

2013

## Quality of care: analyzing the relationship between hospital quality score and total hospital costs

Jordan Andrew Newell  
*Louisiana State University and Agricultural and Mechanical College*

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QUALITY OF CARE: ANALYZING THE RELATIONSHIP BETWEEN  
HOSPITAL QUALITY SCORE AND TOTAL HOSPITAL COSTS

A Thesis

Submitted to the Graduate Faculty of the  
Louisiana State University  
Agricultural and Mechanical College  
in partial fulfillment of the  
requirements for the degree of  
Master of Science

in

The Department of Agricultural Economics and Agribusiness

by  
Jordan A. Newell  
B.S., Louisiana State University, 2011  
December 2013

## **Acknowledgements**

Several people have played a pivotal role in my thesis research. I would like to thank each of these people individually. My wife, Laura, was pivotal to my progress in advancing and completing this research. Dr. Keithly consistently offered his advice and counseling throughout the various phases of my research. Dr. Portier was very generous in funding my research as well as providing guidance throughout the research process. I am grateful for Dr. Fannin allowing me to access the American Hospital Association data as well as serve on my committee and offer his advice at various points along the way. I am very grateful for Dr. Gelpi and Anna Wang and their assistance with programming my model in SAS. I would also like to thank Dr. Nedelea for his advice and recommending key pieces of literature to review. Greg Olson was also very helpful in assisting with the organization of the model data in Excel.

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## **Abstract**

As healthcare costs and premiums have increased in the recent past, hospitals are forced to try to provide healthcare on tight budgets. In many cases, quality is often sacrificed in an effort to manage patient wait-times and costs. This research attempted to add to the existing body of knowledge of quality of care by defining a relationship between quality of care provided and total hospital costs. This study used the 2006 American Hospital Association's Annual Survey Database and the 2006 Hospital Compare dataset to meet the data requirements for the study. A log-log, as well as a translog, cost function was used to estimate the relationship between quality of care provisioned for community acquired pneumonia and heart failure and total hospital costs. Regressors for the cost function included hospital outputs, inputs and wages as well as variables for patient-mix, case-mix, ownership status and medical school affiliation. Ultimately this study concluded that by increasing the quality of care score associated with community-acquired pneumonia by ten percent would decrease total hospital costs by 2.44 percent. However, several improvements were found that would improve the ability of the quality of care data and estimation methodologies to more comprehensively represent quality.

## **Chapter 1: Introduction**

### **1.1 Introduction to the Thesis**

In a generation with ever-rising healthcare costs, emphasis must still be placed on the quality of the healthcare service provided. Healthcare providers face pressures to lower cost of healthcare while still providing a high quality service. Quality improvement efforts can raise economic concerns, as much remains to be learned concerning the relationship between quality of care improvements and total costs associated with healthcare provision.

### **1.2 Goals and Objectives**

Rural hospitals commonly serve as the only form of healthcare in rural areas. These hospitals also have been known to be fragile economic entities as they often provide healthcare to non-paying customers and are dependent on federal reimbursements to remain open. How fragile each hospital is depends on the hospital's volume of patients, efficiency, and reimbursement rates (Moscovice and Stensland 2002). Urban hospitals, while much less fragile, can nevertheless be inefficient. Thus, as health costs and spending rise, these hospitals must still place emphasis on maintaining a high quality of service while managing a large budget (Rosko 2001).

Thus, it is important to investigate how quality of care improvements will affect total hospital costs for both rural and urban hospitals. As the ultimate goal for all types of healthcare facilities should be to provide high quality service for the lowest possible costs, two consequences of quality emphases exist for these rural and urban hospitals. First, quality of care improvements could increase operating

costs by increasing patient and staff interaction time and requiring more investment by the hospital per patient. On the other hand, quality of care improvements could result in decreased total hospital costs by a reduction in costs associated with medical errors and reducing readmission rates.

The general objective of the study is to answer the following research question: From a hospital total cost function, what is the effect of emphasizing quality of care on total measurable hospital costs for selected rural and urban hospitals? This can be accomplished by addressing several specific objectives. Specifically this study aimed to:

1. Use quality of care scores from the 2006 Hospital Compare dataset and the 2006 American Hospital Association (AHA) Annual Survey Database to identify rural and urban hospitals to be included in the study;
2. Develop a total cost function that is representative of total hospital operating costs and includes an independent variable for quality of care score as well as cost of inputs, outputs, wages, patient-mix, case-mix and other pertinent economic indicators; and
3. Analyze the results for each included hospital, estimating total costs and correlation of quality of care score to total hospital costs.

### **1.3 Background Information**

As the Affordable Care Act was signed into law March 23, 2010, for better or for worse, change was on the horizon. As is often the case with complex laws, different parts of the Affordable Care Act are becoming effective at different times, the earliest having started June 21, 2010 ([healthcare.gov](http://healthcare.gov)). Although there continue

to be many debates over the new healthcare law, a looming physician shortage is generally accepted.

The Center for Workforce Studies' Association of American Medical Colleges produced a report in October 2012 that covered recent studies and reports on physician shortages in the United States. The AAMC Center for Workforce Studies projects a 124,000 full-time equivalent physician shortage by 2025. The U.S. Department of Health and Human Services projects a shortage of approximately 55,000 physicians in 2020. Merritt, Hawkins and Associates, a health care consulting firm, projects a shortage of 90,000 up to 200,000 physicians and predicts that average wait times for medical specialties to increase well beyond the 2004 average of a two to five weeks (AAMC 2012).

With such a large patient-to-physician ratio, the incentive will be to spend less time with each patient in an effort to manage patient wait times. This may ultimately result in a decreased quality of care provided. Although medical errors will occur even with high quality healthcare, a systematic focus on the reduction of medical errors is a critical factor to the provision of high quality healthcare services (Chassin et al. 1998). Further, research has shown how costly medical errors can be. Carey and Stefos (2011) estimate the marginal cost of a medical error to be \$22,413. Therefore, as medical errors can be costly, it is important to investigate the reality of the relationship between quality of care provided and total hospital costs in an effort to understand how to maintain quality and costs simultaneously.

Until 2001, quality of care information was not readily available to the public. Quality of care was originally measured using structural, process or outcome data.

Structural data involve characteristics of physicians and hospitals, like specialty or ownership. Process data include information surrounding the interaction between a physician and a patient or other health care professionals and patients, like particular test ordered. Outcome data refer to subsequent health statuses of patients. These data were combined in various methods to determine a quality assessment. Methods included a health care professional reviewing data on a case-by-case basis, evaluating the provision of care by process criteria or using *a priori* criteria to evaluate where observed outcomes were comparable to predicted outcomes (Brooks et al. 1996).

In November 2001, the Department of Health and Human Services announced a Quality Initiative to utilize accountability of health care providers via public disclosure. The Initiative was designed to empower consumers with quality of care information to ultimately generate an incentive for providers and clinicians to improve quality of care provided. The Medicare Prescription Drug, Improvement, and Modernization Act of 2003 required hospitals to provide quality data according to ten quality measures. The quality data began appearing in the 2004 Medicare Cost Report. Currently, hospitals report quality data on the ten quality measures as well as other measures voluntarily provided (HQI CMS 2008).

Quality measures included a common occurring reason for hospitalization and measures to grade quality of health care provided in response. The major quality measures include: acute myocardial infarction, heart failure, and

pneumonia. Specific measures that serve as quality of care indicators are given in Table 1.1<sup>1</sup>. These indicators are then used to generate a percentage that is recorded

Table 1.1: Hospital Quality Measure Indicators

	Department Prior to Initial Antibiotic Received in the Hospital
	Adult Smoking Cessation Advice/Counseling
	Initial Antibiotic Received within 6 Hours of Hospital Arrival
	Appropriate Initial Antibiotic Selection
	Influenza Vaccination
	PN 30-day Mortality
Surgical Care Improvement Project (SCIP)	Prophylactic Antibiotic Received One Hour Prior to Surgical Incision
	Prophylactic Antibiotic Selection for Surgical Patients
	Prophylactic Antibiotics Discontinued within 24 Hours After Surgery End Time
	Surgery Patients with Recommended Venous Thromboembolism (VTE) Prophylaxis Ordered
	Surgery Patients Who Received Recommended Venous Thromboembolism (VTE) Prophylaxis Within 24 Hours Prior to Surgery to 24 Hours After Surgery
Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS)	Communication with nurses
	Communication with doctors
	Responsiveness of hospital staff
	Pain management
	Communication about medicines
	Discharge information
	Cleanliness of hospital environment
	Quietness of hospital environment
	Overall rating of hospital
	Willingness to recommend hospital
Children's Asthma Care	Use of relievers for inpatient asthma
	Use of systemic corticosteroids for inpatient asthma

<sup>1</sup> Source: 2008 report on the Hospital Quality Initiative of the Center for Medicare and Medicaid Services.

(Table 1.1 continued)

Acute Myocardial Infarction (AMI) – Heart Attack	Aspirin at Arrival
	Aspirin Prescribed at Discharge
	ACE Inhibitor or Angiotensin Receptor Blocker (ARB) for Left Ventricular Systolic Dysfunction
	Adult Smoking Cessation Advice/Counseling
	Beta-Blocker Prescribed at Discharge
	Beta-Blocker at Arrival
	Fibrinolytic Therapy Received within 30 Minutes of Hospital Arrival
	Primary Percutaneous Coronary Intervention (PCI) within 90 Minutes of Hospital Arrival
	AMI 30-day Mortality
Heart Failure (HF)	Discharge Instructions
	Evaluation of Left Ventricular Systolic Function
	ACE Inhibitor or Angiotensin Receptor Blocker (ARB) for Left Ventricular Systolic Dysfunction
	Adult Smoking Cessation Advice/Counseling
	HF 30-day Mortality
Pneumonia (PN)	Oxygenation Assessment
	Pneumococcal Vaccination
	Blood Culture Performed in the Emergency

in the Medicare Cost Report as a quality of care score for respective hospitals (HQI CMS 2008). Implementing these scores into a total cost function will provide insight on whether expenditures in quality of care improvements ultimately lead to increased total hospital costs or reduced total cost resulting from less money spent on medical errors.

#### 1.4 Overview of Related Previous Research

Health care in the United States is a very debated political “hot” topic as well as a very profitable industry for some hospitals, but an expensive industry for nearly all hospitals.. Not surprisingly, health care literature is very diverse and widely available. From medical studies critiquing surgical techniques and new scientific developments to health care economics and efficiency studies, a vast amount of health care literature can be found. This study will particularly focus on health care economics and the relationship between quality of care and total hospital costs. As

the cost/quality relationship can be challenging to pinpoint and include in a cost function, existing literature differs on the exact nature of the relationship. The following review of literature will cover both sides of the argument as well as other studies contributing to the foundation of the current study at hand.

Fleming (1991) provided insight to the nature of the relationship between hospital cost and quality of care provided. The cost functions used in the study included variables for cost determinants and outcome indicators of quality (mortality and readmission indices). The cost functions were estimated using 1985 patient discharge data from 656 hospitals. Discharge data, obtained from 1985 MEDPAR file, was comprised of demographic information as well as diagnosis related group, procedures involved and death if applicable. Results showed the models to have good fit with the data ( $R^2 > .95$ ). Other findings showed a convex marginal cost curve, with higher costs at the low and high ranges of quality. At average levels of quality, costs and quality shared negative relationship, in that increases in quality resulted in cost savings. Ultimately, the author concluded that the nature of the relationship between cost and quality depends on the measures employed, patient mix and the type or status of hospitals included in the analysis (Fleming 1991).

A more recent study, Jha et al. (2009), sought to determine structural characteristics like nurse staffing levels and whether low-cost hospitals had better performance on Hospital Quality Alliance indicators (i.e. whether lower costs were associated with higher quality of care statistics). Multiple data sources were used in constructing the models for this study including: Center of Medicare Services

Hospital Cost Reports, Area Resource File, Medicare Provider Analysis and Review, Hospital Quality Alliance program and the American Hospital Association Annual Survey Database. Estimations were subjected to chi-square and t-tests, as appropriate, to compare various hospital characteristics on the burden of costs they incur. The authors concluded that their estimations produced no evidence that low-cost hospitals provide higher-quality care. Low-cost hospitals actually showed lower performance scores on process-based quality indicators for acute myocardial infarction and congestive heart failure compared to their high-cost hospital counterparts.

Recognizing insufficient availability of quality of care data, Jha et al. (2005) developed quality metrics that they referred to as the “Hospital Quality Alliance Program”. The program focuses on the ten standard indicators established by the Joint Commission of the Center for Medicaid and Medicare Services (CMS). This study’s main contribution to literature was creating a public database containing a vast amount of quality of care data on acute myocardial infarction, congestive heart failure and pneumonia for 3558 hospitals.

Lang et al. (2004) performed a systematic review on the effects of nurse staffing on patients, nurse employees and hospital outcomes. Their review covered 490 articles but focused mainly on 43 meeting certain inclusion criteria. This study is worth mentioning as it contributes to understanding how quality of care is related to nurse staffing levels. Although the focus of the study was to determine whether minimum nurse staffing requirements should be regulated among all acute care hospitals, the authors found that quality of care is directly impacted by nurse-

patient ratios. Lower nurse-patient ratios were associated with lower quality of care provided. This was observed as lower nurse-patient ratios coincided with greater failure to rescue (death within 30 days of a treated patient), more pneumonia cases, urinary tract infections and pressure ulcers. These lower ratios also resulted in more needle-stick injuries and increased length of stay as well as more indications of nursing burnout.

Sloan et al. (1998) investigated whether cost and quality of care for Medicare patients differed among hospitals of various ownership types (i.e. nonprofit, for-profit, government, teaching status). While the current literature is predominated with using process data to indicate quality, these authors utilized post-discharge outcomes as an indicator of quality. A trade-off exists in that quality of care is inherently a process based on the provisioning of care, so assumptions must exist in utilizing outcome data that subsequent negative health outcomes are directly correlated to poor quality of care and not some other external factor. However, their conclusions still provide unique insight to the relationship of hospital cost and quality of care. Eleven years of Medicare data were used to determine the effect of hospital ownership on quality of care provided. Ultimately, the authors concluded that quality did not vary by ownership status, but Medicare payments were greater to for-profit hospitals, indicating that costs were greater at for-profit hospitals.

As a lower quality of care is assumed to be associated with a higher occurrence of medical errors, it is important to understand the impact of medical errors on short-term and long-term hospital costs as well as patient outcomes. Encinosa and Hellinger (2008) estimated the effect of medical errors on medical

expenditures, death, readmissions and outpatient care within 90 days post-surgery. Using data from 161,004 surgeries, the authors identified 14 potentially preventable adverse medical events [i.e. patient safety indicators (PSIs)]. The PSIs were divided into seven groups: technical problems, infections, pulmonary and vascular problems, metabolic problems, wound problems and nursing-sensitive events. The authors estimated a propensity score to match similar surgeries, a control without a PSI and a comparable patient case where a PSI occurred.

Further, five separate regressions were estimated in an attempt to analyze: 90-day expenditures, index hospital expenditures, 90-day readmission expenditures, 90-day outpatient expenditures and 90-day outpatient drug expenditures. Results showed that 2.6 percent (4140) of the 161,004 surgeries had at least one of the 14 PSIs. When compared with control non-PSI surgical events, excess payments for the seven PSI classes ranged from \$646 to \$28,218 on a case-by-case basis. Thus, depending on the PSI occurring, excess expenditures could cost \$28,218 for each occurrence. The authors concluded that their results make a business case for investments in quality (eg., Increasing nurse-patient ratios) as the 14 PSIs were responsible for \$1.47 billion in excess expenditures occurring 90 days post-surgery in 2002.

Similarly, Zhan and Miller (2003) assessed excess length of stay, costs and deaths attributable to medical injuries occurring during hospitalization. For purposes of analysis, the researchers used patient safety indicators (PSIs) from the Agency for Healthcare Research and Quality (AHRQ) to isolate medical errors occurring during hospitalization. Regression analysis was utilized to estimate

excess outcomes (length of stay, costs, etc...) that were attributable to medical errors and to compare with controls via matching analyses. Excess lengths of stay attributable to PSIs ranged from 0 days for neonate injury to almost 11 days for postoperative sepsis. Excess charges spanned from \$0 for obstetric trauma to \$57,727 for postoperative sepsis. Excess mortality ranged from 0% for obstetric trauma to 21.92% for postoperative sepsis. Effects varied among the PSIs with postoperative sepsis and postoperative wound dehiscence being the most severe. These results indicate that quality improvement investments could result in cost reductions in the long run by reducing costs associated with patient safety indicators.

Chen et al. (2010) represents another study investigating the relationship encompassing hospital cost of care, quality of care and readmission rates. Specifically, this study investigates whether low-cost hospitals discharging patients sooner for cost-savings in the short-run incur greater inpatient costs in the long-run as readmission rates increase. Data needs were provided by Medicare Provider Analysis and Review (MedPAR), Inpatient Prospective Payment System (PPS) Impact File, Area Resource File, American Hospital Association and Hospital Quality Alliance Program. Ultimately, the data consisted of 3146 hospitals, 518,473 patient discharges, and 400,068 patients for congestive heart failure. The data for pneumonia contained 3152 hospitals, 443,564 discharges and 399,841 patients. To conduct the analysis, the authors first created a relative cost index (ratio of observed mean cost of care versus predicted cost of care). Then, regression analysis was used to determine hospital cost of care for fiscal quarters each year 2004-2006.

Lastly, quality of care summary scores for pneumonia and congestive heart failure were determined for each fiscal quarter in each year 2004-2006. The authors ultimately concluded that the overall relationship between cost of care and quality of care is inconsistent and that limited evidence was available to conclude whether low-cost hospitals incurred higher long-run costs and readmission rates.

Li and Rosenman (2001) outlined how to estimate hospital costs using a generalized Leontief function. The authors used a panel data set from Washington State hospitals during 1988-1993 and argue that estimation results indicate that the Leontief function is a better fit for estimating hospital costs than a translog function. Patient days, outpatient visits, various prices for inputs and capital were main independent variables used to estimate total hospital costs in the long-run, as capital was allowed to change. The authors' main conclusion was that the Leontief function was advantageous as the panel data framework allowed them to take into account unobserved heterogeneity across hospitals by accounting for unobserved factors such as quality and managerial ability. The authors stated that an estimation bias would exist with the translog as some observations would be lost and variables omitted in order to utilize OLS to estimate the hospital cost function.

Carey and Stefos (2011) outline theoretical and practical challenges to controlling for quality of care provisioned in a hospital cost function. The authors created a short-run, translog model using data from various sources including: Medicare Cost Reports, state administrative data, the American Hospital Association Annual Survey Database and the Agency for Healthcare Research and Quality's Healthcare Cost and Utilization Project State Inpatient Databases. The dependent

variable was total hospital costs. Independent variables included: number of hospital beds, number of discharges, number of outpatient visits, average length of stay, Medicare case-mix inpatient index, hospital ownership type and cost-increasing adverse events like patient safety indicators as well as several other variables. Capital-related investments spanned several years and thus were not included, as the model was a short-run cost function

The authors used the PSIs in two ways to control for quality: entering risk-adjusted event rates and summing the number of events occurring across the 15 included PSIs for each observation. The authors determined the marginal cost of an adverse event to be \$22,413. They concluded that this makes a business case for inpatient safety and provisioning a higher quality of healthcare.

As this literature review has outlined the studies with opposing views concerning quality of care and hospital costs, it is apparent that further research is needed to further identify aspects of the complex relationship concerning quality of care and hospital costs. As the Medicare Cost Reports started including quality of care data in 2004, studies concerning quality of care measurements and hospital costs published prior to 2004 were not included in this literature review. There is an abundant amount of literature concerning quality of care. As a result, this literature review included only those studies having the greatest impact to the foundation of this study.

### **1.5 Organization of the Thesis**

The remainder of this thesis includes the conceptual framework, results and discussion sections. The datasets used for analysis along with the conceptual

framework are presented in Chapter 2. Model results are then presented in Chapter 3. Chapter 4 concludes the thesis by discussing the model results, study flaws and limitations, as well as noting improvements to build upon this research.

## **Chapter 2: Conceptual Framework**

As multiple studies have shown a reduction of medical errors (i.e. higher quality of care) can result in cost savings, this study aspires to contribute to the available literature by analyzing how total hospital costs are related quality of care. Chen et al. (2010) aimed to do this but could not conclude a statistically significant relationship between hospital costs and quality based on their data. It was hoped that further improvements in the availability of data that encompasses quality of care would have provided a more expansive dataset allowing for greater identification of the relationship between quality of care and cost of care.

### **2.1 Theoretical Cost Function**

In relating the underlying theory to this research, the hospital is a multi-product firm producing output in the form of inpatient, outpatient and emergency healthcare services. Derivation of the cost function according to cost minimizing conditions has been outlined in many microeconomic textbooks (Henderson and Quandt, Varian, etc.). The details outlined in microeconomic textbooks explain how profits are maximized for a firm by finding optimal levels of outputs that are efficient in minimizing cost. As the primary focus of this study is to significantly relate quality of care provisioned and total hospital costs, the detail in the theory of the cost function will be relied upon but not elaborated upon in this research. For a detailed explanation of this process, see Gaynor and Anderson (1995) as these authors highlight the cost minimization problem and the derivation of the hospital cost function that estimates observable hospital costs.

The conceptualization of cost minimization can be represented by:

$$\text{Minimize } TC = f(\text{Outputs, Inputs, Wages, Patient-mix, Case-mix, Quality, Control, Rural or Urban Status, Geography, Academic Affiliation}) \quad (1)$$

For the multiproduct firm, the hospital, *total costs (TC)* are the total hospital costs associated with producing a given level of output. Total hospital costs are also believed to be a function of *outputs, inputs, wages, patient-mix, case-mix, heart failure quality, pneumonia quality, rural/urban status, geography, control and academic affiliation*.

*Outputs* for the hospital consist of the healthcare services offered, i.e. inpatient admissions, outpatient visits and emergency department visits. As additional visits to the hospital require additional investment, i.e. wages, supplies, etc., *outputs* should share a direct relationship with total hospital costs. *Inputs* refers to the total number of beds at each institution. As each bed must require investment by the hospital to generate revenue, *inputs* is expected to bear a positive relationship with total costs. *Wages* is representative of the total payroll expense per full-time equivalent employee. Again, a direct relationship is expected for *wages* and *total costs*, as each additional employee hired by the hospital should increase total costs due to the required investment by the hospital, i.e. salary, pensions, insurance, etc.

*Patient-mix* was the percentage of total inpatient admissions paid for with Medicaid and Medicare. There is a leaning among the literature of only including Medicare patient data in a patient-mix variable (Gaynor and Anderson 1995, Carey and Stefos 2011, Li and Rosenman 2001). Although Medicare and Medicaid are

federal and federal/state reimbursement programs respectively, this study includes a summation of both as a percentage of total inpatient admissions at each facility, as it was expected that total costs would increase with a higher number of patients from either reimbursement system, either by a payment gap through the Prospective Payment System or by cost being driven up through a Cost-Based Reimbursement System. Further, Colwill et al. (2008) support the inclusion of Medicaid as the population above age 65 demands healthcare at twice the rate of the population below 65.

*Case-mix* represented the ratio of inpatient admissions to outpatient visits for each respective hospital. As Niederman et al. (1998) suggest, inpatient stays in the hospital are exponentially more expensive than outpatient visits for the same illness or medical treatment. Thus, a higher *case-mix* should be positively related to higher *total hospital costs*, holding all other factors constant. Further, *quality* refers to the congestive heart failure quality of care score or the community acquired pneumonia quality of care score. As Carey and Stefos (2011) indicated, a higher quality of health care is assumed to be associated with fewer patient safety indicators, i.e. medical errors. As these authors also pointed out how costly medical errors are, it is expected that increases in quality of care score for both heart failure and pneumonia should negatively impact total hospital costs. However, Jha et al. (2009) conclude that low-costs hospitals are associated with lower quality of care, when quality was based on performance of process measures for acute myocardial infarction and congestive heart failure.

Indicators for rural/urban status, hospital control type, geographic location and medical school affiliation are also a function of total hospital costs. *Rural hospitals* are often smaller and thus offer fewer specialized services than *urban hospitals*. Thus, having a *rural* hospital status should be associated with lower *total costs*, as *rural hospitals* are not fronting the high operating cost associated with providing complex medical services like cardiothoracic, orthopaedic and neurological consults and procedures. It was anticipated that relationships between *total costs* and *control* would not vary greatly with control type, as Sloan et al. (2001) found that cash flows did not vary greatly among for-profit, non-profit and government hospitals.

*Geography's* influence on total costs is expected to vary by state, however the ultimate reason for the inclusion of this variable was to control for differences in cost of living by selecting for a similar geographic region, the South-Central Census East and West divisions as determined by the 2000 census grouping. Lastly, *academic affiliation* is believed to positively affect *total costs*. Hospitals associated with a medical school are expected to generate higher total costs, on average, when compared to their non-academic counterparts.

A summary of the variables, expected relationships between these variables and *total costs*, and data sources used in generating the variables included in the analysis are presented in Table 2.1.

Table 2.1: Variable Definitions, Locations and Expectations

<b>Variable</b>	<b>Definition</b>	<b>Data Source</b>	<b>Hypothesized Relationship</b>	<b>Dataset Information</b>
<b>Total Cost</b>	total facility expenses excluding bad debt	2006 AHA Annual Survey UTIL table	n/a	dollar value for yearly total costs
<b>Outputs</b>	sum of the total inpatient admissions, outpatient visits and emergency room visits	2006 AHA Annual Survey UTIL table	Positive	numeric value for sum of all visits and admissions
<b>Inputs</b>	total facility beds set up and staffed	2006 AHA Annual Survey UTIL table	Positive	numeric value for number of hospital beds
<b>Wages</b>	total facility payroll expenses per total facility full-time equivalent personnel	2006 AHA Annual Survey UTIL table	Positive	number value for wage per FTE employee
<b>Patientmix</b>	total inpatient admissions belonging to Medicare and Medicaid patients	2006 AHA Annual Survey UTIL table	Positive	Percentage reflecting Medicare/Medicaid patients
<b>Casemix</b>	ratio of inpatient admissions to outpatient visits	2006 AHA Annual Survey UTIL table	Positive	Ranges from 0-1 reflecting ratio of IP to OP
<b>Qualhf</b>	summary score for congestive heart failure quality	2006 Hospital Compare Dataset	n/a as the literature is not consistently specify	percentage reflecting how often measure indicators are performed
<b>Qualpn</b>	summary score for community acquired pneumonia	2006 Hospital Compare Dataset	n/a as the literature does not consistently specify	percentage reflecting how often measure indicators are performed
<b>CBSA</b>	Core based statistical area used to determine rural/urban status	2006 AHA Annual Survey DEM table	<b>Higher at Urban</b>	<b>Rural</b> →non-qualifying or micropolitan <b>Urban</b> →metropolitan or subdivision
<b>Control</b>	type of authority responsible for establishing policy concerning overall operation of the hospital	2006 AHA Annual Survey DEM table	Higher at Non-profit and Government Controlled	Government non-federal (city, county, state or hospital district), Non-profit (church, other), For-profit (partnership or corporation), Federal Government
<b>Geog</b>	Geographic region	2006 AHA Annual Survey DEM table	varying	State code for KY, AL, LA, TX, TN, AR, MS, OK
<b>Mapp</b>	medical school affiliation	2006 AHA Annual Survey DEM table	Positive with Schools	1→YES 2→NO

## 2.2 The Translog Cost Function

To assess the nature of the relationship between total hospital cost and quality of care, a translog cost function was adopted from Capps. et al. (2010) and modified by several independent variable additions including: *Quality, Case-mix,*

*Geog*, *Mapp* and *CBSA*. The following represents the generic translog functional form. Appendix A contains the specific translog model employed in the current analysis.

$$\ln C = \alpha + \sum \beta_x \ln(x) + 1/2 \sum \beta_{xx} \ln(x)^2 + 1/2 \sum \beta_{xy} \ln(x) \cdot \ln(y) + \sum \beta_z Z \quad (2)$$

C is representative of *total hospital costs*, while X represents each of the logarithmically transformed independent variables, i.e. *outputs*, *inputs*, *wages*, *patient-mix*, *case-mix* and heart failure and pneumonia *quality* scores. Y also represents these variables, but is specifically representative of only the variables used in the interaction terms, i.e. *outputs*, *inputs*, *wages* and *patient-mix*. However, *patient-mix* is partially interacted, while the rest are fully interacted. Z is representative of the linear variables, which include *CBSA*, *geography*, *control* and *academic affiliation*.

As noted, *total cost* represents total operating costs for each hospital. *Outputs* refer to the sum of inpatient admissions, outpatient visits and emergency department visits and is fully interacted with *inputs* and *wages*. *Inputs* include a quasi-fixed variable representing the total number of beds at each respective hospital. *Inputs* was fully interacted with *wages* and *outputs*. *Wages* is the average payroll expense per full-time equivalent employee, and again is fully interacted with *inputs* and *outputs*.

However, *patient-mix* reflects the percent of hospital inpatient admissions covered by Medicare or Medicaid and is only interacted with *CBSA*. Although the literature leans towards only including Medicare patient-mix information, Colwill et al. (2008) support the inclusion of Medicaid as the population above age 65

demands healthcare at twice the rate of the population below 65. Also, Medicare and Medicaid patient-mix data were summed together in one variable, as total costs were expected to share a direct relationship with each of these patient populations. Hospital *control* includes dummy variables indicating for-profit or non-profit status and federal or local government ownership. *Quality* is composed of the composite score for pneumonia and heart failure for each represented hospital. *CBSA* is a variable representing urban or rural hospital status. *Geog* refers to the state code indicating the state the hospital is found in. *Case-mix* represents the ratio of inpatient admissions to total outpatient visits. Lastly, *academic* is a dummy for medical school affiliation (equal to 1 if a hospital has an academic affiliation, zero otherwise).

The basic economic theory underlying this translog cost function and explaining its utilization is found in multiple studies (Carey and Stefos 2011, Vassilis Aletras 1999, Capps et al. 2010). It is generally accepted that the translog offers greater flexibility than the log-log cost function. Aletras (1999) offers that the translog is flexible because “it makes fewer assumptions about unknown technology, respects the multi-product nature of hospitals and provides reasonable estimates of economies near the sample means”. Capps et al. 2010 and Carey and Stefos 2011 both concur that the translog offers flexible substitution among the interactions. Within the literature, there is a leaning towards the translog (see Gaynor and Anderson (1995)). These authors utilized the translog and described its derivation under cost minimization conditions. However, the primary ‘drawback’ to estimating the translog cost function relative to a more parsimonious model (e.g.,

the log-log model) relates to the large number of parameters that need to be estimated within the context of the translog model (i.e., squared terms and interaction terms). This increases the probability of encountering multicollinearity and, hence, difficulty of isolating the influence of the individual variables on total costs.

### 2.3 The Log-Log Cost Function

Although the healthcare economic literature leans towards utilizing a translog cost function, some studies advocate using a Cobb Douglas (log-log) cost function depending on the objectives for each individual study. Carey and Stefos (2011) argue that the major drawback to the translog is collinearity due to the large number of parameters included in the translog as interaction and squared terms. Also, these authors noted that estimation precision is sacrificed to utilize the flexible form. Thus, in an effort to truly estimate the relationship between quality of care score and total hospital costs, this study employs a log-log model that is nested within the translog model.

The following cost function is the mechanism employed by this research to relate the cost of producing output for the firm, the hospital, as a function of output and related variables, i.e. healthcare provisioned and other pertinent factors to be explained.

$$\ln C = \alpha + \sum \beta_x \ln(x) + \beta_{xz} \ln(x) \cdot Z + \sum \beta_z Z \quad (3)$$

The generic functional form representative of the log-log model as it relates to hospital costs is given in Equation 3. The dependent variable, total hospital cost, is represented the logarithmically transformed dependent variable and is denoted

as  $\ln C$ . The logarithmically transformed “X” represents several independent variables including: outputs, inputs, wages, patient-mix, case-mix, and quality score for both pneumonia and heart failure. All variable definitions and expectations are listed in Table 2.1, but it is noteworthy to mention that inputs are quasi-fixed, i.e. factors that cannot be readily varied in response to unexpected realizations of demand. Further, the hospitals choose quasi-fixed inputs before demand is realized (Gaynor and Anderson 1995). “Z” represents the non-logarithmically transformed independent variables. These variables were dummies for rural/urban status, geographic region, hospital control type and medical school academic affiliation.

The interaction term in the above model refers to the interaction between patient-mix and rural/urban status. This interaction was included in the model as rural hospitals and urban hospitals that are Medicare certified often operate under different reimbursement programs. Rural hospitals, particularly critical access hospitals, participate in cost-based reimbursements, while urban hospitals use a prospective payment system.

Table 2.1 includes specific definitions and dataset originations for each variable. It is hypothesized that outputs, inputs, wages, patient-mix and case-mix would all be positively related to total hospital costs.; It is further hypothesized that the quality variables would display an inverse relationship, as a reduction of cost is expected with higher quality and fewer medical errors.

## **2.4 Interpretation of the Parameter Estimates**

The interpretation of the coefficient estimate varies depending on the relationship between the dependent and independent variables (i.e. log-log and log-

linear). Log-log refers to both the dependent and independent variables being logarithmically transformed. A log-log relationship requires that each variable be greater than zero, as the logarithm is only defined for positive numbers. A log-linear relationship exists when the dependent variable is logarithmically transformed, while the independent variable is not (Hill et al. 2011).

For the independent variables logarithmically transformed (i.e. sharing a log-log relationship with the dependent variable in this specific model), variable interpretation hinges on the value of the coefficient estimate. A positive coefficient estimate is indicative of a direct or positive relationship between the independent a dependent variable. In other words, if one of the variables were to increase, the other would also increase, and vice versa. However, if the coefficient estimate is greater than 0 but less than one ( $0 < \beta < 1$ ), then the dependent variable (y) is an increasing function of the independent variable (x). In other words, as the dependent variable (x) increases the slope decreases also. If the coefficient estimate is greater than one, the function increases at an increasing rate (i.e slope increases as (x) increases).

Alternatively, if the coefficient estimate is less than zero, an inverse relationship exists between the variables. As the elasticity is the coefficient estimate in models containing this log-log relationship, the coefficient estimate can be interpreted as the resulting percent increase or decrease of the value of the dependent variable associated with a one percent increase in the independent variable, while holding all other factors constant. In other words, a 1-percent change in Outputs is expected to generate a  $\beta_1$  percent change in *total cost*.

Parameter estimates ( $\beta_x$ ) for the translog cost function, however, do not represent elasticities, as is the case for the log-log cost function. The parameter estimates must be used to calculate partial derivatives, which would then reflect the elasticity. For the purposes of this research, partial derivatives were calculated for total hospital costs with respect to pertinent independent variables (quality score for pneumonia and heart failure, outputs, inputs, wages, patient-mix and case-mix). The elasticities ( $\epsilon$ ) imply that a one-percent change in  $x$  (quality, outputs, etc.), holding all else constant, results in a “ $\epsilon$ ” percent change in total costs.

Lastly, interpretation of the log-linear relationship is a little less complex. When the dependent variable is logarithmically transformed and the independent variable is not, the coefficient estimate is used to determine the percentage change in total costs resulting from a change in the independent variable. The interpretation is that, holding all else constant, a one-unit increase in the independent variable will lead to a  $100 \times \beta$  percent change in the dependent variable. The following results exemplify this interpretation as well as the log-log interpretation.

## **2.5 Data**

Data requirements for the model used in this study were met by the utilization of two datasets, the 2006 American Hospital Association’s Annual Survey and the September 2007 release of the Hospital Compare dataset. The September 2007 release was used because it contained quality data for fiscal year 2006. The AHA Annual survey data provides a comprehensive review of U.S. hospitals based on survey results. The dataset provides data concerning information on approximately

6,500 hospitals. The information is organized into demographic, utility and service tables that consist of services provided, organizational structure, inpatient and outpatient utilization, expenses and other budget information, physician arrangement, geographic indicators as well as many other parameters (aha.org 2013)

The Hospital Compare dataset is publicly available through the Centers for Medicare and Medicaid Services. This dataset is part of the Hospital Quality Initiative, which requires all Medicare certified hospitals to report quality data in an effort to make quality of care publicly available. This allows patients to have foreknowledge of the quality of care available and to be able to choose what institution they would like to receive their health care from. This public disclosure is expected to create incentive for hospitals to provide higher quality.

The Hospital Compare dataset includes only acute care and critical access hospitals. The dataset reported quality information for pneumonia, acute myocardial infarction and heart failure. Each health complication had a set of measures associated with it (see Table 1.1 in section 1.3 Background Information). These measures were various forms of treatment for the associated complication. The specific quality data included the percent of the time each measure was performed and the total number of opportunities each institution had to perform each measure.

The quality information provided by Hospital Compare was used to first calculate a summary score for each condition for each institution and ultimately a composite score for each institution. The methodology for determining summary

and composite scores is found in Shwartz et al. (2008) as well as Jha et al. (2009). The first step in determining each institution's summary scores is to multiply the percent, which represents the percent of the time each measure for each condition is performed, by the total sample size. This results in the number of times each institution performed each specific measure. This process is repeated for each measure for each condition for each institution in the dataset. The final step in the summary score calculation is to sum all of the performed measures for each condition and divide it by the sum of the sample size. The resulting percentage associated with each condition is the respective institution's quality of care score for that condition. Finally, composite scores were determined for each institution by averaging all of its summary scores. An unweighted average was used for reasons described in Jha et al. (2005)<sup>2</sup>.

Several steps were taken to eliminate unnecessary data and select for only what was needed for the cost function. As the American Hospital Association's Annual Survey included information for all types of hospitals and healthcare facilities, the first step in compiling the data required for the model was to select for acute care and critical access hospitals only. This was due to the fact that these were the only types of facilities included in the Hospital Compare dataset.

The next step was to select for a particular geographic area in an effort to eliminate any biases that would result from differences in the cost of living for varying geographic areas. The Census South East and West divisions were selected

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<sup>2</sup> Jha et al. (2005) conducted chi-square tests for both weighted and unweighted results. The performance scores that were weighted and those unweighted were similar in magnitude and direction.

and all remaining areas removed from the dataset. The East division included Kentucky, Tennessee, Alabama and Mississippi. The West division included Arkansas, Louisiana, Texas and Oklahoma.

As the AHA data were spread over multiple database tables, the next step in compiling the model-only required dataset was to eliminate all institutions that were not represented in each table. The dataset was then divided according to urban or rural classification. This was accomplished by selecting for a particular core-based statistical area (CBSA). Defined by the White House Office of Management and Budget in 2003, a core-based statistical area consist of a county, counties or equivalent entities that has a population center of at least 10,000 people, plus adjacent areas related by possessing a high degree of social and economical integration as measured through commuting ties to the core area ([census.gov](http://census.gov)).

The AHA demographic table included four CBSA types: rural, metropolitan, micropolitan and division. Rural refers to those counties that do not meet the minimum population criteria of 10,000 people. A metropolitan CBSA is a county that has an urban center of more than 50,000 people. Micropolitan refers to the counties with a population between 10,000 and 49,999 people. A division CBSA refers to metropolitan areas with a population of 2.5 million or greater that have been subdivided into several metropolitan divisions ([reference.mapinfo.com](http://reference.mapinfo.com)).

For the purposes of this study, rural hospitals were those hospitals existing in either a rural or micropolitan CBSA, while urban hospitals resided in either a metropolitan or division CBSA. This methodology of grouping rural and urban hospitals as such was adopted from the Agency for Healthcare Research and

Quality's Healthcare Utilization Project (HCUP). HCUP produced a Nationwide Inpatient Sample Design Report, which outlines the databases and software associated with the inpatient survey results. In the report, HCUP groups rural and urban hospitals according to the previously described methodology ([hcupus.ahrq.gov](http://hcupus.ahrq.gov))<sup>3</sup>.

After isolating the AHA dataset according to geographic region and further by rural or urban CBSA type, the final step to composing the data needed for the model involved matching the remaining Annual Survey data to the Hospital Compare data. The American Hospital Association data mainly uses its own ID system, but the demographic table includes a medical provider number that corresponds to a particular healthcare providing institution. This process involved simply matching the medical provider numbers in each dataset.

Ultimately, the composite quality of care score was the only information extracted from the Hospital Compare dataset. The quality of care score was calculated by the previously described methodology adopted from Schwartz et al. (2008) with one minor difference. To allow for a larger number of observations, the composite score was only determined using data from pneumonia and heart failure. As Schwartz et al. outlined, a summary score cannot be determined for any condition that does not have at least 30 patients seen for at least one of the measures for that condition. A great number of hospitals in the final dataset did not meet this criterion for acute myocardial infarction. Thus, composite scores were

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<sup>3</sup> The Office of Management and Budget has since updated the delineations of Core Based Statistical Areas. The February 2013 updates can be found here: <http://www.whitehouse.gov/sites/default/files/omb/bulletins/2013/b13-01.pdf>.

only determined from the summary scores for pneumonia and heart failure rather than deleting these observations from the dataset.

From the demographic table of the Annual Survey database, CBSA type based on 2003 definitions, state code, hospital control and medical school affiliation were extracted. From the utility table, the extracted information included: total costs, wages, hospital inputs, hospital outputs, case-mix as well as patient-mix. Wages were calculated by dividing total payroll expenses for each facility by the number of fulltime equivalent employees. The Hospital outputs variable was the sum of total inpatient admissions, emergency room visits and outpatient visits for each hospital. The total number of beds at each institution represented quasi-fixed inputs. Patient-mix was the percentage of total inpatient admissions paid for with Medicaid and Medicare. Lastly, case-mix was the ratio of total inpatient admissions to outpatient visits for each facility.

The final dataset consisted only of data needed for the model variables. All other information about each facility was removed. The total number of included observations was initially 593, with 217 consisting of rural hospitals and 376 for urban. Finally, observations considered to be outliers (i.e., those not falling within three standard deviations of the continuous variables) were deleted and this process yielded a total of 551 usable observations. As previously mentioned, a rural hospital was considered one existing in either a micropolitan or rural CBSA, while an urban hospital was one from a metropolitan or division CBSA.

Summary statistics related to the 551 observations included in the final analysis are presented in Table 2.2. Total cost ranged from \$3.34 million to \$697.8

million with a mean of \$104.1 million. Outputs spanned from a minimum of 6,494 visits to a maximum of 646,847 visits, while averaging 128,580.34 visits to each hospital. The number of hospital beds ranged from 11 to 773, with the average being 187.7.

Table 2.2: Summary Statistics Associated With Variables Used in the Final Dataset

Variable	N	Mean	Std. Dev.	Minimum	Maximum	Units
Totalcost	551	104,072,507	113,289,320	3,341,110	697,812,811	\$
Outputs	551	128,580	108,609	6,494	646,847	visits
Inputs	551	187.74	159.55	11.00	773.00	beds
Wages	551	43,449	9,718	13,332	71,352	\$
Patient-mix	551	0.70	0.10	0.35	0.97	%/100
Case-mix	551	0.10	0.05	0.01	0.31	Ratio
QualityHf	551	0.81	0.10	0.19	0.98	%/100
QualityPn	551	0.85	0.07	0.35	0.98	%/100

The average wage per full-time equivalent employee for each hospital ranged from a minimum of \$13,312 to \$71,352 with an average of \$43,449. The ratio of inpatient admissions covered only by Medicaid/Medicare to total inpatient admissions ranged from 0.35 up to 0.97 while averaging 0.70. Case-mix, the ratio of inpatient admissions to outpatient visits, spanned from 0.01 to 0.31, with the average being

0.097. Heart failure quality scores ranged 0.19 to 0.98 with an average score of 0.81. Finally, pneumonia quality scores started at a minimum of 0.35 and climbed to 0.98 with the average being 0.85.

## Chapter 3: Results

### 3.1 Introduction to Results

As the ultimate objective of this study was to determine the relationship between quality of care and total hospital costs, two variations of a cost function were estimated in an effort to find the best fit as well as determine whether quality of care is statistically significant in relation to hospital costs. The first model was a traditional log-log model, with *total costs*, *outputs*, *inputs*, *wages*, *patient-mix*, *case-mix*, *heart failure quality* and *pneumonia quality* logarithmically transformed. The linear variables for this model included *geography*, *control*, *rural status* and *academic affiliation*. The second model was estimated as a translog model with *total costs*, *outputs*, *inputs*, *wages*, *patient-mix*, *case-mix*, *heart failure quality* and *pneumonia quality* logarithmically transformed. The translog model contained squared terms as well as full interactions for *outputs*, *inputs* and *wages*. Lastly, a partial interaction for *patient-mix* and *rural status* was included in both models.

The following sections in the results chapter highlight all relevant results of this study. Although multicollinearity existed among variables in both models, the models were largely in agreement among the statistically significant parameter estimates and elasticities. Also, the continuous variables were given more consideration when reporting results, as these variables served a greater purpose in fulfilling the overall objectives of this study. When interpreting individual parameter estimates, all other variables are held constant whether explicitly stated or not.

### 3.2 Log-Log Regression Results

Relevant model results associated with the log-log model are presented in Table 3.1, while Appendix A contains the complete model results. The log-log model results indicated a good fit ( $R^2=0.961$ ), as well as the overall model being significant ( $P<0.001$ ). All of the continuous variables, with the exception of the variable *heart failure quality* ( $P=0.4785$ ), were statistically significant. Although both quality variables did not return significant, this study was able to significantly confirm the relationship between *total costs* and *pneumonia quality of care*. From the *pneumonia quality* results, it was found that a 10% increase in *pneumonia quality of care* score should generate a 2.44% decrease in *total costs*, holding other factors constant ( $\beta_Q = -0.244$ ,  $P=0.0348$ ).

The remainder of the continuous variables were found to be statistically significant ( $p<0.0001$ ). All of the variables confirmed to theoretical expectations except *patient-mix* and *heart failure quality*. *Outputs*, *inputs*, *wages* and *case-mix* each share a direct relationship with *total costs* as expected. *Patient-mix*, however, shares an inverse relationship with *total costs*. A 10% increase in *patient-mix* is expected to generate a 5.79% decrease in *total costs*, holding all else constant ( $\epsilon_{PM} = -0.579$ ), implying that as the percentage of Medicare/Medicaid inpatients increases, total costs are expected to decline. It is possible that Medicare and Medicaid patient cases are less complex and thus less expensive for the hospital to provision services, as Medicare and Medicaid will place financial responsibility on patients for physician-ordered services associated with inappropriate diagnoses ([www.cms.gov](http://www.cms.gov)). As *case-mix* increases by 10%, *total costs* will increase by 4.45%,

all else constant ( $\beta_{CM}=0.445$ ). The positive relationship between *case-mix* and *total cost* is expected given the fact that an inpatient visit costs much more than an outpatient visit.<sup>4</sup>

A 10% increase (decrease) in *outputs* (i.e., the sum of inpatient admissions, outpatient visits and emergency department visits) results in an estimated 7.94% increase (decrease) in *total costs* ( $\beta_0=0.794$ ,  $SE=0.03$ ). This finding, in conjunction with the high level of statistical significance, implies that there is some economies to scale in the hospital setting. A 10% increase (decrease) in *inputs*, represented by the total number of hospital beds, was estimated to generate a 3.22% increase (decrease) in *total costs* ( $\beta_I=0.322$ ). The magnitude of the parameter estimate associated with the total number of hospital beds appears plausible since an increase in bed number should be associated with increased costs, as a hospital must make investments in staff and supplies to be able to generate revenue from the beds. Finally, a 10% increase in *wages* was found to result in a 5.23% increase in *total costs* ( $\beta_W=0.532$ ). This estimate, to the extent that the model is correctly specified, suggests that wages represent approximately one half of the total hospital costs after controlling for other relevant factors.

For each of the class variables (*geography*, *rural status*, *hospital control* and *academic affiliation*), one of the levels for each was selected as a baseline parameter for comparison. For *geography*, Texas was the basis for comparison between the state a hospital resides in and its relationship with total costs. When compared to Texas, hospitals existing in Tennessee were found to have slightly higher *total costs*.

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<sup>4</sup> This claim is supported by Niederman et al. (1998), which confirmed that inpatient costs are much higher than outpatient costs for the same medical issue.

More specifically, these hospitals in Tennessee can be expected to have an estimated 11% higher total costs than hospitals in Texas, when controlling for all other variables.

For rural or urban hospital status, an urban CBSA status was set as the base for comparison purposes with rural CBSA. Results indicate that hospitals existing in a rural CBSA have lower total hospital costs than hospitals existing in an urban CBSA after controlling for other factors. However, caution should be employed with respect to this inference since a statistically significant difference was not observed. Also, being affiliated with a medical school was found to be associated with 8.5% higher *total hospital costs* in comparison to not being affiliated with a medical school ( $p=0.002$ ).

Lastly, four of the ten levels for the *hospital control* class variable reported back as significant. *For-profit corporate* ownership was the baseline for comparison for the control variable. *State run* hospitals, when compared to for-profit corporate hospitals, will have 18% higher total costs, when controlling for all remaining variables. *Non-profit* hospitals, that are not religiously affiliated, are found to have 6.2% higher total costs than for-profit hospital corporations. Lastly, *Church-run non-profit* hospitals will have 9.5% higher costs in comparison to *for-profit corporate* hospitals, while controlling for the remaining variables.

Table 3.1. Log-Log Regression Results

Independent Variable	Coefficient Estimate ( $\beta$ )	Pr > [t]	Elasticity ( $\epsilon$ )
loutputs	0.794	<0.0001	0.794

(Table 3.1 continued)

Independent Variable	Coefficient Estimate ( $\beta$ )	Pr > [t]	Elasticity ( $\epsilon$ )
linputs	0.322	<0.0001	0.322
lwages	0.523	<0.0001	0.523
lpatientmix	-0.325	0.0002	-0.579→rural -0.325→urban
lcasemix	0.445	<0.0001	0.445
lqualityhf	0.054	0.4785	0.054
Lqualpn	-0.244	0.0348	-0.244
Lpatientmix*CBSA	-0.254	0.0876	--
Kentucky	0.021	0.5888	--
Tennessee	0.119	0.0006	--
Alabama	-0.019	0.6060	--
Mississippi	-0.023	0.6382	--
Arkansas	0.054	0.2744	--
Louisiana	0.065	0.0748	--
Oklahoma	-0.044	0.2888	--
Rural	-0.080	0.1581	--
State Control	0.180	0.0283	--

(Table 3.1 continued)

Independent Variable	Coefficient Estimate ( $\beta$ )	Pr > [t]	Elasticity ( $\epsilon$ )
County Control	-0.030	0.5641	--
City Control	-0.181	0.0689	--
City/County Control	0.138	0.1388	--
Hospital District	0.064	0.0738	--
Church Non-profit	0.095	0.0139	--
Non-profit	0.062	0.0291	--
Partnership For-Profit	0.008	0.8446	--
Medical School	0.085	0.0041	--

### 3.3 Translog Regression Results

Some summary results associated with the translog model are presented in Table 3.2 while complete results, including the correlation matrix, are found in Appendix B. In general, the translog model was found to be statistically significant ( $p < 0.0001$ ) with a good fit ( $R^2 = 0.966$ ). Furthermore, while many of the individual parameter estimates were not found to be statistically significant, most elasticities associated with the continuous variables were found to be statistically significant; the notable exception being the elasticities associated with the two quality variables. Furthermore, in agreement with the log-log findings and agreement with *a priori*

expectations, *patient-mix* was the only variable not returning with confirmation of the *a priori* sign.

Based on the translog results, a 10% increase in *outputs* was found to increase *total costs* by an estimated 8.21%, all else held constant ( $\epsilon=0.821$ ). The translog analysis also indicates that a 10% increase (decrease) in the quasi-fixed variable *inputs* (i.e., number of hospital beds) results in an estimated 3.02% increase (decrease) in *total costs*, all else constant ( $\epsilon=0.302$ ). A 10% increase (decrease) in *wages* can be expected to generate a 5.66% increase (decrease) in *total costs*, holding all other variables constant ( $\epsilon=0.566$ ).

With respect to rural hospitals, a 10% increase in *patient-mix*, the portion of inpatient admissions covered only by Medicaid and Medicare, is expected to generate a 5.23% decrease in *total costs* ( $\epsilon=-0.523$ ), which is significantly more than that associated with urban hospitals (i.e., a 2.96% decrease). Results associated with the translog model further indicate that a 10% increase in *case-mix*, i.e. the ratio of inpatient admissions to outpatient visits, results in an expected 4.71% increase in *total costs*. Lastly, the elasticities for *heart failure quality* and *pneumonia quality* were 0.005 and -0.204 respectively though in neither case were the elasticities associated with quality statistically significant in the translog model analysis.

With respect to geographical differences, hospitals in *Tennessee* and *Louisiana* were found to have significantly higher costs compared to the base state (i.e., Texas). Specifically, hospitals based in *Tennessee* exhibited costs almost 13%

higher than those of Texas-based hospitals while costs among Louisiana hospitals were found to exceed those in Texas by 8.2%. Additionally, *rural status* was marginally significant ( $P=0.064$ ) while indicating that rural hospitals have total costs estimated to be approximately 10% lower than the total costs for urban hospitals.

Table 3.2. Translog Regression Results

Parameter	Coefficient Estimate	P > [t]	Elasticity ( $\epsilon$ )	P > [t]
loutputs	0.158	0.8577	0.821	<0.0001
sqloutputs	0.086	0.004	--	--
linputs	-0.234	0.796	0.302	<0.0001
sqlinputs	0.098	0.0003	--	--
lwages	0.421	0.855	0.566	<0.0001
sqlwages	0.305	0.800	--	--
lpatientmix	-0.296	0.0007	-0.523 $\rightarrow$ rural -0.296 $\rightarrow$ urban	<0.0001 0.0007
lcasemix	0.471	<0.0001	0.471	<0.0001
lqualhf	0.005	0.949	0.005	0.949
lqualpn	-0.204	0.0698	-0.204	0.0698
loutputs*linputs	-0.103	0.029	--	--
loutputs*wages	-0.074	0.414	--	--
linputs*wages	0.710	0.415	--	--
lpatientmix*rural	-0.227	0.120	--	--
Rural	-0.104	0.064	--	--
Kentucky	0.0457	0.242	--	--

(Table 3.2 continued)

Parameter	Coefficient Estimate	P > [t]	Elasticity ( $\epsilon$ )	P > [t]
Tennessee	0.127	0.0002	--	--
Alabama	-0.001	0.970	--	--
Mississippi	-0.016	0.738	--	--
Arkansas	0.0752	0.123	--	--
Louisiana	0.082	0.022	--	--
Oklahoma	-0.054	0.180	--	--
State	0.164	0.042	--	--
County	-0.009	0.850	--	--
City	-0.208	0.032	--	--
City/County	0.097	0.288	--	--
District	0.037	0.289	--	--
Church	0.077	0.041	--	--
Other Non-Profit	0.048	0.081	--	--
Partnership	0.005	0.899	--	--
Academic	0.038	0.200	--	--

Lastly, of the *hospital control* variables, three were significant, five were not, and the for-profit corporate control status served as the baseline for comparison. *Church-run non-profit* hospitals, in comparison to *for-profit corporate* hospitals, were found to have 7.8% higher *total costs*, when controlling for all other variables. A similar result was observed as *state-run* hospitals were found to have 16% higher total costs in comparison to *for-profit corporations*. Alternatively, *city-government* run hospitals were seen to have 2.1% lower *total costs* than their *for-profit corporate* counterparts.

## Chapter 4: Discussion of the Model Results

### 4.1 Outputs

As noted, with respect to the log-log model analysis, a 10% increase in *outputs* can be expected to generate a 7.94% increase in *total hospital costs*, while holding all else constant ( $\beta_0=0.794$ ). By comparison, based on the translog model analysis, a 10% increase in *outputs* can be expected to generate an 8.21% increase in *total costs*, which is in close agreement to that of the log-log model. Given that *outputs* was defined as the sum of total inpatient admissions, outpatient visits and emergency room visits, a positive relationship between *outputs* and *total costs* is expected given that each additional visit or admission to the hospital requires additional hospital resources. These resources are in the form of extra supplies and staff.

As each visit to the hospital requires a bed, staff or both, the model findings seem plausible, particularly when compared to the findings for *inputs* and *wages*. The elasticities for *inputs* and *wages* are 0.322 and 0.523 respectively<sup>5</sup>. It only makes sense for *outputs'* elasticity to be higher than *inputs* and *wages*, given the fact that the number of visits a hospital can see is a function of the staff and number of beds. In other words, the costs increases associated with taking additional visits to the hospital should be higher than the increases associated with *inputs* and *wages*.

Additionally, these results are further confirmed given that they are inline with estimates from previous studies. Carey and Stefos (2011) found that the number of outpatient visits had a higher influence on total costs in comparison to

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<sup>5</sup> These elasticities were from the log-log results, which were in very close agreement with the translog.

the effect observed for the number of beds. Similarly, Gaynor and Anderson (1995) estimated the cost elasticities for hospital admissions and outpatient visits to be 0.235 and 0.346 respectively, while beds and wages returned as 0.107 and 0.397 respectively. Thus, confidence can be placed in these plausible findings, as they are inline with comparable literature.

Lastly, these findings are also what one would expect to observe for hospital *outputs* and *total costs* at the means. It should not hold that the effect of *outputs* on *total hospital costs* would always be significantly different from zero. This relationship should only hold predominately at the mean levels of *outputs*. A saturation point should exist at the upper levels of *outputs* where the effect on *total costs* is not significantly different from zero.

## 4.2 Inputs

Recall from the results section that *inputs* returned significantly for the individual parameter estimate in the log-log model but not with the translog. As the parameter estimates are not representative of cost elasticities from the translog model analysis, of primary concern was the statistically significant cost elasticity for *inputs*. The log-log results indicated that as *inputs* are increased by 10%, *total costs* are expected to increase by 3.22%, holding all other variables constant ( $\beta_1=0.322$ ). From the translog, a 10% increase in inputs can be expected to generate a 3.02% increase in *total costs*, while holding all other variables constant ( $\epsilon=0.302$ ). This result confirms the *a priori* expectation that *inputs* would be positively related to *total hospital cost*.

Recall that *inputs* refers to the total number of beds at each included hospital. It was initially expected and subsequently confirmed that an increase in the number of beds at each hospital would be associated with an increase in total hospital costs. Each hospital bed will require further investment by the hospital for it to eventually generate revenue. This investment is most likely in the form of wages. A nursing staff will be assigned to the bed twenty-four hours a day. Facility services will need to maintain proper function of the bed. Although hospitals will have private or contract physicians that self-bill, most hospitals employ hospitalists that will do rounding on admitted patients occupying hospital beds. Also, patients in hospital beds will often receive medications intravenously, which the hospital would have previously purchased. These patients also receive meals while they are admitted, that have been prepared in a facility staffed and funded by the hospital. Further, each bed also must have been purchased or leased. Thus, the direct relationship observed between *inputs* and *total hospital costs* is as expected due to the staffing requirements and hospital investments associated with each hospital bed.

Further, these results seem perfectly plausible when analyzed in conjunction with the findings for *wages* and *outputs* as well as with findings from previous hospital cost analyses<sup>6</sup>. One should not expect that *inputs* would have greater influence on *total costs* than *wages* or *outputs*. Although the number of beds limits the level of *outputs* for each hospital, *inputs* should display, as they do, less of an influence on total costs than *outputs*. Also, as a bed cannot generate revenue

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<sup>6</sup> These results are also inline with previous studies estimating hospital costs with inputs as the logarithmically transformed number of beds. See Gaynor and Anderson (2005) and Carey and Stefos (2011).

without a staff, *wages* should bear greater influence on *total hospital costs* in comparison to *inputs*. Therefore, confidence can be placed in the current study's estimate of *inputs*, as it is fitting among the remaining results and inline with estimates of comparable literature.

However, this observed direct relationship is only expected to be prevalent at the means. Beyond the mean at the upper ranges of *inputs*, it is expected that a threshold exists where the subsequent addition of beds would not increase *total costs* or would negligibly affect *total hospital costs*. At or above this threshold, it is believed that the current staff servicing the patients in hospital beds can cover an additional bed without quality suffering and extra staffing being required.

### **4.3 Wages**

The *wages* variable was representative of the total payroll expense incurred by the hospital per full time equivalent employee. *Wages* was logarithmically transformed in each of the model runs. *Wages* returned significant in the log-log model but not in the translog model. More importantly, however, the elasticity for *wages* did return as statistically significant for the translog ( $P < 0.0001$ ).

From the log-log, it was observed that as *wages* increases by 10%, *total costs* are expected to increase by 5.23%, while holding all other variables constant ( $\beta_w = 0.523$ ). As expected due to the nested nature relating the two model forms, the translog results also indicated a positive wage/total costs relationship ( $\epsilon = 0.566$ ). From the translog, a 10% increase in *wages* is expected to generate a 5.66% increase in *total costs*.

Further, both the log-log and the translog findings are in very close agreement and confirm their *a priori* expectation that a positive relationship exists for *wages* and *total costs*. At the mean of wages, *total costs* should increase when increasing payroll expenses. As the hospital hires another employee, a direct increase should be observed in total costs. Further, in order for each employee to be able to do their job, it is very likely that the hospital will make additional investments for each employee. This investment can be in the form of a computer or another item that is an additional purchase by the hospital that, in turn, enhances the ability of each employee to serve their respective role in the provisioning of healthcare services. Also, the hospital also likely has some form of insurance policy, life or health, or provides contribution to retirement accounts for employees. Thus the direct, positive relationship observed for *wages* and *total costs* is as expected. However, this relationship is not likely to be prevalent beyond the means. Beyond the means, it is likely that each additional wage paid by the hospital will not significantly influence total costs in a manner different from zero.

Further, the estimates for *wages* in this study seem plausible when compared among its peers in the current study as well as with estimates from another study. Gaynor and Anderson (1995) estimated the cost elasticity of *wages* to be 0.397, which was higher than the estimate for the number of beds yet lower than the estimate observed for the sum of hospital admissions and outpatient visits. This same relation to *inputs* and *outputs* for *wages* was found to exist in the current study. This relation is as expected also. Hospital beds are limited not only by the patient demand, but also by the number of staff that the hospital can economically

employ to service the patients occupying these beds. Thus, *wages*' perceived influence on *total costs* should be greater than the affect noticed for *inputs*. Also, as the number of visits provided by a hospital is a function of the number of beds and the staff that is economically feasible to employ, it is logically expected that *outputs* would exhibit greater influence on *total costs* in comparison to *wages*.

#### **4.4 Patient-mix**

*Patient-mix* is representative of the percent of inpatient admissions to a hospital that are covered only by Medicaid and Medicare. This variable was included not only because hospitals can receive federal and state reimbursements for seeing and treating these patients but also because of the coverage gap between what Medicare pays for certain hospital services and what private or work health insurers would normally pick up. Medicaid information was included as a hospital can receive joint reimbursements, i.e. federal and state, for seeing eligible patients. Although the literature leans towards only including Medicare patient-mix information, Colwill et al. (2008) support the inclusion of Medicaid as the population above age 65 demands healthcare at twice the rate of the population below 65. Also, Medicare and Medicaid patient-mix data were summed together in one variable, as total costs were expected to share a direct relationship with each of these patient populations.

From the log-log results concerning urban hospitals, it was observed that a 10% increase in *patient-mix* is expected to generate a 3.25% decrease in *total costs*, holding all else constant ( $\epsilon = -0.325$ ). Alternatively, for rural hospitals it was observed that increases in *patient-mix* by 10% could be expected to generate a

5.79% decrease in *total costs* ( $\epsilon=-0.579$ ). Similarly, the translog findings indicated that, as *patient-mix* increases by 10%, *total costs* at urban hospitals can be expected to decrease by 2.96%, holding all else constant ( $\epsilon=-0.296$ ). Also from the translog estimates, rural hospitals should experience 5.23% decreases in *total costs* in response to *patient-mix* increases of 10%, holding all else constant ( $\epsilon=-0.523$ ).

These results agree as expected, but are contradictory to their *a priori* expectation. As rural hospitals often have less complex patient cases than those seen at urban hospitals, it is expected that the decreases observed in total costs responding to patient-mix increases would be larger at rural hospitals than urban ones. Rural hospitals often only employ physicians in the primary care specialties. As few specialists are employed, complex patient cases, i.e. autoimmune disorders, gastrointestinal illnesses, etc., must be referred on to larger hospitals that have the staff to treat these cases. Thus, the agreeing model results are as expected.

However, both model estimates for *patient-mix* contradict their initial expectation. It was initially expected that increases in *patient-mix* would be associated with increases in *total costs*. This expectation was based on the premise that hospitals participating in costs-based reimbursement programs would only have the incentive to increase *total costs*, as it is being covered subsequently by federal and state reimbursements. Similarly, it was expected that hospitals participating in the Prospective Payment System of reimbursements would see increases in *total costs*, as a payment gap would be left between what the hospital routinely charges for a given service and what Medicare and Medicaid pay.

Although the inverse relationship was not initially expected, a logical explanation exists for the observed relationship between *patient-mix* and *total costs*. First, the complexity of the cases covered by Medicaid and Medicare must be analyzed. It is likely that Medicaid/Medicare patients are not offered the same services that a patient with private insurance is. Advanced beneficiary notices (ABNs) can be issued to a patient when the hospital expects that a particular service will not be covered by Medicaid or Medicare ([www.cms.gov](http://www.cms.gov)). These ABNs indicate to the patient that the service might not be covered, and he or she would be responsible for the price of the service. This would essentially alleviate a payment gap for complex medical cases seen at hospitals for Medicare and Medicaid patients, as the patients that refused to pay for the uncovered services would essentially become a less expensive medical case for hospitals to treat. Thus, as *patient-mix* increases, it is feasible for decreases in total costs to be achieved.

Another tangent explanation for the inverse patient-mix/total costs relationship involves other cost saving actions hospitals can take. Although this could be considered unethical, a hospital focused on profit maximization could limit the burden associated with serving uninsured patients by utilizing generic drugs for injections and prescriptions or by limiting the amount of services provided in each visit. For example, an uninsured patient could not be referred to radiology for x-rays during a routine visit, while a privately insured patient would be. However, it is not valid to assume that each hospital focused on profit maximization when healthcare is a service industry and many non-profit hospitals were included in the data.

Lastly, these observed inverse relationships are expected to be prevalent at the means. However, beyond the means, increases in *patient-mix* would likely have less and less of an impact on total costs.

#### 4.5 Case-mix

Case-mix is representative of the ratio of total inpatient admissions to total outpatient visits. This variable was included in both model runs as it was assumed that a larger portion of hospital visits occurring in an inpatient setting are correlated with higher total operating costs for each respective hospital. Both model results were statistically significant and indicated a positive relationship between *case-mix* and *total costs* and were thus in agreement as expected. Further, both model findings for *case-mix* confirmed the *a priori* expectation that *case-mix* and *total costs* shared a direct relationship.

From the log-log model it was observed that, a 10% increase in *case-mix* can be expected to generate a 4.45% increase in *total costs*, while holding all else constant ( $\epsilon=0.445$ ). The translog results indicated that, as *case-mix* increases by 10%, *total costs* can be expected to increase by 4.71%, holding all other variables constant ( $\epsilon=0.471$ ). These results confirmed *the a priori* expectation that a higher case-mix would be associated with higher costs.

Both model results indicate a positive relationship between case-mix and total costs and are in agreement as expected due to the log-log being nested within the translog. At the means, it is expected that more inpatient admissions should distinctly increase total costs. An inpatient visit, on average, should cost

considerably more than an outpatient visit. Outpatient visits generally use a small portion of time and services, depending on whether surgery or a routine check-up is involved. Inpatient stays require physician and nurse monitoring 24 hours a day. These visits will potentially have an IV, which is a constant supply of some medication of diluted fluid given intravenously to the patients. The price of a bed must also be taken into account. Had this relationship returned as anything other than positive at the mean, flaws would have likely existed in either the models or the data. However, beyond the means, a saturation point likely exists where adding an additional inpatient admission would not drastically increase *total hospital costs*.

#### 4.6 Quality

Quality represented a summary score for pneumonia and heart failure in each of the models. Traditionally acute myocardial infarction is also included in quality scores, but the majority of the included hospitals did not meet standards for inclusion set by Schwartz et al. (2008). *Pneumonia quality*, but not *heart failure quality*, was observed to be statistically significant in the log-log model. From the translog, neither summary score was found significant, but *pneumonia quality* was distinctly closer to being significant than *heart failure quality*. Further, as neither summary score was statistically significant in the translog analysis, primary focus is directed towards the more plausible log-log results.

From the log-log model, a 10% increase in *pneumonia quality* could be expected to generate a 2.44% decrease in *total costs*, while all other variables were held constant ( $\beta_Q = -0.244$ ). Although not significant, the results for heart failure quality score indicated a positive relationship with total hospital costs, while

pneumonia quality score indicated an inverse relationship. Under the assumption that increases in quality of care are associated with fewer medical errors, this inverse relationship seen with *pneumonia quality* seems plausible. Further, Carey and Stefos (2011) estimate the marginal cost of a medical error to be \$22,413. Although this estimate was based on medical errors that can occur outside of the treatment of pneumonia, the principle still exists that reducing the number of errors associated with pneumonia treatment should reduce *total hospital costs*. This was confirmed for *pneumonia quality* in the log-log findings, as the results indicated that that increases in the *pneumonia quality* variable would have an inverse impact on *total costs*.

Further, this result seems plausible, as the measure indicators for pneumonia are not highly costly to increase their frequency. Refer back to table 1.1 for the specific pneumonia measure indicators. Taking oxygen assessments and blood cultures, offering smoking counseling, and administering antibiotics are not costly measures to take in the grand scheme of services offered by the hospital. Thus, it makes sense that the log-log results indicate that increasing the frequency of the occurrence of these items would reduce *total costs*. However, it is not likely to assume that all quality measures have the same returns on investments, as some measure indicators are likely highly expensive to increase their usage in efforts to increase quality.

#### **4.7 Limitations**

As quality returned insignificant in both model runs (*pneumonia quality* from the log-log model was the only truly significant result), limitations in the quality

data must be discussed. Several methodological improvements exist affecting the applicability of estimating quality from the Hospital Compare dataset from Center of Medicare & Medicaid Services (CMS). First, the inclusion criteria outlined by Schwartz et al. 2008, as well as Jha et al. (2009), allows for inconsistencies when determining summary and composite scores from the Hospital Compare data. Next, it must be questioned whether this dataset, as it sits with the 2006 release, is comprehensive enough in representing quality of care, as hospitals can spend millions of dollars purchasing medical software or hiring a quality monitoring staff in an effort to increase quality. Lastly, it must be addressed whether the health measures used to indicate quality of care are the most appropriate to represent quality in the hospital setting or if comparable commonly occurring medical conditions could be substituted.

The basic premise outlined in the methodology found in Jha et al. (2009) indicated that a minimum of 30 observations must exist for one of the indicators for each health condition. Recall that each health condition, pneumonia or heart failure, had several indicators of quality. For example, heart failure quality of care is determined based on several indicators including: whether discharge instructions were issued, whether the systolic function of the left ventricle was evaluated, whether smoking cessation counseling was given, as well as several other measures. If one of these indicators has 30 or more observations, then a quality score can be determined for heart failure at that respective hospital. This creates inconsistencies as one indicator for a particular measure can have 30 observations and the rest fewer for one hospital, while data for another hospital has 100 or more observations

for each of the indicators. This inconsistency can result in biases affecting the estimation of quality. Consider the following examples.

10146 JACKSONV Heart Fail	Heart Failure Patients Given Smoking Cessation Advice/Counseling	100%	8	1	8	0.92379
10146 JACKSONV Heart Fail	Heart Failure Patients Given ACE Inhibitor or ARB for Left Ventricular Systolic I	91%	11	1	10.01	
10146 JACKSONV Heart Fail	Heart Failure Patients Given Discharge Instructions	86%	35		30.1	
10146 JACKSONV Heart Fail	Heart Failure Patients Given an Evaluation of Left Ventricular Systolic (LVS) Fu	96%	49		47.04	
10146 JACKSONV Pneumoni	Pneumonia Patients Assessed and Given Influenza Vaccination	90%	10	1	9	0.87718
10146 JACKSONV Pneumoni	Pneumonia Patients Given Smoking Cessation Advice/Counseling	100%	29		29	
10146 JACKSONV Pneumoni	Pneumonia Patients Assessed and Given Pneumococcal Vaccination	84%	45		37.8	
10146 JACKSONV Pneumoni	Pneumonia Patients Whose Initial Emergency Room Blood Culture Was Perfor	85%	66		56.1	
10146 JACKSONV Pneumoni	Pneumonia Patients Given the Most Appropriate Initial Antibiotic(s)	82%	77		63.14	
10146 JACKSONV Pneumoni	Pneumonia Patients Given Initial Antibiotic(s) within 4 Hours After Arrival	79%	80		63.2	
10146 JACKSONV Pneumoni	Pneumonia Patients Given Oxygenation Assessment	100%	90		90	

450801 CHRISTUS Heart Fail	Heart Failure Patients Given Smoking Cessation Advice/Counseling	100%	80		80	0.92953
450801 CHRISTUS Heart Fail	Heart Failure Patients Given ACE Inhibitor or ARB for Left Ventricular Systolic I	94%	304		285.76	
450801 CHRISTUS Heart Fail	Heart Failure Patients Given Discharge Instructions	86%	501		430.86	
450801 CHRISTUS Heart Fail	Heart Failure Patients Given an Evaluation of Left Ventricular Systolic (LVS) Fu	97%	636		616.92	
450801 CHRISTUS Pneumoni	Pneumonia Patients Assessed and Given Influenza Vaccination	89%	66		58.74	0.90853
450801 CHRISTUS Pneumoni	Pneumonia Patients Given Smoking Cessation Advice/Counseling	100%	133		133	
450801 CHRISTUS Pneumoni	Pneumonia Patients Given the Most Appropriate Initial Antibiotic(s)	89%	243		216.27	
450801 CHRISTUS Pneumoni	Pneumonia Patients Assessed and Given Pneumococcal Vaccination	86%	258		221.88	
450801 CHRISTUS Pneumoni	Pneumonia Patients Whose Initial Emergency Room Blood Culture Was Perfor	95%	288		273.6	
450801 CHRISTUS Pneumoni	Pneumonia Patients Given Initial Antibiotic(s) within 4 Hours After Arrival	78%	331		258.18	
450801 CHRISTUS Pneumoni	Pneumonia Patients Given Oxygenation Assessment	100%	401		401	

10052 LAKE MAR Heart Fail	Heart Failure Patients Given ACE Inhibitor or ARB for Left Ventricular Systolic I	50%	2	1	1	0.37581
10052 LAKE MAR Heart Fail	Heart Failure Patients Given Smoking Cessation Advice/Counseling	29%	7	1	2.03	
10052 LAKE MAR Heart Fail	Heart Failure Patients Given Discharge Instructions	25%	32		8	
10052 LAKE MAR Heart Fail	Heart Failure Patients Given an Evaluation of Left Ventricular Systolic (LVS) Fu	46%	52		23.92	
10052 LAKE MAR Pneumoni	Pneumonia Patients Assessed and Given Influenza Vaccination	57%	7	1	3.99	0.7193
10052 LAKE MAR Pneumoni	Pneumonia Patients Given Smoking Cessation Advice/Counseling	45%	20	1	9	
10052 LAKE MAR Pneumoni	Pneumonia Patients Whose Initial Emergency Room Blood Culture Was Perfor	85%	20	1	17	
10052 LAKE MAR Pneumoni	Pneumonia Patients Assessed and Given Pneumococcal Vaccination	17%	29		4.93	
10052 LAKE MAR Pneumoni	Pneumonia Patients Given the Most Appropriate Initial Antibiotic(s)	79%	34		26.86	
10052 LAKE MAR Pneumoni	Pneumonia Patients Given Initial Antibiotic(s) within 4 Hours After Arrival	78%	36		28.08	
10052 LAKE MAR Pneumoni	Pneumonia Patients Given Oxygenation Assessment	100%	54		54	

450668 SIERRA MI Heart Fail	Heart Failure Patients Given Smoking Cessation Advice/Counseling	95%	58		55.1	0.69007
450668 SIERRA MI Heart Fail	Heart Failure Patients Given ACE Inhibitor or ARB for Left Ventricular Systolic I	76%	186		141.36	
450668 SIERRA MI Heart Fail	Heart Failure Patients Given Discharge Instructions	35%	374		130.9	
450668 SIERRA MI Heart Fail	Heart Failure Patients Given an Evaluation of Left Ventricular Systolic (LVS) Fu	92%	431		396.52	
450668 SIERRA MI Pneumoni	Pneumonia Patients Given Smoking Cessation Advice/Counseling	90%	51		45.9	0.87303
450668 SIERRA MI Pneumoni	Pneumonia Patients Assessed and Given Influenza Vaccination	84%	76		63.84	
450668 SIERRA MI Pneumoni	Pneumonia Patients Given the Most Appropriate Initial Antibiotic(s)	86%	168		144.48	
450668 SIERRA MI Pneumoni	Pneumonia Patients Assessed and Given Pneumococcal Vaccination	90%	246		221.4	
450668 SIERRA MI Pneumoni	Pneumonia Patients Whose Initial Emergency Room Blood Culture Was Perfor	87%	258		224.46	
450668 SIERRA MI Pneumoni	Pneumonia Patients Given Initial Antibiotic(s) within 4 Hours After Arrival	72%	268		192.96	
450668 SIERRA MI Pneumoni	Pneumonia Patients Given Oxygenation Assessment	99%	329		325.71	

Figure 4.1. Hospital Compare Data From Two Texas and Two Alabama Hospitals

The above examples illustrate the potential biases previously mentioned. As illustrated, a large number of indicator observations or a small number can result in a poor or a respectable quality score. The first two hospitals listed each have respectable quality scores, while the latter two have poorer scores, particularly for

heart failure. The biases result as one score has many observations supporting it, while the other score has minimal observations behind it.

However, improvements to the methodologies, listed by CMS, Jha et al. (2009) and Schwartz et al. (2008), for calculating quality scores using the Hospital Compare data could negate any potential biases. By giving weight to the quality metrics bearing distinctly more observations, these biases likely would not exist.

Further, it must be discussed whether the data included in the Hospital Compare dataset is truly representative of differences existing in quality among various hospitals. For example, suppose a rural hospital is still operating off of paper medical records, while an urban hospital has hired a quality monitoring staff and purchased a multi-million dollar medical software program with digital medical records that is designed to reduce medical errors. According to the Hospital Compare dataset as it currently exists, it is possible that these two hospitals could achieve the same quality of care score if they performed each of the indicators listed for pneumonia, heart failure and acute myocardial infarction at the same rate.

In an effort to truly represent quality in a quality of care score, it should not be possible that one hospital spending millions of dollars in an effort to increase quality and one not should receive the same quality score based on how each institution treated pneumonia, heart failure or acute myocardial infarction according to several indicators. Chaudhry et al. (2006) indicate that several hospitals that have made large investments in health information software have achieved increases in quality at their respective institution.

Similarly, Bates et al. 1999 highlights three specific impacts that advanced health information systems can have concerning quality. First, health information systems can directly increase quality by getting physicians and other healthcare providers the information and decision support they need, while they are interacting with patients in real time. Next, health information systems can improve efficiency and quality by using adverse event monitors and communicating them to providers. Lastly, health information systems allow for quality measurement in a less expensive but more comprehensive manner than previously available. Thus, to truly analyze the relationship between quality of care and total costs, advancements must be made in the quality of care data to factor into account non-treatment quality indicators like having advanced health information software or having a quality monitoring staff.

Lastly, on a tangent note, the question must also be asked whether the three measures, pneumonia, heart failure and acute myocardial infarction, are appropriate measures for indicating quality or whether their indicators are comprehensive enough. As pneumonia, heart failure and acute myocardial infarction are rather commonly occurring health conditions, their usefulness in assessing quality is likely not the problem.

The indicators for each of these conditions are likely not aptly comprehensive to accurately indicate quality. The argument can be made that the measure indicators are insufficient, as they do not have any way to address external factors like patient satisfaction, readmission rates or investments in quality that affected the treatment of these issues. These factors directly affect or represent

quality of care for pneumonia, heart failure and acute myocardial infarction. Thirty-day mortality is included in the current measure indicators, but this would only be enhanced with readmission data, as it is likely that some patients might have been readmitted within 30 days that did not pass away. Also, if one hospital has made investments that directly affect the treatment of one of these conditions and another hospital hasn't, the addition of this information would be necessary to sufficiently represent quality.

The inclusion of the abovementioned factors would enhance the reliability of the quality information contained in the Hospital Compare dataset. Together with improvements in quality reporting from ever advancing health information software, the relationship between quality of care and total hospital costs can be more accurately represented.

## **Chapter 5: Conclusions and Future Improvements**

### **5.1 Conclusions**

From the log-log model, this study was able to determine that *pneumonia quality's* influence on *total costs* is significantly different from zero. Based on the log-log model analysis, a 10% increase in *pneumonia quality* score was found to result in an estimated 2.44% decrease in total hospital costs. This significant finding seems plausible given that the measure indicators utilized to estimate quality of care associated with pneumonia are not highly costly services to the hospital. Thus,

Although this study could not confirm the nature of the relationship between total hospital costs and measures of quality beyond community acquired pneumonia, several improvements were found that would enhance the quality of care data, and thus the ability to further research the influence of quality of care on hospital costs. Future improvements to the methodologies and data used for estimating quality include: addressing investments in quality like purchasing health information software or hiring a quality monitoring staff, the inclusion of readmission data for the common quality indicating measures, the inclusion of patient satisfaction information and advances in the ability of the health information technologies to capture quality of care information.

### **5.2 Future Improvements**

Several improvements exist that could potentially change the outcome of this research. First, rather than making sure at least one measure had 30 observations for determining quality, the results for quality could potentially be improved by

calculating quality scores for pneumonia, heart failure or acute myocardial infarction when each measure indicator had 40 or more observations. Next, including subsequent years of data could potentially improve the overall results for this research. Lastly, increasing the sample geographic range would add a vast amount of hospitals that would only further increase the validity of the current findings.

### **5.3 Policy Implications**

The conclusions reached in this study in conjunction with previous literature have the capability to influence national healthcare policy. Recall that the American Association of Medical Colleges produced a report in October 2012 estimating the physician shortage. The report projects that by 2025 the nation's healthcare system will be operating with a physician shortage ranging anywhere from 55,000 to 200,000. Although healthcare coverage is being extended to the previously uninsured and thus doesn't limit the services offered to these patients, it is not likely that access to care will be maintained. It is logical to assume that decreased access to physicians will subsequently lead to decreases in the overall health of the general population. Thus, as the demand for healthcare services grows, the price of healthcare services is likely to responsively increase.

Also, it is generally accepted that large patient-to-physician ratios generate incentive to spend less time with each patient in an effort to maintain access to care. As quality of care has potential to subsequently be negatively impacted, policy

improvements must be addressed that are aimed to control patient/physician ratios. If not, with the case of community-acquired pneumonia, declines in quality can actually increase the cost of healthcare.

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### Appendix A: Long-Form Translog Cost Function

$$\begin{aligned} \ln(\text{Total Cost}) = & \alpha + \beta_o \ln(\text{Outputs}) + \beta_{oo} \ln(\text{Outputs})^2 + \beta_{il} \ln(\text{Inputs}) + \beta_{ll} \\ & \ln(\text{Inputs})^2 + \beta_w \ln(\text{Wage}) + \beta_{ww} \ln(\text{Wage})^2 + \beta_p \ln(\text{PatientMix}) + \beta_c \ln(\text{Casemix}) + \\ & \beta_{QH} \ln(\text{QualityHF}) + \beta_{QP} \ln(\text{QualityPn}) + \beta_{ol} \ln(\text{Outputs}) * \ln(\text{Inputs}) + \\ & \beta_{ow} \ln(\text{Outputs}) * \ln(\text{Wage}) + \beta_{lw} \ln(\text{Inputs}) * \ln(\text{Wage}) + + \beta_{CN} \text{Control} + \beta_G \text{Geog} + \\ & \beta_M \text{Mapp} + \beta_S \text{CBSA} + \varepsilon. \end{aligned}$$

## Appendix B: Complete Log-Log Model Analysis

Parameter	Estimate	Standard Error	t Value	Pr >  t
patientmix elasticity rural	-0.57901588	0.12451247	-4.65	<.0001
patientmix elasticity urban	-0.32471607	0.08675777	-3.74	0.0002

Parameter	Estimate	Standard Error	t Value	Pr >  t
Intercept	2.532443594	0.58246527	4.35	<.0001
loutputs	0.794493363	0.03114911	25.51	<.0001
linputs	0.321591570	0.03118259	10.31	<.0001
lwages	0.523284772	0.05464454	9.58	<.0001
lpatientmix	-0.324716066	0.08675777	-3.74	0.0002
lcasemix	0.444583798	0.02982952	14.90	<.0001
lqualhf	0.054149300	0.07634485	0.71	0.4785
lqualpn	-0.243774063	0.11520744	-2.12	0.0348
lpatientmix*rural	-0.254299812	0.14857054	-1.71	0.0876
rural	-0.080419420	0.05689595	-1.41	0.1581
Kentucky	0.021416376	0.03959353	0.54	0.5888
Tennessee	0.118956282	0.03434035	3.46	0.0006
Alabama	-0.019242906	0.03728564	-0.52	0.6060
Mississippi	-0.022779013	0.04842081	-0.47	0.6382
Arkansas	0.054458767	0.04977685	1.09	0.2744
Louisiana	0.064558928	0.03616100	1.79	0.0748
Oklahoma	-0.043882542	0.04132617	-1.06	0.2888
State	0.180255072	0.08194016	2.20	0.0283
County	-0.029502268	0.05111303	-0.58	0.5641
City	-0.181406238	0.09951386	-1.82	0.0689
City_county	0.138461484	0.09340041	1.48	0.1388
District	0.064025021	0.03573438	1.79	0.0738
Church	0.094901866	0.03843936	2.47	0.0139
O_nonprofit	0.061596447	0.02815065	2.19	0.0291
Partnership	0.008394416	0.04280805	0.20	0.8446
academic	0.084571693	0.02934373	2.88	0.0041



### Appendix D: Complete Translog Model Analysis

Parameter	Estimate	Standard Error	t Value	Pr >  t
Intercept	7.735563596	11.85525203	0.65	0.5144
loutputs	0.158303284	0.88273515	0.18	0.8577
sqloutputs	0.085617929	0.02989358	2.86	0.0044
linputs	-0.233685766	0.90146820	-0.26	0.7956
sqlinputs	0.097918668	0.02699242	3.63	0.0003
lwages	0.421341630	2.30304609	0.18	0.8549
sqlwages	0.030488058	0.11963964	0.25	0.7990
lpatientmix	-0.295776631	0.08657981	-3.42	0.0007
lcasemix	0.471431219	0.03020302	15.61	<.0001
loutputs*linputs	-0.102687262	0.04702074	-2.18	0.0294
loutputs*lwages	-0.074400531	0.09101199	-0.82	0.4140
linputs*lwages	0.071007684	0.08698959	0.82	0.4147
lqualhf	0.004813172	0.07457463	0.06	0.9486
lqualpn	-0.204359495	0.11248389	-1.82	0.0698
lpatientmix*rural	-0.226937149	0.14500765	-1.57	0.1182
rural	-0.103654702	0.05584327	-1.86	0.0640
Kentucky	0.045708728	0.03898120	1.17	0.2415
Tennessee	0.126980069	0.03346214	3.79	0.0002
Alabama	-0.001373797	0.03627494	-0.04	0.9698
Mississippi	-0.015938653	0.04755849	-0.34	0.7377
Arkansas	0.075187521	0.04862551	1.55	0.1227
Louisiana	0.081896251	0.03554096	2.30	0.0216
Oklahoma	-0.054273920	0.04045428	-1.34	0.1803
State	0.164391358	0.08058274	2.04	0.0419
County	-0.009424659	0.04975081	-0.19	0.8498
City	-0.208188736	0.09672903	-2.15	0.0318
City_county	0.097285317	0.09137195	1.06	0.2875
District	0.037152973	0.03497204	1.06	0.2886
Church	0.077061869	0.03751442	2.05	0.0405
O_nonprofit	0.048352724	0.02761361	1.75	0.0805
Partnership	0.005320444	0.04175225	0.13	0.8987
academic	0.038090534	0.02966674	1.28	0.1997

### Appendix E: Translog Continuous Variable Elasticities

Parameter	Estimate	Standard Error	t Value	Pr >  t
output elasticity	-0.00920551	0.99893312	-0.01	0.9927
input elasticity	-0.40351785	0.85125823	-0.47	0.6357
wages elasticity	0.66573062	3.52921360	0.19	0.8505
patientmix elasticity urban	-0.29577663	0.08657981	-3.42	0.0007
patientmix elasticity rural	-0.52271378	0.12353306	-4.23	<.0001
casemix elasticity	0.47143122	0.03020302	15.61	<.0001

## **Vita**

Jordan Newell, a native of Claiborne Parish, Louisiana, began attending LSU in the fall of 2007. As a student-athlete, he lettered for the Tiger's football team while progressing towards his Bachelor's of Science degree, which he completed in May 2011. He will receive his graduate diploma for Master's of Science in Agricultural Economics in December 2013. He intends to use his degree to become influential in the medical field, particularly with making healthcare services more affordable in rural areas.