
Income: 26-59th Percentile	-.2133608	.2980067	-0.72	0.474
Income: 51-75th Percentile	-.2146847	.3201132	-0.67	0.502
Income: 76-100th Percentile	.1873764	.3267379	0.57	0.566
Admission Source				
Another Hospital	.6780967	.3118193	2.17	*0.030*
Admission Type				
Trauma	1.240542	1.468639	0.84	0.398
Urgent	-.0531673	.3008282	-0.18	0.860
Elective	.7058738	.5501751	1.28	0.199
Bedsize				
Medium	.3830788	.3687067	1.04	0.299
Large	.1924172	.3423809	0.56	0.574
Sample Size = 2,431 Pseudo R Square = 0.5368				

Table 10: Craniotomy for Multiple Significant Trauma

Variable	Coefficient	Standard Error	z Statistic	p value
Children's Hospital	.174389	.1955581	0.89	0.373
Risk (Likelihood of Death)				
Major Likelihood	-2.338432	.2323336	-10.06	*0.000*
Moderate Likelihood	-3.230799	.3577272	-9.03	*0.000*
Minor Likelihood	-4.530649	.7670591	-5.91	*0.000*
Severity (Loss of Function)				
Major Loss	.7998257	.2401637	3.33	*0.001*
Moderate Loss	.5390392	.4794276	1.12	0.261
Age	.0361056	.0187486	1.93	0.054
Female	.3948793	.1935605	2.04	*0.041*
Race	-.0562849	.0281508	-2.00	*0.046*
Income				
Income: 26-59th Percentile	-.2060744	.2590472	-0.80	0.426
Income: 51-75th Percentile	-.0526151	.2626721	-0.20	0.841
Income: 76-100th Percentile	-.2820984	.2844714	-0.99	0.321
Admission Source				
Another Hospital	-.0408574	.3680234	-0.11	0.912
Another Facility	-.0518713	.9443344	-0.05	0.956
Admission Type				
Trauma	-.0134499	.4313064	-0.03	0.975
Urgent	-.469354	.4601063	-1.02	0.308
Elective	.2869909	.7986989	0.36	0.719
Bedsize				
Medium	.8213959	.4847588	1.69	0.090
Large	.3565473	.4535396	0.79	0.432
Sample Size = 823 Pseudo R Square = 0.2872				

Table 11: Abdominal and Thoracic Procedures for Multiple Significant Trauma

Variable	Coefficient	Standard Error	z Statistic	p value
Children's Hospital	-.0112074	.193233	-0.06	0.954
Risk (Likelihood of Death)				
Major Likelihood	-2.272201	.2144065	-10.60	*0.000*
Moderate Likelihood	-3.094492	.2576161	-12.01	*0.000*
Minor Likelihood	-4.797543	.4580762	-10.47	*0.000*
Severity (Loss of Function)				
Major Loss	.7828574	.224229	3.49	*0.000*
Moderate Loss	.464911	.5182235	0.90	0.370
Age	-.0073669	.0219192	-0.34	0.737
Female	.4328766	.1896772	2.28	*0.022*
Race	-.0380226	.0274151	-1.39	0.165
Income				
Income: 26-59th Percentile	.2007085	.2430451	0.83	0.409
Income: 51-75th Percentile	.3049756	.2412513	1.26	0.206
Income: 76-100th Percentile	.582111	.2632574	2.21	*0.027*
Admission Source				
Another Hospital	-.6804333	.5144582	-1.32	0.186
Another Facility	-.3171294	.9300929	-0.34	0.733
Admission Type				
Trauma	.3815686	.364508	1.05	0.295
Urgent	.1905721	.3245567	0.59	0.557
Elective	-1.304455	1.111648	-1.17	0.241
Bedsize				
Medium	.329794	.4626184	0.71	0.476
Large	.1483629	.4401589	0.34	0.736
Sample Size = 1,463 Pseudo R Square = 0.2679				

Table 12: Musculoskeletal and Other Procedures for Multiple Significant Trauma

Variable	Coefficient	Standard Error	z Statistic	p value
Children's Hospital	-.0136917	.3115545	-0.04	0.965
Risk (Likelihood of Death)				
Major Likelihood	-2.048925	.4116134	-4.98	*0.000*
Moderate Likelihood	-2.855341	.4945517	-5.77	*0.000*
Minor Likelihood	-3.421526	.5746055	-5.95	*0.000*
Severity (Loss of Function)				
Major Loss	.1128129	.3964667	0.28	0.776
Moderate Loss	-.1577477	.6303433	-0.25	0.802
Age	-.0188197	.0415617	-0.45	0.651
Female	.0772732	.3077138	0.25	0.802
Race	-.1066262	.0513975	-2.07	*0.038*
Income				
Income: 26-59th Percentile	-.2645659	.3742454	-0.71	0.480
Income: 51-75th Percentile	-1.04393	.4417396	-2.36	*0.018*
Income: 76-100th Percentile	-.7838071	.4644532	-1.69	0.091
Admission Source				
Another Hospital	-1.181646	1.037503	-1.14	0.255
Another Facility	1.903274	.7963721	2.39	*0.017*
Admission Type				
Trauma	-.8631454	1.086599	-0.79	0.427
Urgent	-1.731041	1.032962	-1.68	0.094
Bedsize				
Medium	16.48189	.8934493	18.45	*0.000*
Large	16.61668	.8622409	19.27	*0.000*
Sample Size = 2,378 Pseudo R Square = 0.1955				

Table 13: Multiple Significant Trauma without Operating Room Procedure

Variable	Coefficient	Standard Error	z Statistic	p value
Children's Hospital	-.1026227	.2038642	-0.50	0.615
Risk (Likelihood of Death)				
Major Likelihood	-4.083311	.318385	-12.83	*0.000*
Moderate Likelihood	-5.22013	.366382	-14.25	*0.000*
Minor Likelihood	-5.773606	.4709483	-12.26	*0.000*
Severity (Loss of Function)				
Major Loss	1.489629	.2557025	5.83	*0.000*
Moderate Loss	.2498588	.4641306	0.54	0.590
Minor Loss	.6573149	1.118076	0.59	0.557
Age	-.0249942	.0165994	-1.51	0.132
Female	-.2105109	.2001803	-1.05	0.293
Race	-.0520755	.0287175	-1.81	0.070
Income				
Income: 26-59th Percentile	-.1237094	.2507567	-0.49	0.622
Income: 51-75th Percentile	-.0240693	.2661233	-0.09	0.928
Income: 76-100th Percentile	-.4830434	.3078594	-1.57	0.117
Admission Source				
Another Hospital	.4189921	.3223812	1.30	0.194
Another Facility	-.717591	1.177614	-0.61	0.542
Admission Type				
Trauma	-.0345899	.4763995	-0.07	0.942
Urgent	-.2900152	.3522595	-0.82	0.410
Elective	.3149896	.5949486	0.53	0.597
Other	1.347043	1.338976	1.01	0.314
Bedsize				
Medium	-.1246339	.3948242	-0.32	0.752
Large	.3448492	.3538838	0.97	0.330
Sample Size = 3,342 Pseudo R Square = 0.5290				

The major finding is that children's hospitals do not appear to deliver higher quality medical care in the form of significantly lower mortality rates. The coefficients on the children's hospital beta was negative for five of the diagnoses and was positive for craniotomy for multiple significant trauma and other injury, poisoning, and toxic effect discharges. The unconditional mortality at children's hospitals was also higher for other injury, poisoning, and toxic effect discharges. None of these coefficients were significant. From these findings, two conclusions may be suggested: (1) Hospital type does not make a difference in determining medical outcome and (2) The controls used to ameliorate selection bias were insufficient.

I cannot argue whether the risk and severity controls were sufficient, of course, because selection bias is unobservable. I can show the impact of the risk and severity controls by showing regressions results omitting these variables. Tables 14-20 show the results.

Table 14: Craniotomy for Trauma

Variable	Coefficient	Standard Error	z Statistic	p value
Children's Hospital	-.0475828	.1530802	-0.31	0.756
Age	.0173814	.0119592	1.45	0.146
Female	.0280037	.1649034	0.17	0.865
Race	-.0060607	.0214062	-0.28	0.777
Income				
Income: 26-59th Percentile	-.2040788	.1932542	-1.06	0.291
Income: 51-75th Percentile	-.2680366	.1970295	-1.36	0.174
Income: 76-100th Percentile	-.3252719	.2156201	-1.51	0.131
Admission Source				
Another Hospital	-.6494986	.2859203	-2.27	*0.023*
Another Facility	-.185664 -	.7703661	0.24	0.810
Admission Type				
Trauma	1.198523	.3109661	3.85	*0.000*
Urgent	-.8055506	.2963569	-2.72	*0.007*
Elective	-1.919433	1.049721	-1.83	0.067
Other	2.176354	1.262494	1.72	0.085
Bedsize				
Medium	.0510515	.2895363	0.18	0.860
Large	.2612626	.2550029	1.02	0.306
Sample Size = 2,047 Pseudo R Square = 0.0592				

Table 15: Craniotomy Except for Trauma

Variable	Coefficient	Standard Error	z Statistic	p value
Children's Hospital	-.4708617	.2182682	-2.16	*0.031*
Age	.0286346	.0144249	1.99	*0.047*
Female	.0659567	.1838202	0.36	0.720
Race	-.0201866	.0284123	-0.71	0.477
Income				
Income: 26-59th Percentile	-.5600535	.2679871	-2.09	*0.037*
Income: 51-75th Percentile	-.1024958	.2436587	-0.42	0.674
Income: 76-100th Percentile	-.3540682	.2631605	-1.35	0.178
Admission Source				
Another Hospital	.6352492	.2478539	2.56	*0.010*
Another Facility	1.186389	.4576324	2.59	*0.010*
Admission Type				
Urgent	-.5553093	.2589342	-2.14	*0.032*
Elective	-1.856737	.3921181	-4.74	*0.000*
Bedsize				
Medium	-.3404443	.3414042	-1.00	0.319
Large	-.0199635	.2881819	-0.07	0.945
Sample Size = 5,613 Pseudo R Square = 0.1512				

Table 16: Other Injury, Poisoning, or Toxic Effect Discharge

Variable	Coefficient	Standard Error	z Statistic	p value
Children's Hospital	.6969552	.1796288	3.88	*0.000*
Age	.0004173	.0121417	0.03	0.973
Female	-.4317819	.1764058	-2.45	*0.014*
Race	.0114772	.0260255	0.44	0.659
Income				
Income: 26-59th Percentile	-.105612	.2249584	-0.47	0.639
Income: 51-75th Percentile	-.2830474	.2422264	-1.17	0.243
Income: 76-100th Percentile	-.0653184	.2356538	-0.28	0.782
Admission Source				
Another Hospital	1.315569	.2261795	5.82	*0.000*
Admission Type				
Trauma	-.0509523	1.040583	-0.05	0.961
Urgent	.0154445	.2248462	0.07	0.945
Elective	.3117806	.3919192	0.80	0.426
Bedsize				
Medium	.3899012	.2680825	1.45	0.146
Large	.0445656	.2488985	0.18	0.858
Sample Size = 2,431 Pseudo R Square = 0.0741				

Table 17: Craniotomy for Multiple Significant Trauma

Variable	Coefficient	Standard Error	z Statistic	p value
Children's Hospital	.0742984	.1643986	.45	0.651
Age	.0561311	.0161373	3.48	*0.001*
Female	.4641514	.1599622	2.90	*0.004*
Race	.4641514	.1599622	2.90	*0.004*
Income				
Income: 26-59th Percentile	-.1698321	.2140802	-0.79	0.428
Income: 51-75th Percentile	-.1253394	.2171676	-0.58	0.564
Income: 76-100th Percentile	-.4046974	.2363593	-1.71	0.087
Admission Source				
Another Hospital	.1277247	.3044787	0.42	0.675
Another Facility	.4689427	.790699	0.59	0.553
Admission Type				
Trauma	-.0084476	.361604	-0.02	0.981
Urgent	-.7905	.3911654	-2.02	*0.043*
Elective	.0641048	.6167546	0.10	0.917
Bedsize				
Medium	.5574304	.4010916	1.39	0.165
Large	.0844665	.379237	0.22	0.824
Sample Size = 825 Pseudo R Square = 0.0363				

Table 18: Abdominal and Thoracic Procedures for Multiple Significant Trauma

Variable	Coefficient	Standard Error	z Statistic	p value
Children's Hospital	-.0822176	.1633307	-.50	0.615
Age	.0139738	.0200159	0.70	0.485
Female	.3960907	.1608351	2.46	*0.014*
Race	-.0089974	.0233444	-0.39	0.700
Income				
Income: 26-59th Percentile	-.0044725	.2093534	-0.02	0.983
Income: 51-75th Percentile	.2412797	.2054677	1.17	0.240
Income: 76-100th Percentile	.4198169	.2261427	1.86	0.063
Admission Source				
Another Hospital	-.3199556	.447456	-0.72	0.475
Another Facility	.2549758	.7883053	0.32	0.746
Admission Type				
Trauma	.1989957	.3151461	0.63	0.528
Urgent	.2865035	.2715913	1.05	0.291
Elective	-1.303064	1.042657	-1.25	0.211
Bedsize				
Medium	.5052228	.4089758	1.24	0.217
Large	.4321656	.3903907	1.11	0.268
Sample Size = 1,470 Pseudo R Square = 0.0176				

Table 19: Musculoskeletal and Other Procedures for Multiple Significant Trauma

Variable	Coefficient	Standard Error	z Statistic	p value
Children's Hospital	-.0171453	.2943431	-.06	0.954
Age	.0268238	.0414238	0.65	0.517
Female	.0064445	.292395	0.02	0.982
Race	-.097645	.0488088	-2.00	*0.045*
Income				
Income: 26-59th Percentile	-.4040355	.3570194	-1.13	0.258
Income: 51-75th Percentile	-.9144057	.4203266	-2.18	*0.030*
Income: 76-100th Percentile	-.7679525	.4439497	-1.73	0.084
Admission Source				
Another Hospital	-.8435303	1.021629	-0.83	0.409
Another Facility	2.149298	.6745556	3.19	*0.001*
Admission Type				
Trauma	-.3680598	1.026095	-0.36	0.720
Urgent	-1.865166	1.024695	-1.82	0.069
Bedsize				
Medium	14.80122	.805988	18.36	*0.000*
Large	15.10529	.7872222	19.19	*0.000*
Sample Size = 2,381 Pseudo R Square = .0695				

Table 20: Multiple Significant Trauma without Operating Room Procedure

Variable	Coefficient	Standard Error	z Statistic	p value
Children's Hospital	.1279642	.1460122	.88	0.381
Age	-.0066317	.0124346	-0.53	0.594
Female	-.2342061	.1446274	-1.62	0.105
Race	-.0190776	.0207864	-0.92	0.359
Income				
Income: 26-59th Percentile	-.0187262	.1792906	-0.10	0.917
Income: 51-75th Percentile	-.1993624	.187033	-1.07	0.286
Income: 76-100th Percentile	-.5265405	.227376	-2.32	*0.021*
Admission Source				
Another Hospital	.5403055	.2280616	2.37	*0.018*
Another Facility	-1.038759	1.021647	-1.02	0.309
Admission Type				
Trauma	.1829518	.3648288	0.50	0.616
Urgent	-.5854328	.2579588	-2.27	*0.023*
Elective	.368841	.4148038	0.89	0.374
Other	1.266469	.8277551	1.53	0.126
Bedsize				
Medium	-.0148016	.2916797	-0.05	0.960
Large	.2594405	.2586004	1.00	0.316
Sample Size = 3,342 Pseudo R Square = .0218				

These tables show that selection may or may not be an issue for each of the diagnoses. When risk and severity were controlled for, the coefficient on the children's hospital variable was never significant. However, when risk and mortality were not controlled for, the coefficient on the children's hospital variable was significant for craniotomy except for trauma and other injury, poisoning, or toxic effect diagnoses. Mortality at children's hospitals was significantly lower (at the .05 level) for craniotomy except for trauma while mortality at children's hospitals was significantly higher (at the .000 level) for other injury, poisoning, or toxic effect diagnoses.

Patient and hospital characteristics were sometimes significant. For craniotomy for trauma, when risk and severity were controlled for, trauma admissions were significant at the .05 level. When risk and severity were not controlled for, admissions from another hospital (such as transfer admissions) were significant at the .05 level, trauma admissions were significant at the .000 level, and urgent admissions were significant at the .01 level.

For craniotomy except for trauma, when risk and severity were controlled for, age was significant at the .01 level, admissions from another health care facility were significant at the .05 level, and elective admissions were significant at the .01 level. When risk and severity were not controlled for, age was significant at the .05 level, income in the 26th-59th percentile of the patient's zip code was significant at the .05 level, admission source was significant at the .01 level, and urgent admissions were significant at the .05 level and elective admissions were significant at the .000 level.

For other injury, poisoning, or toxic effect diagnoses, when risk and severity were controlled for, admissions from another hospital were significant at the .05 level. When risk and severity were not controlled for, sex was significant at the .01 level and admission source was significant at the .000 level.

For craniotomy for multiple significant trauma, when risk and severity were controlled for, both sex and race were significant at the .05 level. When risk and severity were not controlled for, age was significant at the .001 level, sex and race were significant at the .01 level and urgent admissions were significant at the .05 level.

For abdominal and thoracic procedures for multiple significant trauma, when risk and severity were controlled for, sex and income in the 76^{th}-100^{th} percentile of the patient's zip code was significant at the .05 level. When risk and severity were not controlled for, sex was significant at the .01 level.

For musculoskeletal and other procedures for multiple significant trauma, when risk and severity were controlled for, race was significant at the .05 level, income in the 51^{st}-75^{th} percentile of the patient's zip code and admission from another health care facility were significant at the .01 level, and hospital bedsize was significant at the .000 level. When risk and severity were not controlled for, race and income in the 51^{st}-75^{th} percentile of the patient's zip code were significant at the .05 level, admission from another health care facility was significant at the .001 level, and hospital bedsize was significant at the .000 level.

For multiple significant trauma without an operating room procedure, when risk and severity were controlled for, no variables were statistically significant in the model. When risk and severity were not controlled for, income in the 76th-100th percentile of the patient's zip code, admission from another hospital, and urgent admissions were significant at the .05 level.

When risk and severity were controlled for, risk was always highly significant and of the right sign and pattern. Severity was significant for six of the diagnoses, most often when there was major loss of function. What the risk and severity controls did was to ensure that I compared like cases. Once again, I found that holding all else equal, children's hospitals do not have significantly lower mortality rates.

Including risk and severity measures is an important advancement for administrative databases such as the KID. Before the KID 2003 was released, I planned on analyzing data from the KID 2000 database, which did not include information on APR-DRG, risk, and severity. The best control I would have been able to employ was to use codes from the International Classification of Diseases 9th Revision (ICD-9-CM) to narrow down diagnostic categories even further. ICD-9-CM codes provide enormously greater detail than Medicare DRG codes[7], which was the only DRG coding system available in the KID 2000. Hopefully, administrative datasets will continue to provide a greater amount of information to help researchers continue to answer questions about medical care and health.

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[7] Meeting with Dr. Robert Kanter.

Would an IV have worked if data on distance to hospital had been available? Moran and Kanter find that it using an IV works for New York State, but they do not generalize their findings for a national sample. Furthermore, there is no evidence that Moran and Kanter controlled for case-mix.

What do these findings mean for children's hospitals? Although children's hospitals do not provide significantly better care in the form of lower mortality rates, they still are valuable assets for their communities. They contribute to a community's quality of life and provide other services and clinics for children and families. The presence of a children's hospital shows how much a community is invested in children, society's most vulnerable population, and the presence of a children's hospital may determine whether a community is able to attract families and businesses. Children's hospitals also serve as a recruiting tool for the hospital, as most pediatricians and pediatric surgeons prefer to work in a children's hospital. Children's hospitals also serve as a marketing and fundraising tool for the hospital, and can be used strategically to help hospitals expand their market shares and increase revenues. Increased revenues are especially important as hospitals that treat a disproportionate number of Medicaid patients or provide free care, such as children's hospitals, are not reimbursed for all of the services they provide.

Moreover, mortality is not the only indicator of quality. As described earlier in this paper, quality is multifaceted, and there are many components of it, including mortality. In-hospital mortality is only one way to assess hospital quality, although it is a crucially important measure.

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