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Multiple Regression Analysis of Factors Concerning Cardiovascular Profitability Under Health Care Reform

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This is to certify that the doctoral study by

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Walden University
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Abstract

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Doctoral Study Submitted in Partial Fulfillment

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Abstract

Cardiovascular (CV) patients receive one-third of the care and account for $444 billion of the health care costs in the United States. The cardiovascular service line (CVSL) in hospitals contributes to the profitability influenced by elements of resource dependence theory (RDT). The purpose of this study was to understand whether the regression model of hospital characteristics and outcomes would predict profitability in a CVSL through the cost-to-charge ratio (CCR). The use of a general linear model and multiple regression analysis to examine the 2012 National Inpatient Sample from the Healthcare Cost and Utilization Project allowed estimates from a weighted sample of discharges from all hospitals in participating states. Transformation to dichotomous, independent variables preceded analysis of CV-conditions by discharges. An analysis of variance included in the validated model of grouped strata predicted a level of profitability through the CCR, $(4, 509) = 129.83$, $p < .001$, $R^2 = .505$. Mortality was not a significant predictor in the regression model. The 3 characteristic variables with an inverse relationship to the CCR, which resulted in favorable profitability for CVSL, included large, academic, and private for-profit institutions. Prior research aligns well to the study, which emphasized the importance of RDT. Leaders in health care organizations may choose to employ decision making that is dependent upon big data and reference to internal resources to achieve reform expectations. Predictive modeling may aid in the strategic direction of health care organizations. Social implications of this study include hospitals striving to enhance the value proposition by centering care activities around the person over rationing finite resources by condition.

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Section 1: Foundation of the Study

With sweeping health care reform, hospital leadership determines the best course of action to maintain favorable reputation and profitability (Ryan et al., 2014; Shih & Dimick, 2014). Multiple considerations relative to resources, quality efforts, and hospital characteristics may predict the level of profitability realized in an era of reform expectations. Health care organizations under reform measures face external constraints and competition, which scarce resources are elements of the environment in a resource dependence model (Yeager et al., 2014). Under The Patient Protection and Affordable Care Act (ACA), much remains unknown about the external effects toward health care decision-making and administrative capacity (Lee, Austin, & Pronovost, 2015). Further, minimal understanding subsists relative to the cardiovascular service line (CVSL), a profitable service offering in acute care centers. An empirical approach to account for the ACA variables for CVSL performance may provide a framework for health care and hospital strategy considering the dynamic environment of limited resources.

Background of the Problem

Since the 1980s, concerns of health care quality relative to costs has created much attention, when the 1999 seminal work by the Institute of Medicine, *To err is human*, highlighted the need for agencies to track and improve health care (Boyer, Gardner, & Schweikhart, 2012). With the importance of quality improvement and cost effectiveness of health care delivery in the United States, leaders in health care attempt to understand the relationship between costs and outcomes (Dehmer et al., 2014). The pay-for-performance (P4P) model tasks leaders to control costs, while enhancing quality to maintain the survivability of health care organizations (Breslin, Hamilton, & Paynter, 2014; Volland, 2014). Health care leaders need to address failures in health care delivery (Berwick & Hackbarth, 2012). Failures include lack of accountability toward quality and outcomes with results appearing publicly through the Internet and other sources (e.g., Hospital Compare; Lazar, Fleischut, & Regan, 2013).

Customers may have a choice at which facility to seek care, yet insurance constraints and locality may restrict which care to seek (Pauly, 2011; Zygourakis, Rolston, Treadway, Chang, & Kliot, 2014). Leaders in health care must recognize the relationship between outcomes and associated costs to enhance value (Hearld, Alexander, & Shi, 2014). Consideration of value is important for patients because of the associated safety and outcomes of care, along with enhanced efficiency and service (i.e., costs, access, and experience; Trastek, Hamilton, & Niles, 2014). In addition, the value of care (i.e., cost-effectiveness) varies over time and across locations because of variation of resources, efficiencies, and structure of costs, yet no true consensus exists in the United States concerning the role of cost-effectiveness in health care decision-making (Anderson et al., 2014).

A CVSL remains an opportune service line in the hospital setting for cost reduction and quality improvement activities (Lowe, Partovian, Kroch, Martin, & Bankowitz, 2013). Several cardiovascular (CV) procedures performed in the hospital setting involve the wasteful use of hospital resources and nonvalue added outcomes for patients (Chan et al., 2011; Lowe et al., 2013). The effects of ACA may continue to challenge CVSL because of the overwhelming costs of cardiovascular care (Ferguson & Babb, 2014).

Problem Statement

Cardiovascular patients receive one-third of the care and account for $444 billion of the health care costs in the United States (Ding, 2014; Matlock et al., 2013). The profitability of the CV service line remains critical in a hospital environment of diminished payments where one-third of the costs do not contribute to outcomes that achieve maximum Medicare reimbursement (Ding, 2014; Leleu, Moises, & Valdmanis, 2014). The general business problem is the loss of profitability for hospital leaders through payment penalties (Pratt & Belliot, 2014; Ryan, Sutton, & Doran, 2014; Tajeu, Kazley, & Menachemi, 2014). The specific business problem of CVSL leaders is the loss of 1.5% and 3% of Medicare payments vis-à-vis health care reform (Anderson et al., 2014; Centers for Medicare & Medicaid Services [CMS], 2014b; Chatterjee & Joynt, 2014; Ferdinand et al., 2011; Gordon, Leiman, Deland, & Pardes, 2014; Lee et al., 2015; Oshima & Emanuel, 2013).

Purpose Statement

The purpose of this quantitative, multiregression study is to examine significant predictor variables of resources and outcomes. The independent predictor variables are the sites of CV delivery and characteristics, associated outcomes, and resources for cardiovascular conditions. The dependent, outcome variable is the cost of health care delivery. The targeted population includes all-payer beneficiaries of acute care hospitals in the United States that received a cardiovascular procedure. Accessibility of this population occurs through the Healthcare Cost and Utilization Project (HCUP) through The Agency for Healthcare Research and Quality (AHRQ) data in acute care hospitals (McDermott, Stock, & Shah, 2011). The geographic location for this study includes eligible hospitals in the United States because of the high incidence of cardiovascular disease found in the country (Ferdinand et al., 2011). This study may contribute to social change by highlighting delivery characteristics in CVSL, which remain important under reform efforts for superior quality (Emanuel et al., 2012). This study may influence the business environment by informing health care leaders in aligning costs to reform efforts, which match the transformation of health care to growth, enhanced quality, and reduced inefficiencies (McConnell, Chang, Maddox, Wholey, & Lindrooth, 2014; Volland, 2014).

Nature of the Study

The quantitative method for this study provides an empirical approach to reveal associated relationships and predictor elements. The quantitative method involves an inclusion of variables for assessment of empirical merit (Campbell & Stanley, 2010; Mukamel, Haeder, & Weimer, 2014; Pandya, Gaziano, Weinstein, & Cutler, 2013; Schousboe et al., 2014; Yang et al., 2012). Because health care research focuses on enhancing effectiveness and efficiencies of the delivery of service, quantitative methods are most appropriate in such inquiry (Bowling, 2009).

A qualitative method to explain the relationship between outcomes and costs may lessen the focus to test stated hypotheses (Wisdom, Cavaleri, Onwuegbuzie, & Green, 2012). I considered a qualitative method for this study, yet rejected this method because collecting data from patients or hospital administrators for CV conditions (i.e., quality outcomes) presents privacy and confidentiality concerns that pose a risk to the efficient completion of this study. Therefore, a qualitative study was not appropriate for this examination.

A mixed methods study encompasses both qualitative and quantitative studies (Bryman, 2012). The appropriateness of a mixed methods study involves the need to address different research questions, while employing an empirical approach to strengthening the study by moderating natural weaknesses of single-method approaches. The potential to perform a triangulation for data analysis within a single study was not a consideration because of the chosen level of detail for this study (Bryman, 2012). I did not pursue mixed methods because of the inherent weakness of the qualitative component.

The selection of multiple regression to determine hospital profitability enables the identification of the independent effects on profits (Leleu et al., 2014). A health care leader uses regression for statistical information and forecasting, which allows leaders to position resources in an advantageous manner (Bowling, 2009). An open-ended data collection through interviews or observations of patients to establish themes or narrative analysis will not allow the desired level of empiricism to reveal associated relationships and predictor elements of resources and quality outcomes (Bryman, 2012; Lee & Cassell, 2013). As such, the research question inquires about a possible relationship among variables and associated predictive levels.

Research Question

For this study, the focus is how well the predictor variables of outcomes, resources, and hospital characteristics predict the profitability through costs in the cardiovascular setting. An examination of potential relationships between outcomes, costs, and resources positions well for a multivariate regression study (Chiang, Wang, & Hsu, 2014; Flynn, Speck, Mahmoud, David, & Fleisher, 2014; Trybou, De Regge, Gemmel, Duyck, & Annemans, 2014). The pursuit of a predictive level between these factors attempts to eliminate uncertainty in the inquiry and exposes the elements to disconfirmation (Campbell & Stanley, 2010). The research question is the following: What levels of hospital characteristics, resources, and outcomes accurately predict profitability in a CVSL?

Hypotheses

$H1_0$: The various predictors of hospital characteristics and outcomes will not predict the profitability in a CVSL.

$H1_a$: The various predictors of hospital characteristics and outcomes will predict the profitability in a CVSL.

Theoretical Framework

The theory under examination is resource dependency theory (RDT), where there exists a gap in its application toward health care decision-making and administrative capacity (Yeager et al., 2014). The use of RDT toward a CVSL further extends this gap. First described by Thompson in 1967 and subsequently Pfeffer and Salancik in 1978, RDT provides a theoretical framework for health care (Yeager et al., 2014). In addition, past studies applied the interaction between organization and environment, with research dedicated to the decisions needed under a given level of uncertainty (Dickson & Weaver, 1997; Duncan, 1972).

The fundamental constructs of RDT in health care involve the (a) dynamic and competitive environment of health care and demands a strategic focus of resources, (b) organizational decisions that are based upon the external environment, (c) dependency of internal resources to function and survive (i.e., survival certainty), (d) a manager who serves as a representation of leadership, facilitator of resources, and who is cognizant of the external environment, and (e) restrictions that are placed upon organizations by their environmental conditions (Hayek, Bynum, Smothers, & Williams, 2014; Hsieh et al., 2010; Pfeffer & Salancik, 1978; Yeager et al., 2014). Organizations influenced by RDT will act upon market factors, regulations, and munificence, which hospitals remain highly dependent upon for public programs such as Medicare and Medicaid (Fareed & Mick, 2011). As applied to this study, the external constraints placed upon hospital organizations under the concepts of RDT may demonstrate expected outcomes shaped by the resources and costs. Resources may range from excessive to scarce, and the RDT perspective expects organizations to develop strategies relative to resource use in their organizations. Larger health care organizations hold superior internal resources, which benefit the system by flexibility and economies of scale, as an inequitable nature of hospitals, outcome results will vary from hospital-to-hospital (Fareed & Mick, 2011).

Definition of Terms

The definition of terms enables a researcher to provide a clear meaning of technical, health care, and medical-specific terms used in the study. Providing the definition of terms used in a paper might enable readers to have a clear understanding of the study. The following items related to the study under reform measures, medical conditions, and both coding and classification terms.

Accountable care organizations (ACO): Boyer et al. (2012) defined ACOs as a group of providers responsible for quality and costs for a specified population who provide data to assess performance, continuous quality improvement efforts, and practice evidence-based, care management.

Acute care hospitals: Hospitals with the ability to deliver care to patients with a wide array of sudden, urgent, and emergent illnesses and injuries. Without prompt intervention, the risk of death or disability increases. Multiple clinical functions of such hospitals include emergent, trauma, and surgery care (Hirshon et al., 2013).

Acute myocardial infarction (AMI): Clinical diagnosis dependent upon the patient's symptoms, electrocardiogram changes, and biochemical markers to include myocardial injury or death (Shen et al., 2014).

Case mix index (CMI): Medicare accounts for the severity of disease of inpatients and adjusts for the national average of disease care to explicit hospital costs (Pratt & Belliot, 2014).

Centers for Medicare & Medicaid Services (CMS): A federal agency and branch of the U.S. Department of Health and Human Services. CMS administers Medicare and

Medicaid, along with other partnerships with state programs for beneficiaries; Health Insurance Marketplaces, and a source for health care data and information for professionals, U.S. federal and state governments; and consumers. Medicare is the largest insurer in the United States, with1 billion claims per year (Centers for Medicare & Medicaid Services, 2014c).

Congestive heart failure (CHF): CHF is a medical condition that occurs when the heart cannot pump enough blood to meet the body's demand to include one or both: The heart does not replenish the needed blood supply or the heart inadequately pumps blood to rest of the body (Gafoor et al., 2015).

Diagnosis related groups (DRGs): The Medicare Severity-Diagnosis Related Groups are classifications of patients dependent upon the resources consumed, disease, and severity of illness, and links to a fixed payment for inpatient hospital stays (Medicare, 2014).

Fee-for-service: A payment plan for providers to receive fees based upon unbundled medical care of enrollees that relies on the quantity of care (Centers for Medicare & Medicaid Services, 2014c).

Mortality and mortality rate: The death of a medical beneficiary to include the characteristics of the death (i.e., demographics, cause of death, mortality). The rate includes the whole population at-risk for disease, the time element, and the number of deaths occurring in a given time and population (Centers for Medicare & Medicaid Services, 2014c).

Pay-for-performance (P4P): Pay-for-performance indicates reimbursement or financial incentives linked to quality performance (i.e., high-quality care; Ryan & Damberg, 2013; Ryan et al., 2014).

Assumptions, Limitations, and Delimitations

Assumptions

In this study, I assumed the archived data available specific to all-payer beneficiaries represented the selected population for the cardiovascular-specific conditions subjected to inquiry. The premise of the study was that CVSL remains an integral business and clinical unit in acute care hospitals with organizational reliance on its profitability (Lindrooth et al., 2013). The underlying foundation of the study involved an internal perspective of a single service line with overlapping features in the external context of health care reform.

Limitations

The scope of this study excluded health care outside the United States. The study was not generalizable internationally or relatable to health care entities outside of the hospital setting. Available incentive and actual payment data include period, time, term differences, denominator differences, and varied incentive measures (e.g., AMI mortality; Ryan et al., 2014). Further, the use of administrative claims data raises concerns about reliability because of measurement error. Limitations of administrative data versus clinical data includes (a) less detailed presentation of the patient and (b) potential for differences of coding by hospital (Suter et al., 2014). Data acquired included administrative billing data, which involved submitted claims for payment in selected clinical areas (Panzer et al., 2013).

Quality outcomes remain underreported, which can lead to underestimation or overestimation of healthcare application and costs (Farmer, Black, & Bonow, 2013). Data in the Hospital Compare include performance data for more than 3 years with updates annually, yet are still not peer-reviewed (Suter et al., 2014). The conditions covered in Hospital Compare limit a few of the services offered in an acute care setting because of the expensive manual processes used, which prohibits an inclusive array of clinical conditions (Panzer et al., 2013).

The data used included the 2012 National Inpatient Sample (NIS) from the HCUP. This database accounted for 95.7% of the population with 44 states in the United States through improved national estimates. States excluded from the 2012 NIS include Maine, New Hampshire, Delaware, Washington D.C., Alabama, Mississippi, and Idaho.

Delimitations

Because of the aggregated and public nature of the reported statistics, no data involved health information or personally identifiable information and instead focused on health care services of facilities and providers (ResDAC, 2014). The use of administrative data is a practical approach with information relative to the scope of CV diseases and quality outcomes (Panzer et al., 2013). Specific patient-level data were exempt from the study, thereby limiting the level of patient specificity. The sample depended on demographic and proportional sampling with a final sample that included national estimates of several million records. Finally, the predictor variables excluded elements of hospital-acquired conditions, which account for 25% of the payment penalties under the P4P model (Centers for Medicare & Medicaid Services, 2014a). The chosen population sample in the study accounted for such elements in the hospital setting.

Significance of the Study

Value

The purpose of this quantitative study method was to examine the relationship between quality outcomes and resources to costs used in an acute care setting, an often poorly understood relationship (Hussey, Wertheimer, & Mehrotra, 2013). Furthermore, focusing upon costs alone does not provide intrinsic value for value-based care (Alyeshmerni, Ryan, & Nallamothu, 2015). Publicly available data to establish a correlation or disprove a relationship between each variable allows an empirical approach: Measures linked to reimbursement in a P4P model that includes volume, structure, outcomes, and processes (Lazar et al., 2013). Because hospitals remain sensitive to revenues and reputation, the potential to enhance both revenue and reputation through quality improvement increases the significance for the organization and the benefits of optimal costs to accomplished quality (Ryan et al., 2014). Hospitals with profitable service lines tend to invest in quality and compete for patients over unprofitable service lines (Navathe et al., 2012). Surgeries and other specialty procedures benefit health care organizations by profitability and revenue generation (Anderson, Golden, Jank, & Wasil, 2012).

Contribution to Business Practice

The advancement of this study may aid health care and cardiovascular leaders in strategies and decisions that will benefit health care organizations. Strategic performance in health care involves the considerations of the quality of care, cost efficiencies, and services provided (Dagher & Farley, 2014). Health care organizations have a leading influence on both the health of patients and communities (Eggleston & Finkelstein, 2014). Challenges, such as the ability to contain health care costs remain important as the ACA attempts drastic Medicare spending decreases (Emanuel et al., 2012). In addition, leaders in health care management attempt to increase the quality and enhance patient-centeredness while managing scarce financial resources, the linkage between quality and patient satisfaction simplify some of these priorities (Tajeu, 2014).

Patients choose hospitals dependent upon favorable reputation, yet providers will position resources away from lower reimbursement to maintain financial sustainability and competitiveness (Lindrooth et al., 2013). The results of this study may help cardiovascular service line leaders, health care administrators, and other stakeholders in cost control, quality endeavors, and accountability toward value-based care in a hospital setting (Krumholz et al., 2013). Successful performance under the P4P elements may insure no penalties and potential rewards. The rapid developments and redevelopments of reform remain relevant because of the additive chaos to health care leaders' decision-making (Chukmaitov, Harless, Bazzoli, Carretta, & Siangphoe, 2014). The efficiency of hospital operations is a critical element of concern for leaders in health care (Nigam, Huising, & Golden, 2013). The efficiency measurements include entity, inputs, and outputs that determine cost and outcome performance (Ding, 2014).

Value is an element beneficial to all stakeholders in health care delivery (Trastek et al., 2014). One definition of value involves whether a positive result occurs from the actual care to include outcomes, safety, and satisfaction (Anderson et al., 2014). Another definition of value well-defined by the customer is the outcome achieved per dollar spent (Porter, 2010). Value defined in health care are the outcomes per unit of cost, essential for stakeholders and identified in the Institute of Medicine's 100 priorities for further research (e.g. accountability toward costs, care processes, and outcomes; Krumholz, 2013; Matlock et al., 2013).

Implications for Social Change

Cardiovascular diseases place a burden upon health care spending, to include lost worker productivity and disability, and are the leading causes of death in the United States (Ferdinand et al., 2011; Pearson et al. 2013). The commitment to reduce costs is a commitment to serving the patient (Morris & King, 2013). Health care delivery systems have a responsibility to enhance care outcomes for communities and society (Eggleston & Finkelstein, 2014). The value provided to communities and society involves lower costs, which may allow available resources to benefit further public sectors (e.g., public health, education, transportation, and the environment; Gordon et al., 2014).

Health care systems should be accountable for providing optimal value of health care (Trastek et al., 2014). The pressure to transform from a volume-based delivery model to a value-based model is a result of consistent poor outcomes, unsustainable costs, and persistent disparities (Eggleston & Finkelstein, 2014; Krumholz, 2013). Inversely, the concern of health care leaders toward economic consequences benefits communities because of the resolve to enhance the cardiovascular delivery value proposition (Anderson et al., 2014).

A Review of the Academic and Professional Literature

Most literature included in the research for this study dates no later than 5 years, a factor contributive to the ever-changing landscape of health care. An inquiry was conducted of multiple sources to gather the administrative, manager, physician, staff, clinical, and community perspectives of this topic in cardiovascular services. I used both Walden University's Library article database and books as either a primary source or secondary through Google Scholar. Subsequently, the following databases archived include ABI/INFORM complete, Business Source Complete/Premier, ProQuest Central, Science Direct, Sage Journals, Journal of American Medicine, and Wolters Kluwer Health. The primary sources of information for this literature review are peer-reviewed articles. Key words and phrases used to search the databases include *Accountable Care Organizations, business, cardiology, cardiology mortality, cardiovascular, competition, costing, cost control, economics, expenditures, health care, health care administration, hospital, hospital finances, hospital readmissions, outcomes, The Patient Protection and Affordable Care Act, pay for performance, quality, resource dependence theory, value-based purchasing, waste,* and *waste elimination.* Research of the aforementioned databases returned several scholarly, peer-reviewed references for the purposes of a literature and academic review.

The organization of the review includes a discussion of the theoretical framework of RDT and its implications with ACA and hospital organizations. Next, a brief overview of prior studies relative to health care costs, quality, and outcomes establishes the foundation for progressive research. After this section, a detailed summary of the ACA and associated expectations are prerequisite, which leads to the various elements of the ACA as measurements. The subsequent sections detail the hospital characteristics, resources, and costs in the CV arena of acute care hospitals. Finally, the summary of previous correlational and empirical studies develops into the business need for CV profitability research concerning external reform constraints.

Resource Dependence Theory and Reform

A gap exists in the application of RDT toward health care decision-making and administrative capacity (Yeager et al., 2014). The use of RDT toward a defined service line such as CV further extends this gap. Interestingly, the use of RDT in research predominates in health care, management, and strategy; it also aligns well to empirical examinations of organizations (Davis & Cobb, 2010).

First described by Thompson in 1967 and subsequently Pfeffer and Salancik in 1978, RDT provides a theoretical framework for health care (Yeager et al., 2014). The key constructs of RDT in health care involve the (a) the dynamic and competitive environment of health care and demands a strategic focus of resources, (b) organizational decisions are based upon the external environment, (c) there is a dependency of internal resources to function and survive, (d) the manager serves as a representation of leadership, facilitator of resources, and is cognizant of the external environment, and (e) restrictions are placed upon organizations by their environmental conditions (Hayek et al., 2014; Pfeffer & Salancik, 1978; Yeager et al., 2014). Organizations influenced by RDT may act upon market factors, regulations, and munificence, which hospitals remain highly dependent upon for public programs such as Medicare and Medicaid (Fareed & Mick, 2011). As applied to this study, the RDT holds that expected outcomes and value are shaped by the resources and costs expended from the external constraints placed upon hospital organizations. Ultimately, studies with a determined level of profitability within any industry are associated positively as significant predictors of organizational performance (Dess & Beard, 1984).

Whether accreditation bodies, regulatory groups, or social services agencies, many external organizations attempt to control the internal activities of other organizations (Pfeffer & Salancik, 1978). A consequence of Medicare price cuts may be the containment of operating costs and resources (White & Wu, 2014). Instead of viewing hospitals as cost-minimizing firms, a fresh perspective of hospitals is revenue-seeking entities, suitable because of the adjustments made by such organizations through quality and costs (White & Wu, 2014). Resources may range from excessive to scarce, and the RDT perspective expects organizations to develop strategies relative to resource use in their organizations. Larger health care organizations hold superior internal resources, which benefit the system by flexibility and economies of scale, as an inequitable nature of hospitals, and outcome results will vary from hospital-to-hospital (Fareed & Mick, 2011; Shortell, Wu, Lewis, Colla, & Fisher, 2014). Another outlook of

RDT is an organization's ability to curtail uncertainty and dependence of health care reform through resources (Shortell et al., 2014).

Medicare influences the payment for providers, which may affect the private markets by competing for medical resources through complex transactions (White & Wu, 2014). A $1 decrease in a Medicare payment for surgical service typically leads to a $1.30 decline in private payments, further substantiating that Medicare exerts influence over private payment amounts (White & Wu, 2014). Medicare influences the market by shifting resources across regions (i.e., RDT).

As such, business actors under RDT may depend upon the diversification of business units (e.g., CVSL) and increase its relative power (Xia & Li, 2013). The Advisory Board Company defined a CVSL as providing an administrative body, a distinct budget, and an integrated strategic plan with a shift from acute care to cross-continuum care (Khan, 2014). In applying this theory in the hospital industry, these resources may represent patients, physicians, and equipment obtained by growing a hospital's market share. A hospital's survival is a function of success of operations and alignment of its power affairs within the environment; therefore, an organization can reduce its interdependencies by acquiring incentives, and inversely, reduce penalties from the environment (McCue, 2011).

Previous Studies

Limited studies exist on understanding the relationships between health care costs and quality outcomes in CVSL with literature concerning the health literacy of CV conditions (Peterson et al., 2011; Rumsfeld et al., 2013). One approach includes the examination of the variation that exists in CV care, which includes the discrepancies of use and costs (Matlock et al., 2013). Another perspective involves the exploration of waste reduction programs targeting cardiac-device procedures that suggest opportunities for facilities to design successful waste reduction programs (Lowe et al., 2013). The usual route of prior studies involves the examination of correlational relationships with single quality drivers, which associate to hospital characteristics (Theokary & Ren, 2011).

Because medical care is a service industry, challenges inherent to produce quality differ from the production of a product (Stock, McDermott, & McDermott, 2014). No other industry of service demands the complex P4P, the schemata designed to obtain quality service (Pauly, 2011). In consumer models, individuals accept service involving higher prices for superior quality regardless of the costs to provide the service (Pauly, 2011). Organizations with superior quality may lead toward sustainability in the market, yet depend upon the consumer whether the service is of value at the established costs. With complexities unique to health care, reform activity challenges organizations to prioritize resources to document and improve quality outcome data (Boyer et al., 2012).

Patient Protection and Affordable Care Act and Effects

The ACA was a 2010 piece of legislation that extended health care coverage to many uninsured citizens and focused on the costs, quality, and accessibility of health care (Ehlke & Morone, 2013). The use of regulations, external rewards and penalties while balancing costs with benefits extended this aim (Pauly, 2011). The ACA provides endorsement to Hospital Value-Based Purchasing (HVBP) for all acute care hospitals in the United States (Ryan & Damberg, 2013).

Traditional issues under examination in health care comprise of costs, quality, and access (Leleu et al., 2014). Specific intentions of ACA are to reduce cost shifting (i.e., decrease the number of uninsured seeking care), enhance quality of care, and decrease readmissions, with each item placing stress upon a hospital’s operating cash flow (Pratt & Belliot, 2014). The implementation of ACA aims to strengthen the Medicare Hospital Insurance Trust Fund by $575 billion over 10 years (Centers for Medicare & Medicaid Services, 2014a). However, much remains unclear regarding the cost containment means of P4P to improve quality (Ryan & Damberg, 2013). Because the U.S. government is in large, an important component of the health care landscape, it continues to affect the health care delivery system. Health care organizations need to consider a strategy toward the ACA and accountability to costs (Dagher & Farley, 2014). The current use of P4P incentives raises questions whether P4P raises the level of quality (Ryan et al., 2014).

Because of ACA, the effects of Medicare hospital payments (i.e., productivity adjustment) challenge leaders to discover ways to be more productive. Hospitals may not respond appropriately, an estimation of Medicare rates in 2040 are to be half of the commercial market payments (Frakt, 2014). Such a payment schema forces hospitals to prepare for the future (Dagher & Farley, 2014). Three scenarios of the hospital response to Medicare shortfalls include cost shifting to other payers, cutting costs, and reduction of profitability, creating the environment for closures and consolidations (Frakt, 2014).

Hospital Compare

Hospital Compare, launched in 2005 by CMS, includes information regarding quality from various sources (Zoghbi, Gillis, & Marshall, 2013). Hospital Compare is another avenue for researchers to investigate outcome data and beneficiary expenses, yet is limited to Medicare beneficiaries and abstracted information of 97% of hospitals. Over 4,000 hospitals participate in Hospital Compare, a public access point that allows comparison of hospitals of CMS process of care measures. Hospitals receive 2% of Medicare revenues to collect these data (Boyer et al., 2012).

Hospital Compare includes hospital readmission rates, mortality, and expenses per Medicare beneficiary whereas the expense is a function of hospital care by location (Pratt & Belliot, 2014). A hierarchal condition category indicates risk level of Medicare beneficiaries, where a higher score equates to higher costs (Erden et al., 2014). The effects of the ACA lead health care systems to align delivery to incentives (Eggleston & Finkelstein, 2014).

The American Hospital Association data. The American Hospital Association (AHA) is a reputable source of high-quality data dependent upon the surveying of participating hospitals (Everson, Lee, & Friedman, 2014). The survey includes information such as ownership kind, teaching standing, bed size, and safety net classification (Herrin et al., 2014). The AHA files allow provider or organizational information, and associated characteristics (Bradley, Penberthy, Devers, & Holden, 2010). Accordingly, these hospital characteristics involve elements linked to quality and cost data. Prior to 2012, the AHA linked to the NIS for hospitals identification.

Hospitals are now identified through state-identifiers for HCUP states. The past ability to link AHA data to the NIS depended upon the variables desired such as bed size, ownership, and teaching status (HCUP, 2014d).

National inpatient sample (NIS). The AHRQ sponsors a hospital inpatient database, which aids researchers and health care leaders in areas associated to costs, access, quality, and outcomes of care (HCUP, 2014d). As of 2012, 44 States participate in the NIS that covers 95.7% of the United States population (HCUP, 2014d). Because of the sample redesign to capture 100% of all hospitals, improved variance estimates resulted. The samples of discharges from included hospitals are discharge-level, not actual, patient-level files (HCUP, 2014d). Patient-level files link a specific patient with demographic information and any outcomes associated to a given beneficiary (Brecker et al., 2014). Finally, a link between AHRQ and CMS allows cost information by specific hospital (HCUP, 2014d).

Hospital Value-Based Purchasing Domains

HVBP is the Centers for Medicare & Medicaid Services' mandate for acute care hospitals to receive rewards or penalties based upon the improvement and achievement of specific quality measures (Dupree, Neimeyer, & McHugh, 2014). The establishment of value-based purchasing in 2011 under ACA of 2010 allowed two mechanisms of performance: improvement and achievement (i.e., P4P; Dupre et al., 2014). Because the HVBP design is new, the ability to study its effects on quality and costs is distinctive. The impetus behind HVBP and P4P is that people and organizations react to incentives

(Jha, 2013). Accordingly, enhanced quality and care should occur as result of incentivized measures.

Under the value-based purchasing paradigm, the successes in the quality of high-performing hospitals may not be enough to offset the lower quality in low-performing hospitals (Lindrooth et al., 2013). The HVBP involves the largest P4P program to date (i.e., Premier Hospital Quality Incentives Demonstration [HQID]; Jha, 2013). The HVBP may have a significant financial effect on acute care centers (Dupree et al., 2014). The inpatient Medicare payments will move from a withheld amount of 1% to 3% by 2017, creating an incentive pool of rewards and penalties (Dupree et al., 2014).

Mortality. The AHRQ provides data relative to risk-adjusted models to calculate differences in inpatient mortality (Romley, Jena, O'Leary, & Goldman, 2013). The use of mortality rates in hospital quality data focuses upon in-hospital outcomes. Hospital Compare provides publicly reported data that shows in-hospital mortality rates for 30-day post, hospital admission of AMI, CHF, and pneumonia. The availability of mortality rates in-hospital continues to be practical and conceptual; the data readily available versus an extended assessment. Death rates escalate in the weeks following discharge, an important outcome for hospital assessment (Drye et al., 2012). Risk-standard mortality rates, used by CMS as a linkage to disease and death rate estimations, assist in the determination of calculated outcomes, which in-hospital mortality links with between-hospital variation over 30-day measures (Drye et al., 2012).

Cardiac Related Outcome Measures

In 2007, CMS began to record mortality rates for CHF and AMI with hospital-specific 30-day risk-standardized rates for both conditions in (Suter et al., 2014). Cardiology core measures include mortality and readmissions measures (Zoghbi et al., 2013). In states with public reporting for PCI (e.g., Massachusetts, Pennsylvania, and New York), a lower probability exists for high-risk Medicare beneficiaries to receive PCI because of the potential for reported mortality (Joynt, Blumenthal, Orav, Resnic, & Jha, 2012; Kupfer, 2013). No discernable difference exists between the hospitalization and survival rates of acute and nonacute heart attack (Alyeshmerni, Froehlich, Lewin, & Eagle, 2014). Surgical services (e.g., coronary artery bypass graft) demand much attention under the HVBP provisions because seven of the 12 processes of care involve surgery care. Both AMI and CHF, often associated with comorbidities, contribute to higher readmission rates versus other conditions (Erdem et al., 2014a).

Hospital Characteristics

The link between volume and operational performance in health care settings involves research with multiple elements (e.g., production volume, quality, costs, and hospital patient volume). Hospitals that care for a high volume of patients and designated as an academic facility for both AMI and CHF diseases tend to have lower process quality (Theokary & Ren, 2011). The effects of market pressures result in the health care provider's ability to deliver care. Positive profitability by payer group occurs in Medicare, Medicaid, and private payers (Leleu et al., 2014). Because of the various ownership types of hospitals, organizations have different financial priorities. Despite ownership type, hospitals' financial survivability remains the same through traditional markets and budgetary limitations (Leleu et al., 2014). Hospital characteristics that contribute to readmission rates include availability of beds, discharge rate, and occupancy (Erdem et al., 2014a). Hospital characteristics for research involve number of beds, authority (e.g., public or private), and type (e.g., academic versus nonacademic). The price of services at academic institutions usually exceeds the prices of other health care venues to incorporate complex patient conditions and poor integration of services (Washington, Coye, & Feinberg, 2013).

Multiple measures indicate hospital profitability to include total revenue minus total costs. A hospital with excessive beds indicates inefficiencies of costs, and the reduction of resources improves profitability to include excess use of medical staff by 41% and beds by 33% (Leleu et al., 2014). Hospital characteristics for research, located in the final rule file of the CMS Inpatient Prospective Payment System, includes Medicare designation of certain comorbidities (i.e., Hierarchal Condition Categories) through ICD-9 codes (Gu et al., 2014). The staffing count (i.e., FTE) exists in the AHA's annual survey (White & Wu, 2014). A RDT perspective of hospital characteristics (i.e., larger bed sizes, newer facilities, and system affiliated) involves the examination of resource availability to measure how well a facility does in securing resources (McCue, 2011).

Spending and Cost Control in Hospitals

To define the product of hospitals, the creation of DRGs bolstered the single most significant policy to enhance quality and steady costs (Goldfield, 2010). CMS project health care spending is projected to grow to 19.6% of the gross domestic product (GDP) in 2021, yet others suggest this figure as overstated (Gordon et al., 2014). While hospitals remain highly dependent upon public programs such as Medicare and Medicaid, a gap exists over the feasibility and sustainability of Medicare relative to spending, performance, rising costs, and its future (Blendon & Benson, 2013; Fareed & Mick, 2011). The commitment to enhance the value of health care spending rests central to reform, albeit debatable on how to achieve (Romley et al., 2013). Many recommendations for cost control and health care reform exist for transformational health care (McClellan, 2011; Nigam et al., 2013).

Medicare and Medicaid entitlement represents much of the spending in the United States that will pose a majority of the deficit cut efforts in the U.S. federal government (Alyeshmerniet et al., 2014). Traditional payment oriented toward volume over quality, misaligned incentives, and disjointed delivery are the principle drivers of health care costs (Centers for Medicare & Medicaid Services, 2014a). However, the ACA is a turning point in health care history to staunch the uncontrollable rate of spending. Prior attempts to reduce costs include triple-tier pharmaceuticals, the outmigration of inpatient to outpatient services, and provider network limitations (Pauly, 2011). Further, empirical studies have demonstrated limitations how the present static and short-term effects slow health care costs and improve quality (McClellan, 2011).

Under Medicare provisions, regardless of payer, comprehensive cost measures include all aspects of patient care while being admitted to the hospital. Examples of such elements include drugs, supplies, recovery, and imaging (McDermott et al., 2011). Cost containment for limiting fee-for-service and capitation-based reimbursement remains relevant in reform (Anderson et al., 2014). At the hospital level, profitability in a service line rests upon the endogenous factors (i.e., cost containment; Navathe et al., 2012).

Cardiovascular Costs

The United States lacks nationwide data of associated cardiovascular costs, and often include merged or double-counted information (Ferdinand et al., 2011). Because cardiovascular care represents one-third of the patient volume in the United States, $444 billion in disease costs, and is significant to hospital profitability, controlling costs in cardiology is important for leaders (Ding, 2014). Expenditures in CV care involve higher costs, with the delivery of care involving pacemakers, defibrillators, coronary catheters, stents, and cardiac valves; each are a remarkable source of cost in the CV environment, yet there is no improved risk reduction (Alyeshmerni et al., 2014). The importance of cost control, while enhancing quality and safety to the survivability of health care organizations, stands as a critical association (Breslin et al., 2014). Literature prior to the passing of the ACA and thereafter supports the notion that when hospitals cut costs, reductions in valuable services occur as well (Kaplan & Witkowski, 2014).

Possible Relationship: Costs and Quality Outcomes

ACA includes outright Medicare cuts and rewards for high-quality outcomes. Quality does not undergo compromise because of cost containment and reduced payments. Absent in the literature are studies on the safety and quality outcomes that are tied with the recommended use of resources and value considerations and are further targeted to the most-effective clinical care in cardiology (Anderson et al., 2014; Berwick

& Hackbarth, 2012). Since 1993, there has been no positive correlation between expenditures and risk reduction exists in cardiovascular care (Alyeshmerni et al., 2014).

Several cardiovascular procedures performed in a hospital setting have involved potentially wasteful costs and nonvalue added outcomes for patients (Chan et al., 2011; Lowe et al., 2013). The role of experience as a variable in cost control and productive efficiency reveals a transaction between quality and costs (Ding, 2014). An investigation of operational performance and cost control of cardiology showed an association to experiential quality (Nair, Nicolae, & Narasimhan, 2013). Effects of the satisfaction of patients and defined performance in the modern care reform era include quality, safety, costs, and satisfaction (Chou, Deily, Li, & Lu, 2014; Peterson et al., 2010).

Central to health care reform is an improvement of quality while lowering costs. Despite this edict, some regions exhibit superior quality with increased spending to include studies in congestive heart failure and mortality (Romley et al., 2013). However, an increase in care and higher costs do not equate to better quality or outcomes (Anderson et al., 2014). Studies used to determine the association between high quality and high costs may be inconclusive or controversial, with recommendations for future studies to identify wasteful costs and beneficial spending (Hussey et al., 2013; Joynt & Jha, 2012). Research conducted revealed a 1% reduction in payments and resulted in a 0.4% increase in AMI mortality rates (Frakt, 2014). Likewise, a decline in CVSL profitability through Medicare reimbursement demonstrated an associative risk for 30-day mortality rates (Frakt, 2013). Furthermore, little information exists relative to the differences between patient and hospital characteristics in acute heart failure hospitalization costs (Sharma, Yu, Johnson, & Fonarow, 2014).

The effect of metrics and reporting on quality exist, yet not on the role costs play in the reform structure (Chatterjee & Joynt, 2014). Uncertainty exists for which P4P elements are essential, adequate, and optional for quality improvement (Ryan & Damberg, 2013). A lack of achievement of P4P metrics may lead to lower Medicare reimbursement. Such incidents may result in fewer resources expended for patient care and lowering the quality of care (Lindrooth et al., 2013). The primary effects of a reduction in revenue involve decreasing operating costs, hospitals that lose revenue cut costs whereas a gain in revenue shifts as profit (Frakt, 2014).

Analysis in Health Care Profitability Research

The reduction of Medicare provider payments through ACA carries varying divisive viewpoints, with one view stating that 15% of health care facilities will become unprofitable in 10-years (White & Wu, 2014). Reform measures before the ACA implementation affected various hospital service lines differently, with the estimation of a hospital entity's response to payment cuts dependent upon admission profitability (Navathe et al., 2012). The effects of slow growth rates cause hospitals to compensate with cost shifting or adjustments of cost structure. This implementation of reform has created much uncertainty with concerns facing revenue (Cole, Chaudhary, & Bang, 2014). Lost revenue may force hospitals to cut operating costs, an action seen predominantly in private facilities (White & Wu, 2014).

The direct correlation between quality and reimbursement leads to observable quality (i.e., outcomes; Navathe et al., 2012). As such, superior observable quality leads to a positive reputation, which increases the likelihood that patients seek care from the health care organization. Further, payment reforms depend upon evaluating outcome rates that affect both perception and finances (i.e., reputation and revenue; Shih & Dimick, 2014). Moreover, reductions in reimbursement via reform threaten discretionary quality efforts of resources (Navathe et al., 2012). A multiple regression study to determine hospital profitability enables identification of the independent effects on profits (e.g., hospital characteristics; Leleu et al., 2014).

Factors of hospital profitability include (a) hospital characteristics, (b) internal, leadership decisions (i.e., service offerings), (c) payer and case mix, and (d) external market conditions (Reiter, Jiang, & Wang, 2014). The operating income or excess of revenues over operating expenses define profitability in hospitals (White & Wu, 2014). Navathe et al. (2012) found no association between service line profitability and readmission rates. Multiple factors may influence the relationship between the service line profitability and outcomes as readmission rates to include (a) efforts to reduce the risk of readmission penalties, (b) a hospital’s ability to affect patient care after discharge, and (c) discrepancies in service line profitability (Kripalani, Theobald, Anctil, & Vasilevskis 2014; Navathe et al., 2012). Because CV-related conditions account for the majority of accountable 30-day readmissions, the resources used to sustain performance stands important to ensure minimal to no penalties (Kripalani et al., 2014). Inversely, a study to stimulate the effects of reduced profitability vis-à-vis Medicare reimbursement in a CVSL increased 30-day risk-adjusted mortality (Lindrooth et al., 2013).

A previous study with a regression model of hospital characteristics revealed significant amounts of covariance within various variables (e.g., ownership status, region, size, and academic distinction; Dupree et al., 2014). Correlational study results between the quality of care and patient experience vary yet have never been studied on a national level (Stein, Day, Karia, Hutzler, & Bosco, 2014). A hierarchal logistic regression model used to publicly report data characterized patients within hospitals with risk-adjustment in CMI Suter et al., 2014). The CMS data from 2009 to 2012 showed a disparity of care for CHF and AMI with a likeliness of payment incentives influencing AMI readmission performance (Suter et al., 2014). Operating cash flow had an inverse relationship to mortality rates for AMI, CHF, and pneumonia with confounding factors to include the CMI and spending per patient (Pratt & Belloit, 2014). Public ownership, a hospital characteristic, demonstrated the lowest surgical care score under a mock readmissions research design; this is a possible explanation is a lack of resources (Dupree et al., 2014). One variable included in this study was the ownership status of each hospital to determine the level of predictive value toward profitability.

Various quantitative approaches for the examination of health care costs and resource use are possible, all with the ability to address the characteristics of healthcare resource use and cost data (Briggs, O'Hagan, & Thompson, 2011). Most studies relative to correlations among costs, quality, and hospital finances involved AMI (Lindrooth et al., 2013). Further, a gap in the literature and national surveillance of data exists, which challenges leaders to recognize related costs and resources associated toward the incidence, prevalence, and outcomes of cardiovascular disease (Ferdinand et al., 2011).

Transition and Summary

The literature indicates effects of the external environment (i.e., reform expectations) upon hospital organizations across a myriad of hospital characteristics (Ayed, Hajlaoui, Ayed, & Badr, 2015; Fareed & Mick, 2011; Shortell et al., 2014; Yeager et al., 2014). The CVSL includes conditions that fall under the provisions for health care reform, Medicare reimbursement, and care related expenses. Organizations attempt to maximize reimbursement of such reform expectations to realize maximal profitability. Health care organizations remain dynamic to avoid penalties from reform, effecting revenues and reputation (Cole et al., 2014). Penalties of 1.5% and 3% in 2015 may have significant influences on hospitals with slight profit margins (Centers for Medicare & Medicaid Services, 2014b; Joynt & Jha, 2013).

The problem and purpose statements for this quantitative, multiple regression study support the need to examine how well predictor variables of outcomes and hospital characteristics predict the profitability through reimbursement in the CV setting. An examination of potential relationships between outcomes, costs, and resources used in a CVSL positions well for secondary data analysis of such variables. The pursuit of a predictive level for profitability attempts to add to the limited information relative to the ACA and its effect on CVSL in acute care hospitals under health care reform.

The goals of Section 2 are to present the research design and method for this quantitative, multiple linear regression study. The supporting sections include the role of the researcher, study participants, research method, research design, population and sampling, ethical research, data collection, data collection technique, data organization techniques, data analysis, and reliability and validity. Section 3 includes the presentation of findings, application to professional practice, implications for social change, and further recommendations.

Section 2: The Project

The project section includes a detailed account of the research study with an introduction to the problem statement to establish the context of the project. A description of the role of the researcher in the data collection process and a discussion of the participants follows, including the population description, the total population, sample population, type of sample, ethical considerations, data storage, and the informed consent from participants. Another item reviewed is the chosen research method and design: population, sampling, ethical research processes, data collection instruments, data collection techniques, data analysis, reliability, and validity. Using the results of the study, CVSL leaders and health care administrators may identify various factors concerning CV profitability heightened by the ACA.

Purpose Statement

The purpose of this quantitative, multiregression study was to examine significant predictor variables of resources and outcomes. The independent predictor variables were the sites of CV delivery and characteristics and associated outcomes, resources for, and cardiovascular conditions. The dependent, outcome variable was the cost of health care delivery. The targeted population included hospital beneficiaries of community hospitals in the United States who received care for cardiovascular conditions. Accessibility of this population occurred through AHRQ’s 2012 NIS data derived from community hospitals (McDermott et al., 2011). The geographic location for this study included eligible, acute care facilities in the United States because of the high incidence of cardiovascular disease found in the country (Ferdinand et al., 2011; Go et al., 2014). This study may contribute to social change by highlighting delivery characteristics in CVSL, which remain relevant under reform efforts for superior quality (Emanuel et al., 2012). This study may influence the business environment by informing health care leaders in aligning costs to reform efforts that match the transformation of health care to growth, enhanced quality, and reduced inefficiencies (McConnell et al., 2014; Volland, 2014).

Role of the Researcher

The role of a researcher was to address potential ethical dilemmas prior to advancement of the research (Johnsson, Eriksson, Helgesson, & Hansson, 2014). Maintained perceptions of research included information gathering, exploring, and discovering facts (Stubb, Pyhältö, & Lonka, 2014). As the sole researcher in this quantitative, multiple regression study, responsibility included obtaining rights to beneficiary data through AHRQ. The AHRQ required training and a signed Data Use Agreement (DUA) and Indemnification Clause to access the applicable HCUP databases (see Appendix A). Second, I collected and transformed the appropriate, secondary data with further analysis of hospital characteristics and outcomes of CV-related conditions to predict CVSL profitability vis-à-vis a function of costs. With careful consideration of the research question, available data, and the strengths and limitations of the data, a final task included the analysis of the data, reporting the findings, and providing accurate and appropriately generalizable conclusions derived from the data analysis.

The databases stay consistent with the definition of limited data sets (LDS) under the Health Insurance Portability and Accountability Act (HIPAA) Privacy Rule Privacy Rule and contain no direct patient identifiers. HCUP Data Use Agreement (DUA) training and a signed DUA and Indemnification Clause are prerequisite to order the HCUP databases. The HCUP DUA may provide Walden University's IRB with proof of compliance with the HIPAA Privacy Rule.

The experience I have with the content of the study extends into the acute care hospital leadership role within the CVSL. Although familiar with hospital characteristics, quality, and outcomes as well as related conditions and procedures, limited knowledge existed for such elements to have any predictive value toward profitability. Because the objective, deliberate evaluation involved secondary data provided by the HCUP, associated interventions became unnecessary (Walker, 2005). Consequently, the role of the researcher was nominal because of the absence of actual acquisition and collection of the data, yet reliant to the integrity of the provided data. Further discussion of the study's reliability and validity follow in a subsequent section.

Participants

The public data collected for this study involved secondary data from the HCUP and provided distinct levels of detail intended for economic evaluations of health care delivery (ResDAC, 2014). The advantage of secondary data was access to large, participant samples, generalizability of results, and ethical considerations. As such, the National Committee on Vital and Health Statistics (NCVHS) in 2007 determined the term *secondary* did not match the importance of administrative, health data and instead preferred the terms *reuse* and *continuous use* data (Hripcsak et al., 2014; NCVHS, 2007).

The evaluation of participant hospitals within the United States included the chosen independent variables. Patient-level data accessed from AHRQ's 2012 NIS data sample of discharges from all hospitals provided the research participants or cases through secondary data. Each record in the NIS included the following data elements, yet were not exclusive to (a) primary and secondary diagnoses and procedures, (b) limited patient demographic characteristics, (c) hospital characteristics, (d) expected payment source, (e) total charges, (f) discharge status, (g) length of stay, (h) and severity and comorbidity measures (HCUP, 2014d). The hospital cost-to-charge ratios derived from the CMS Healthcare Cost Report Information System. Other hospital characteristics, including ownership, teaching status, and location exist in the AHA's Annual Survey of Hospitals (Everson et al., 2014; Herrin et al., 2014). The ability to previously link AHA hospital characteristics through the HCUP allowed identification of the chosen variables. Currently, hospital characteristics link through the state-supplied identifiers. All items described were in public domains, yet accessibility and data for this study occurred through a student researcher distinction, yielding no need for involvement by any hospital IRB (HCUP, 2014d).

Research Method and Design

Researchers may choose from three methods to address research questions, each involving varying inquiries, data, and sampling techniques (Lewis-Beck, Bryman, & Liao, 2013). With each method, the research questions would necessitate a formulated approach. Secondary data involve many data points, and the use of qualitative and mixed-methods approaches remain limited. The preferred method for this research inquiry was the quantitative method because (a) of its orientation to my desired professional approach to problem solving, (b) appropriateness for beneficiary data available, (c) alignment to empirically-driven, evidence-based guidelines for fellow health care clinicians and leaders, and (d) the mathematical methodology used best to assess relationships between two or more variables (Kleinbaum, Kupper, Nizam, & Rosenberg, 2008).

Method

The quantitative method for this study provided an empirical approach to reveal associated relationships and predictor elements. The quantitative method involved an inclusion of variables for assessment of empirical merit (Campbell & Stanley, 2010; Mukamel et al., 2014; Pandya et al., 2013; Schousboe et al., 2014; Yang et al., 2012). Because health care research focuses on enhancing effectiveness and efficiencies of the delivery of service, quantitative methods suited the need of this study (Bowling, 2009).

A qualitative method, used to explain the relationship between outcomes and costs, may lessen the focus to test stated hypotheses (Wisdom et al., 2012). I considered a qualitative method for this study, yet rejected it because collecting data from patients or hospital administrators for CV conditions (i.e., quality outcomes) presents privacy and confidentiality concerns that pose a risk to the efficient completion of this study (i.e., HIPAA). A qualitative study may not be appropriate for this examination.

A mixed methods study encompasses both qualitative and quantitative studies (Bryman, 2012). The appropriateness of a mixed methods study involves the need to address different research questions, while employing an empirical approach to strengthen the study by moderating natural weaknesses of single-method approaches. The potential to perform a triangulation for data analysis within a single study was not a consideration because of the level of detail required for this study (Bryman, 2012). I did not pursue a mixed method study because of the inherent weakness of the qualitative component of the scope of this study.

Research Design

Because of the potential for numerous variables and approaches involved in hospital profitability, a multiple regression analysis required an additional complexity over simple correlational analysis (Green & Salkind, 2014). The selection of a multiple linear regression approach to determine hospital profitability enabled the identification of the independent effects on profits (Leleu et al., 2014). A health care leader uses regression for statistical information and forecasting, which allows leaders to position resources in an advantageous manner (Bowling, 2009). An open-ended data collection through interviews or observations of patients to establish themes or narrative analysis did not allow a desired level of empiricism to reveal associated relationships and predictor elements of resources and quality outcomes (Bryman, 2012; Lee & Cassell, 2013). The research question inquired about a possible relationship between variables and associated predictive levels. Therefore, a multiple linear regression continues to remain important in organizational research, yet its intercorrelations between predictor variables (i.e., multicollinearity) challenge the interpretation of multiple linear regression weighting regarding each predictor contributions to the outcome variable (Nimon & Oswald, 2013).

Population and Sampling

A quantitative research project includes a population from which the researcher wishes to draw conclusions from the data; however, the collection of an entire population remains prohibitive (Lewis-Beck et al., 2013). For a quantitative study, the research paradigm is to address relationships among variables and to estimate sample statistics to infer population considerations (Podsakoff, MacKenzie, & Podsakoff, 2012). Although an all-payer sample, CMS remains the largest payer in the United States and collects well over 2 billion data points per year (Brennan, Oelschlaeger, Cox, & Tavenner, 2014), Medicare accounts for the third largest item in the U.S. federal budget, where the number of Medicare recipients will increase from 52 million to 73 million by 2025 (Blendon & Benson, 2013).

The application of administrative data in research limits the usefulness of clinical details, which play a major role in factors attributable to outcomes (Shih & Dimick, 2014). In addition, numerous studies revealed a poor correlation with administrative claims data and direct, clinical data (Sacks et al., 2014). Further, clinical data remains expensive and time-consuming with necessary clinical information used for an accurate risk-adjustment assessment (Sacks et al., 2014). Another consideration is hospital coding where the hospital may practice up-coding to ensure maximum reimbursement or diagnosis (Kim, Kim, & Kim, 2014). The use of administrative claims data to make clinical conclusions was not intended for this study, yet captured the internal factors of CV services in acute care hospitals within the context of a RDT.

The study included Medicare and other payer datasets for a weighted evaluation of institutional features and measures of costs and outcomes. The 2012 NIS HCUP file included a sample of hospital discharge information for community hospitals, with a representation of over 8 million discharges; this sample represented 20% of the overall discharges nationally. The uses and implications of beneficiary data allowed me to approach the study from the institutional perspective where costs and benefits rank primary.

The sampling techniques for this study included a purposive sample of all-payer data acquired through the 2012 NIS. The administrative data, available to the public under provisions, allow studies for comparative effectiveness research and evidence-based research on various health conditions (Erdem et al., 2014b). A nonprobabilistic, purposive sample allowed the selection of elements of the targeted population for fitness and alignment toward the purpose of the research (Daniel, 2012). This included the selection of major diagnostic classification (MDC) of circulatory disorders, a collection of CV-related conditions (i.e., DRGs). The subsets or strata included all-payer beneficiaries receiving care in 2012 from 44 participating states and who received care for CV conditions (i.e., circulatory disorders) and did not limit sampling based on race, gender, or recurrence of care (i.e., discharge-level data).

Individual beneficiary level analysis was not available and would not of added value to the empirical scope of this study (HCUP, 2014d). The files contained discharge-level health information but excluded specified direct identifiers as outlined in the HIPAA Privacy Rule (ResDAC, 2014). In addition, secondary data includes millions of observations versus small sample sizes seen in survey methods (Erdem et al., 2014b).

For multiple regression, the sample size determination involved (a) testing for fit, (b) power for a specific predictor variable, (c) exactness for the fitness of the model, and

(d) exactness of a specific predictor variable (Kelley & Maxwell, 2003). An effective sample size becomes problematic in a multivariate study because of the possible interconnectedness of the parameters; the favored approach is to express the effective sample size through the number of predictor variables (Maxwell, 2000). Further, the minimum sample size of *N* is noted as *N* = 104 + *p*, where *p* represents the predictor variables (Maxwell, 2000). A power analysis using GPower 3 software was conducted to determine the appropriate sample size for this multiple regression study. An a priori power analysis, which assumes a moderate effect size (*F* = .15), α = .05 showed a minimum sample size of 90 participants or cases to achieve a power of .95. The study power range was .80 to .99 with the participant range of 55 to 90 (see Figure 1).

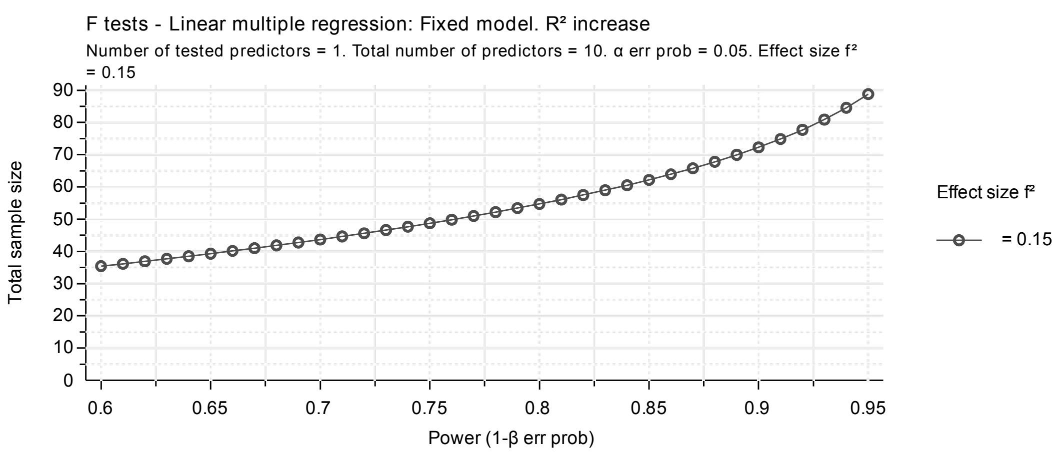

Figure 1: Power as a function of sample size.

Ethical Research

The collection and analysis of data for research for a doctoral proposal at Walden University must meet institutional review board (IRB) criteria. The IRB ensures doctoral students adhere to applicable laws, institutional requirements, and professional standards, while maintaining the values of confidentiality and privacy in research (Stiles & Petrila, 2011). The responsibility to demonstrate credibility and reliability throughout the doctoral study process and chosen method rests upon the researcher (Havard, Cho, & Magnus, 2012). To receive Walden IRB approval, a completed National Institutes of Health certificate of completion of the Protecting Human Research Participants course was necessary (see Appendix B). Despite the use of secondary data involving no identification of human subjects involved in the research for this study, the Walden University required an IRB approval to protect beneficiaries in the secondary data. The IRB approval number assigned for this study is 04-24-15-0438289.

The Belmont Report of 1978 included an outline for the three fundamental ethical principles for human subject research: (a) justice, (b) respect for persons, and (c) beneficence (U.S. Department of Health & Human Services, 1979). As for the use of secondary data, ethical considerations relative to its use include distinction from primary research. Informed consents, used to signal a participant's willingness to be involved in research, are a nonfactor in secondary research (i.e., to show respect for persons) because such data remain available to the public, subject to privacy release approvals and the availability of computing resources (Brakewood & Poldrack, 2013; ResDAC, 2014). Second, beneficence with secondary data involves the safeguard of participant privacy and confidentiality, and advancement of good for its participants, which enhances the social connection to research (Brakewood & Poldrack, 2013).

Password protected and encrypted files, removed of data elements that might permit identification of beneficiaries, protect against potential harm of its beneficiaries

(ResDAC, 2014). In addition, the use of secondary data eliminates contact between the researcher and participants. Next, secondary data of topic selection and generalization may have a positive effect on the subjects of research studies, allowing researchers to pool information from participants and populations to which they might not have access. A concept of secondary analysis includes a nonreactive element (i.e., unobtrusive; Bradley et al., 2010). Moreover, secondary data allow access to homogeneous populations for research. This factor increases the generalizability of findings and the likelihood that individual and social justice mandates meet or exceed expectations (Brakewood & Poldrack, 2013).

If a prohibition of existing, de-identified data sources to evaluate hypothesis in research exists, researchers will certainly be limited in their participant selection (Brakewood & Poldrack, 2013). The collection of health care beneficiaries through anonymized data adheres to the provisions outlined in the HIPAA Privacy Rule. The AHRQ administers the HCUP NIS through the HCUP Central Distributor each summer. Available administrative data includes formatted information concerning beneficiaries, providers, clinical data, and claims. These datasets include accessibility privileges to the public, susceptible to signed privacy release approvals and the availability of electronic retrieval and archiving resources.

Research Identifiable Files contain protected health information at the beneficiary level (ResDAC, 2014). Public Use Files included aggregated summary level health information without beneficiary level data; and do not require a DUA under a Privacy Board review (ResDAC, 2014). Because the study did not use protected health information, yet required item level data, the use of a LDS with beneficiary data encrypted, blanked, or ranged provided the level of detail needed for this study. Any protected and acquired beneficiary data were stored in a password-protected electronic folder, limited and accessible only to me, and will eventually be deleted 5 years upon completion of this study.

Data Collection

The data collection process involves establishment of boundaries and protocols for recording information relative to research (Stanley, 2011). Data acquired for this study included public information used for health care organizations, researchers, and consumers. The disclosure of the characteristics of data collection, instrumentation, and analysis allowed insight of the organization of the study (Polgar & Thomas, 2013). Last, understanding the data collection process may help define the context of the intended research, particularly for application of clinical data (Grant & Schmittdiel, 2015).

Instrumentation

Challenges with data include the expense and time required to acquire with a high degree of responsibility (i.e., regarding protection, storage, and use) (Bradley et al., 2010). With the 2012 NIS, the energy to acquire, download, convert zipped files, align core files appropriately to load files, and prepare the data proved challenging.

An exciting perspective is the future application of clinical data, in combination with existing data to examine non-clinical uses (Hripcsak et al., 2014; Safran et al., 2007). The data used for this research included information from the AHRQ HCUP for designated community hospitals in the United States. The included datasets source provided data relative to the respective study variables. The benefit of administrative data for outcomes is the ability to calculate mortality without an extensive medical chart review.

Utilization data acquired from inpatient files involved: (a) diagnoses, (b) procedures performed, (c) DRGs, (d) hospital identifier, (e) total charges, (f) hospital charactersitcs, and (g) limited, applicable beneficiary demographic information. The 2012 NIS (i.e., inpatient data sets) provided the basis of the independent variables of (a) beneficiary conditions (i.e., circulatory disorders), (b) resources used (i.e., costs, procedures performed), and (c) quality measures (i.e., outcomes).

Mortality. The research conducted to develop AMI and CHF mortality measures exhibited statistical models based on claims data; the models did well in estimating hospital mortality rates compared to models based on medical chart reviews (Medicare, 2014). Mortality measures included as Inpatient quality indicators provide a representative factor of the quality of care through administrative data (AHRQ, 2015). The mortality measure links to specific medical conditions and procedures; and the use in administrative data and research may help uncover disparities in care and overutilization of health care resources (AHRQ, 2015).

Tracking mortality in HCUP data involves in-hospital deaths. In-hospital mortality measures provide an assessment of hospital performance different from 30-day mortality, which subsequently favors hospitals with a shorter LOS (Drye et al., 2012). The HCUP employed stratified bootstrapping in mortality data to account for population statistics through a sample of 500 varying populations to create a realistic representation of hospital types (HCUP, 2014d). Mortality occurring during hospitalization codes to the variable DIED, which will code to MORTALITY for reference under the main model. If a patient died during hospitalization, these variables will equal 1 and conversely equal 0 if patient did not. The coding logic for the mortality data element did not reflect admitting or coexisting diagnoses (HCUP, 2014d).

Hospital characteristics. The NIS included a set of AHA hospital characteristic variables such as bed size, ownership, and teaching status. Hospital characteristics serve well as control variables in quantitative research designs (Reiter et al., 2014). The selection of hospital characteristics added value to health care research because of the extensive application in a variety of research approaches. Examples of previous research inclusive of hospital characteristics involved determination of a correlational value to AMI mortality, regression analyses for readmission penalties, and controlling factors in service line profitability (Curry et al., 2011; Joynt & Jha, 2013; Navathe et al., 2012).

Because HCUP State Partners supply more than 95.7% of the total discharges nationwide, the whole count of discharges within each section involves the actual count of discharges contained in the 2012 NIS data from all hospitals in the United States (i.e., the universe) (HCUP, 2014d). The statewide discharge counts distinguish hospitals using the State Inpatient Database (SID) hospital identifiers, also consisting of AHA data for hospitals in the sample from absent HCUP statewide data (HCUP, 2014d). For the majority of hospitals, the SID hospital identifiers link one-to-one to AHA hospital identifiers. The sample does not include duplicative hospitals in the data; yet, the SID hospital identifiers in the 2012 National Inpatient Sample (NIS) disaggregates the previously combined hospitals in many States, which improves the classification of hospitals and improve variance estimates (HCUP, 2014d; Reiter et al., 2014).

Bed size. Hospital characteristics allow a determination of a hospital's bed size, indicated as an initial predictor variable and valuable for resource determination (Erdem et al., 2014a; Leleu et al., 2014; McCue, 2011). The use of bed size in health care research enables a level of input measurements and service capacity of a hospital (Hsieh et al., 2010). Additionally, the number of beds is an indicator of hospital size (Reiter et al., 2014). The data element provided in the HCUP datasets list bed size as HOSP_BEDSIZE. The bed size variable for this research segregated and eventually defined into three categories of variables SMALL_BEDSIZE (<150 beds), MEDIUM_BEDSIZE (151-449), and LARGE_BEDSIZE (450 and more). The variable was then transformed into three separate dummy variables with the value of 0 negating the indicated bed size and a value of 1 indicative of the bed size. Each classification delineates to a dummy variable value as 0 or 1, with the reference variable set for MEDIUM_BEDSIZE. The strata for bed size remained titled as *hospital bed size* (HCUP, 2014d).

Teaching distinction. Secondary predictor variables included teaching distinction (i.e., academic or non-academic) (Theokary & Ren, 2011). The teaching status of a hospital often shifts the priorities and mission of an individual institution (HCUP, 2014d). Academic centers often serve as a safety net to an indigent population and acquire resources differently (Kastor, 2011; Tallia & Howard, 2012). The variable listing in HCUP data for teaching designation is HOSP_LOCTEACH, with 1 representative of rural, 2 for urban, non-teaching, and 3 for urban teaching status (HCUP, 2014d). The same process was used to transform the single teaching designation variable into only two variables. The combinations of rural and urban hospital variables were combined to create a dummy variable of NON_ACADEMIC_TEACHING. Likewise, the single urban teaching hospital variable was transformed into an all or none dummy value (i.e., 0 or 1) defined as ACADEMIC_TEACHING. For this variable, the creation of a reference variable was not needed because hospitals classify into either academic or non-academic. The strata used for academic distinction identified as "teaching status" (HCUP, 2014d).

Ownership type. Another hospital element is ownership type (i.e., for-profit and not-for-profit), which rounds out the acute care center characteristics for any predictive value (Leleu et al., 2014; Washington et al., 2013). Ownership type remains important because profits from operations may or may not invested into further profitable services (i.e., CVSL) (Cutler & Morton, 2013). As well, the designation of ownership alone is not indicative of the level of quality; further, each type of ownership attempts to increase their market share (Dong, 2015). The 2012 NIS includes data composed of a sample of discharges from participating hospitals within the HCUP. Like prior characteristics of hospitals, ownership may shift the mission of the organization along with internal responses to the external regulations and expectations (HCUP, 2014d). The HCUP data lists ownership as H_CONTRL, where 1 equals government, non-federal, 2 for not-for-profit, and 3 designated for-profit institutions (HCUP, 2014d). The ownership variable was split into two distinct dummy variables with the reference variable as NON_PROFIT_OWNED, which the values of 0 or 1 indicated either

NONFEDERAL_OWNED or FOR_PROFIT_OWNED. The strata in the NIS designated as “ownership” (HCUP, 2014d).

Costs and profitability. A cost-to-charge ratio (CCR) link from AHRQ to CMS’ hospital cost reports (HCRIS) allowed insight of what a hospital billed for services against what the services truly cost (HCUP, 2014a). The CCR included all-payer inpatient cost information with cost*s* reflecting the actual expenses incurred and charges representing the amount a hospital billed for the case (HCUP, 2014a). Specific elements to measure hospital profitability involve ratios of revenue and expenses; operating margin, total margin, operating expenses, and total expenses (Reiter et al., 2014).

The ratio variable of CCR was secondarily linked by the HOSP_NIS hospital identifier from the 2012 NIS Core File as variable CCR_NIS. Further, the CCR serves as information for the profitability vis-à-vis costs and overstated charges. A CCR is often a source to describe a hospital’s finances with a lower ratio equivalent to a larger profit margin on charges (Robinson et al., 2014).

Variable transformation. In both models, the dependent variable CCR was regressed upon the independent, dummy coded variables. Because entering a categorical predictor directly in a linear regression model does not provide the desired outcome, dummy variables representative of the various independent variable groupings were prepared. The need for both dummy and reference variables with more than two values necessitated additional transformation of the independent variables. The recoded dummy variables assigned included reference categories (see Appendix C). The original variables included weighting for national estimates. Conversion of the independent variables enabled exposure of the unweighted counts of each variable. To verify recoding accuracy, comparison through SPSS of old and new variable frequencies conducted revealed matches in count and percentages (see Appendix C).

Data Collection Technique

A statistical analysis of hospital profitability for specific DRGs provides the most useful effect for determining the level of profitability in a service line (Navathe et al., 2012). The availability and expansiveness of administrative data enables research and analyses not before possible (Brennan et al., 2014). The process and outcome measures indicate a hospital's compliance toward evidence-based practices derive from CMS calculations. HCUP files include a sample of hospital discharges. Linkage of timely data between costs, quality, and outcomes will enhance the level of analysis (Brennan et al., 2014). Health services utilization data, commonly referred to as claims data, derives from reimbursement information or the payment of bills. As a rule, elements of information required for a payment determination (i.e., reimbursement) will contain higher quality than other information reported on a claim.

The AHRQ's HCUP combined financial data derived from CMS and other payer's cost reports of hospital data (Reiter et al., 2014). In addition, this data historically linked to AHA Annual Surveys to provide hospital characteristics, yet the 2012 NIS involved the assignment of unique hospital identifiers (Reiter et al., 2014). The HCUP data employs all-payer information from hospital discharges and not by beneficiary (Reiter et al., 2014). Data downloaded from the HCUP 2012 NIS datasets imported directly to SPSS Version 21 for analysis.

Data Analysis Technique

The use of powerful statistical software allowed an analysis of a large sample size including many data processes. The relationship between hospital characteristics, costs, and mortality outcomes focused on specific conditions of circulatory (i.e., CV) conditions via MDC, which determine a level of profitability (Lindrooth et al., 2013). For the application analysis of the data, an import of applicable HCUP 2012 NIS datasets (i.e., Core File, Hospital Data File, and Cost-to-Charge Ratio File) into a statistical program (i.e., SPSS v21) began the data transformation. The mean, median, and mode for descriptive analysis included the raw data and distribution ranges to assess the spread of the data (Tabachnick & Fidell, 2012). Additionally, obtainment of inferential statistics, based upon the sample data set, allowed inferences of the profitability of CVSL through the dependent criterion in hospitals through discharge information. Both descriptive and inferential statistics allowed for an analysis, representation, and potential interpretation (Podsakoff et al., 2012). The quantitative nature of the study shifted toward descriptive and inferential analyses, which the tested the hypothesis through SPSS Version 21.

Because of the fixed nature of the population and non-longitudinal approach (i.e., hospital discharges in 2012), a complex samples, general linear model (GLM) for a finite population correction used to account for the 20% of the discharges from all hospitals in the 2012 NIS were employed primary to a regression analysis. The GLM model is an extension on multiple linear regression for a single dependent variable and goes beyond multiple linear regression in the number of dependent variables that may be analyzed (McCullagh, 1984). An important factor in the addition of GLM is it provides a solution for predictor variables not linearly independent. The sampling error was needed for the remaining 80% of hospital discharges and not for the finite population, which accounted for 8 million discharges (Houchens & Elixhauser, 2014). Finite population correction is preferable in samples with a specific population as seen in the 2012 NIS (Houchens & Elixhauser, 2014). Despite the employment of a GLM, removal of the non-integer weighting variable permitted the CV subpopulation to be normalized in weighting to a value of 1 by dividing the median of the subpopulation weighting value. This transformation alone enabled the bootstrapping function to occur in SPSS for multiple regression modeling.

The HCUP support materials recommended two mechanisms to maintain correct standard error estimates of any subpopulation (Houchens & Elixhauser, 2014). Recommendations included analyzing populations by retaining all the observations in the total sample with a dummy variable of 1 to represent the subpopulation and 0 for all other patients; and another method involved creating a subset with augmented dummy observations representing each hospital (Houchens & Elixhauser, 2014). The choice to retain the entire dataset and assign a dummy variable for circulatory conditions allowed for analyses with all hospitals represented in the model. Although time intensive, this approach was chosen over a smaller subset to minimize the likelihood of omitting or over supplementing the dataset with each hospital. The transformation of the subset population from the entire population represented a shift from 36,484,846 to 4,789,020 discharges (see Appendix C).

To verify a successful download of the data, HCUP recommended validating the data against available national and regional estimates in HCUPnet (Houchens & Elixhauser. 2014). Table 1 demonstrates a query conducted through HCUPnet including summary data for the MDC of circulatory conditions and total mortality and rates versus the 2012 NIS data. This comparison ensured acceptable data conformance (see Table 1).

Table 1

Summary National Estimates Versus 2012 NIS Sample of the Circulatory System

2012 NIS MDC = 5	Total number of discharges	Sample number of discharges	Mortality/Mortality rate
All discharges (HCUPnet)	**4,796,175**	**109,940**	**2.29%**
All discharges (2012 NIS MDC=5)	4,789,020	109,560	2.30%

Note. Total number of weighted discharges in the U.S. based on HCUP 2012 NIS (*n* = 36,484,846). Weighted national estimates from HCUP National Inpatient Sample (NIS), 2012, Agency for Healthcare Research and Quality (AHRQ), based on data collected by individual States and provided to AHRQ by the States. Adapted from "HCUPnet, Healthcare Cost and Utilization Project (HCUP), 2012." Agency for Healthcare Research and Quality, Rockville, MD. Retrieved from http://hcupnet.ahrq.gov/ Accessed May 26, 2015.

Next, a pretest for variable correlation involved analysis through SPSS, which yielded correlation coefficients of 7 variables. Using the Bonferroni approach to address Type 1 errors across 16 correlations, a p value of less than .005 (.05/7 = .007) required for significance. The Bonferroni significance for the MORTALITY variable exceeded .007, a limitation to this study.

The analysis through multiple regression included the varying hospital characteristics of ownership, teaching status, size, and outcomes (i.e., mortality) of a Major Diagnostic Category of CV conditions to predict a hospital's cost-to-charge ratio. Data excluded included any missing data according to the assigned research variables, as well as any pairwise cases to detect missing data, and the subsequent removal of any hospital variables with omitted information. Each hospital ascribed by a reweighted average of CV conditions in a group defined by state, urban/rural, investor-owned/other, and bed size.

To check for data outliers, calculated residuals and Dfbeta were used through the Influence Diagnostics procedure in SPSS (see Figure 2). Because no results demonstrated the minimum and maximum standardized Dfbeta values to be < -2 or > 2, the dataset did not contain any data outliers or influential cases. A test for standardized residuals to check for normality, linearity, and homoscedasticity occurred because a lack of normality in a variable causes homoscedasticity (Yang, 2012).

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Standardized DFBETA Intercept	957804	-.00230	.01071	.0000000	.00102050
Standardized DFBETA SMALL_BEDSIZE	957804	-.69203	.36705	.0000000	.00184226
Standardized DFBETA LARGE_BEDSIZE	957804	-.49413	.17706	.0000000	.00116444
Standardized DFBETA NON_ACADEMIC	957804	-.22504	.55471	.0000000	.00139152
Standardized DFBETA ACADEMIC	957804	-.16639	.28320	.0000000	.00114769
Standardized DFBETA GOVERNMENT_NON_FEDERAL	957804	-.33753	.82538	.0000000	.00230054
Standardized DFBETA PRIVATE_FOR_PROFIT	957804	-.24722	.47608	.0000000	.00131648
Standardized DFBETA MORTALITY	957804	-.01991	.06888	.0000000	.00105558
Valid N (listwise)	957804				

Figure 2. Descriptive statistics for Dfbeta values.

Although an acceptable degree of collinearity may exist between independent variables, excessive collinearity between independent variables thwarts statistical analyses and model prediction (York, 2012). An examination of the collinearity across independent variables was important to discern any high degree of correlation, adding difficulty to discern the effects of each independent variable (Reiter et al., 2014). To address multicollinearity, collinearity diagnostics occurred between each variable (i.e., correlation coefficients, tolerance, and use the variance inflation factor (VIF)) prior to selecting each independent variable into the multiple linear regression model (York, 2012). The results of tests for multicollinearity grouped in conjunction with the model coefficients.

Reliability and Validity

Reliability

The reliability for hospital outcomes rested on the sample of observations (i.e., sample size for associated discharges) (Shih & Dimick, 2014). Reliability in secondary data involves an expectation that the same results will repeat from year-to-year (Shih & Dimick, 2014). Similarly, the closer the information associated to payments, the likelihood increased that the data quality would be superior (ResDAC, 2014). An advanced hierarchal modeling approach may improve the statistical precision of outcome metrics with adjustments for reliability (Shih & Dimick, 2014). Finally, the clinical validity of the included data contained information regarding the services provided for each discharge, along with relevant data considered reliable and valid (ResDAC, 2014).

Validity

Multiple threats to internal and external validity exist, which a researcher needs to address each to support any inferences drawn from the data. Internal threats to validity included interventions effecting the study population, where external threats generalize interventional effects to other populations (Maynard, 2012). Because of the correlational design of the study, threats to internal validity did not apply (Campbell & Stanley, 2010). For the intent of this research, predictor variables with established relationships to the dependent variable of costs, charges, and ultimately profitability established by prior researchers were included (Bowling, 2009; Brennan et al., 2014; Bryman, 2012; Ferdinand et al., 2011; Lee & Cassell, 2013; Leleu et al., 2014; Navathe et al., 2012).

Transition and Summary

Section 2 included the performed, quantitative method and multiple linear regression design suited for this study. The rationale for the use of a quantitative method over qualitative or mixed methods; and support for a regression analysis over both an experimental or quasi-experimental design was presented. In addition, Section 2 included the justification for selecting hospital inpatient beneficiaries as discharges in the United States, the predictor variable of CV outcomes of mortality, as well as hospital characteristics. Further, examination of the dependent variable of profitability through cost-to-charge ratios rounded out the research variables for this study. Finally, Section 2 included the method of collection with reliability and validity considerations.

Section 3 includes the results of the analyses, with interpretive findings and potential application toward the hypothesis. Within the context of the hypothesis, a revisit to the research question confirms any possible relationships and address endorsements for business action and social change. The section and study concludes with recommendations for future research, personal reflections, and an inclusive summary based from significant conclusions.

Section 3: Application to Professional Practice and Implications for Change

The purpose of this study was to examine predictor variables of the CCR. The incorporation of meaningful hospital characteristics and mortality outcomes established by prior research enabled a regression analysis to occur involving a GLM and multiple regression for the final model. Included in Section 3 is the presentation of the findings, assumptions of the research method, applicability towards business practice, implications for social change, call to action, recommendations for future research and conclusion of the study.

Overview of Study

The quantitative multiple regression analysis enabled an examination of the predictive ability of hospital resources, characteristics, and outcomes towards profitability. In this section, the overview of the study, presentation of the findings, applications to professional practice, and social change provide a basis for the recommendations aimed at future research. In a brief summary of the findings, I rejected the null hypothesis and accepted the alternative hypothesis that the selected predictive variables do predict hospital profitability for CV conditions. All predictive variables minus the quality outcome variable of mortality contributed to the overall regression model with statistical significance, $F(4, 509) = 129.83$, $p < .001$, $R^2 = .505$.

Presentation of the Findings

In this section, the presentation of the descriptive statistics, assumption testing, and inferential statistic results lead to a concise summary for the study. Bootstrapping occurred, $\alpha = .05$, yet required conversion of noninteger weighting of the HCUP variables under the regression modeling (Houchens & Elixhauser, 2014). Noninteger weighting disrupted the random nature of the sampling scheme combined with dichotomous variables, and the confidence intervals are alternatives to those produced by the One-Sample Nonparametric Tests procedure or the One-Sample T-Test procedure (Green & Salkind, 2014). An alternative strategy to address a finite population without weighted estimates involved weighting transformation of the subpopulation weight. The reweighting of dichotomous variables involved normalizing the weights by the average of the weighted circulatory variable (i.e., MDC = 5), including non-CV conditions to maintain the entire dataset for standard error estimations. The simple sampling method of 2,000 observations conducted occurred after the transformation of the traditional NIS weighting variable (see Figure 3). The bias thresholds meet or exceed the sampling methods for the associated variables.

Descriptive Statistics[a]

			Bootstrap[b]			
					95% Confidence Interval	
		Statistic	Bias	Std. Error	Lower	Upper
Cost-to-charge ratio	Mean	.32220	.00000	.00015	.32191	.32250
	Std. Deviation	.334362	.000010	.000512	.333371	.335334
	N	957804	0	0	957804	957804
SMALL_BEDSIZE	Mean	.0002	.0000	.0000	.0002	.0002
	Std. Deviation	.03239	.00000	.00113	.03014	.03479
	N	957804	0	0	957804	957804
LARGE_BEDSIZE	Mean	.0002	.0000	.0000	.0002	.0002
	Std. Deviation	.03014	-.00002	.00116	.02789	.03239
	N	957804	0	0	957804	957804
NON_ACADEMIC	Mean	.0004	.0000	.0000	.0004	.0004
	Std. Deviation	.04517	-.00001	.00113	.04286	.04737
	N	957804	0	0	957804	957804
ACADEMIC	Mean	.0001	.0000	.0000	.0001	.0002
	Std. Deviation	.02534	-.00002	.00117	.02296	.02761
	N	957804	0	0	957804	957804
GOVERNMENT_NON_FEDERAL	Mean	.0001	.0000	.0000	.0001	.0001
	Std. Deviation	.02081	-.00004	.00115	.01842	.02307
	N	957804	0	0	957804	957804
PRIVATE_FOR_PROFIT	Mean	.0001	.0000	.0000	.0001	.0001
	Std. Deviation	.02106	-.00001	.00114	.01884	.02319
	N	957804	0	0	957804	957804
DIED	Mean	.02	.00	.00	.02	.02
	Std. Deviation	.334	.000	.001	.332	.336
	N	957804	0	0	957804	957804

a. Weighted Least Squares Regression - Weighted by Normalized Weight

b. Unless otherwise noted, bootstrap results are based on 2000 bootstrap samples

Figure 3. SPSS output for bootstrapping results.

An alternative to employ complex samples GLM to sample the finite population with varying strata allowed the categorical use of dummy variables. The GLM method samples a fraction of a large defined population while accounting for its size and characteristics (Lipsitz et al., 2014). An appropriate sample may have been impossible to obtain *N* weighted cases without forcing inclusion of one or more original cases through examination of the strata variables.

Assumptions of Multiple Linear Regression

The purpose of screening data was to check all assumptions of the multiple linear regression model to include any residual plots, histograms, and normal P-P plots. The evaluated assumptions included multicollinearity, normality, linearity, and independence of residuals. Because of the incorporation of weighted, dummy, and reference variables, tests for assumptions involved corrective factors to gain statistical confidence in a multiple linear regression of nominal predictor variables.

The restriction to graph and test the assumption of linearity was caused by the nature of the independent variables. The relationship between the dependent variable of the CCR and the predictor variables were assessed using SPSS via scatterplot reveal double vertical lines. Because of the use of dichotomous, dummy variables with values of either 0 or 1 (i.e., no or yes), tests for linearity yielded no discernable result (see Appendix C).

A check for the normality assumption of any interval or ordinal values included just the dependent, CCR variable. The dependent variable included continuous figures and was evaluated for the normal distribution of values through a goodness of fit histogram to confirm a natural curve. The dependent variable of CCR included a continuous scale with the range of values of the circulatory subpopulation from .34 to .45 (*M* = .39, *SD* = .02). The assumption of independence of the dependent variable was not violated. The skewed values include the original weighted sample and are moderate towards positive values for the CCR (see Figure 4). The expected and observed cumulative probabilities, while not matching perfectly, are similar. This suggests that the residuals are approximate in distribution; thus, the no violation of this assumption (see Figure 5).

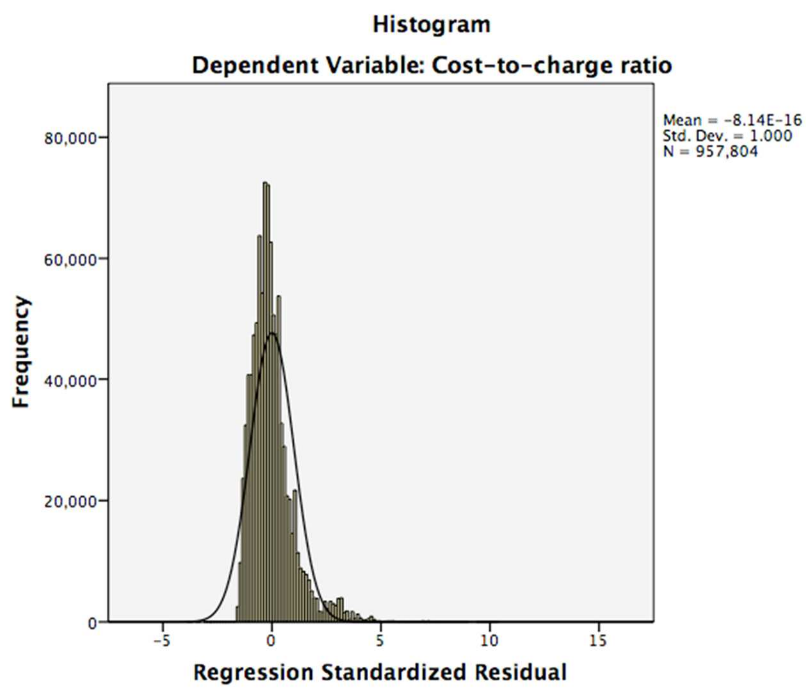

Figure 4. Histogram to assess the distribution of dependent variable.

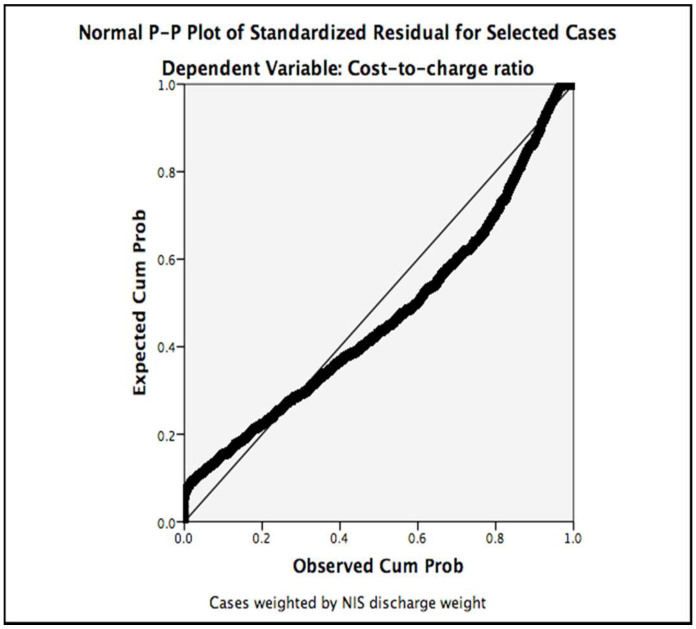

Figure 5. Normal P-P Plot to assess the residuals of the model.

Each predictor variable involved transformation to dichotomous values of 0 and 1, or referenced to 0 across the variable characteristic (i.e., bed size, academic distinction, ownership status) to delineate categories within the provided data with the exception of the previously categorized MORTALITY variable in GLM, or DIED in the multiple regression model. The conversion of the predictor variables to dummy or reference variables allowed evaluation of nominal values in a regression analysis (Hayes & Preacher, 2014).

Multicollinearity

The assessment of multicollinearity, including pairwise correlations between predictors, was not sufficient. Multicollinearity exists with intercorrelated predictor variables of the design matrix (Grégoire, 2014). Because a GLM preceded a regression analysis, an improved method to detect multicollinearity is to regress each predictor variable on other predictor variables and examine the resulting R^2 value (Lenoski, Baxter, Karam, Maisog, & Debbins, 2008). The resulting coefficient of determination, or R^2 = .434 indicated a lack of multicollinearity in the chosen variables.

A secondary measure included the incorporation of tolerance and VIF to assess violations of multicollinearity (see Figure 6). A conservative approach to assess the degree of multicollinearity by VIF involved caution over 5, and the tolerance as a proportion of the regression variance not accounted for by other regressors in the model cautions of values under .20 (Green & Salkind, 2014; Grégoire, 2014; Tabachnick & Fidell, 2012). Neither the tolerance nor the VIF values indicated a significant presence of multicollinearity.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.322	.000		2084.212	.000		
	SMALL_BEDSIZE	.228	.017	.022	13.419	.000	.384	2.602
	LARGE_BEDSIZE	-.093	.017	-.008	-5.456	.000	.439	2.276
	NON_ACADEMIC	.162	.015	.022	11.127	.000	.269	3.723
	ACADEMIC	-.035	.017	-.003	-2.112	.035	.656	1.524
	GOVERNMENT_NON_FEDERAL	.145	.019	.009	7.650	.000	.749	1.335
	PRIVATE_FOR_PROFIT	-.236	.018	-.015	-12.967	.000	.794	1.260
	DIED	.007	.001	.007	6.907	.000	1.000	1.000

a. Dependent Variable: Cost-to-charge ratio

Figure 6. SPSS output with coefficients including collinearity statistics.

Results for Multiple Regression

A GLM, α = .01, was used principally to explore correct estimates for the transformed 2012 NIS finite data. The model summary and effects were evaluated for a complex samples GLM and a given *R*-squared value as a measure of the strength of model fit (Nakagawa & Schielzeth, 2013). A GLM with main effects for hospital bedsize, ownership, academic distinction, and mortality outcome fitted to the data (see

Figure 7). The MORTALITY variable was shown as nonsignificant in the GLM with Bonferroni correction to address Type 1 errors, $p = .490$, resulting in the movement towards, $\alpha = .01$ for the multiple regression analysis.

Tests of Model Effects[a]

Source	df1	df2	Wald F	Sig.	Bonferroni Sig.
(Corrected Model)	6.000	4177.000	55.599	.000	.000
(Intercept)	1.000	4182.000	113.373	.000	.000
SMALL_BEDSIZE	1.000	4182.000	59.240	.000	.000
LARGE_BEDSIZE	1.000	4182.000	23.682	.000	.000
NON_ACADEMIC	.000	4183.000	.	.	.
ACADEMIC	.000	4183.000	.	.	.
GOVERNMENT_NON_FEDERAL	1.000	4182.000	12.257	.000	.000
PRIVATE_FOR_PROFIT	1.000	4182.000	106.920	.000	.000
MORTALITY	1.000	4182.000	.476	.490	.490

Subpopulation: MDC in effect on discharge date = 5

a. Model: Cost-to-charge ratio = (Intercept) + SMALL_BEDSIZE + LARGE_BEDSIZE + NON_ACADEMIC + ACADEMIC + GOVERNMENT_NON_FEDERAL + PRIVATE_FOR_PROFIT + MORTALITY

Figure 7. General linear model effects.

A multiple regression analysis was secondarily conducted to assess the collinearity of independent variables with the Analysis of Variance (ANOVA), model summary, and strata coefficients. A regression analysis was conducted to uncover factors concerning CV profitability through the criterion variable of CCR (see Figures 8-9).

ANOVA[a,b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.793	4	1.448	129.830	.000[c]
	Residual	5.678	509	.011		
	Total	11.470	513			

a. Dependent Variable: Cost-to-charge ratio

b. Weighted Least Squares Regression - Weighted by normal_weight

c. Predictors: (Constant), DIED, Control/ownership of hospital (STRATA), Bed size of hospital (STRATA), Location/teaching status of hospital (STRATA)

Figure 8. ANOVA SPSS output for hospital characteristics and mortality.

Model Summary[b,c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.711[a]	.505	.501	.105615

a. Predictors: (Constant), DIED, Control/ownership of hospital (STRATA), Bed size of hospital (STRATA), Location/teaching status of hospital (STRATA)

b. Dependent Variable: Cost-to-charge ratio

c. Weighted Least Squares Regression - Weighted by normal_weight

Figure 9. SPSS output for multiple regression model summary.

The null hypothesis was that the various predictors of hospital characteristics and outcomes would not predict the profitability in a CVSL. The alternative hypothesis posited that the various predictors of hospital characteristics and outcomes would predict the profitability in a CVSL. The complete regression model was able to significantly predict the profitability through the CCR of CV conditions, $F(4, 509) = 129.83$, $p < .001$, $R^2 = .505$, suggesting the complete model was predictive of the CCR for cardiovascular conditions. Bonferroni Correction enhanced the alpha value of .01 to control for Type I errors under the GLM (Green & Salkind, 2014). The mortality predictor DIED under multiple regression was not a significant predictor $\beta = .005$, $p = .882$ to the regression model.

A second analysis conducted from the GLM model allowed the evaluation of the estimated marginal means for each predictor variable within the strata to demonstrate the type of relationship with the dependent variable by graph, which considers the two-factor analysis of variance (see Appendix C). These findings suggest a negative relationship through a lower CCR for private, academic, and large hospitals, suggestive to a lower ratio with costs lower and charges higher in scale. The standard multiple linear regression noted the following (Green & Salkind, 2014): $\hat{Y} = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_0$, where a β gives the partial slopes of the X variables, and β_0 is the constant. The specific model for pertinent to the research variables: Cost-to-charge ratio = .74 + -.07 (bed size) + -.08 (teaching status) + -.07 (ownership) + .01 (mortality).

Applications to Professional Practice

The purpose of this quantitative study method was to examine the relationship between quality outcomes of mortality and resources to costs used in an acute care setting, an often poorly understood relationship (Hussey et al., 2013). Because managers are often the stewards of resources and make decisions pertinent to organizations, recognition of associated relationships remains essential in a P4P environment (Porter-O'Grady, 2015; Tabish & Syed, 2013). The challenge for research using administrative data is submission to the health care domain that continues to evolve. The application of CV profitability through a ratio of costs to charges is only one method to explore the complexity of health care reimbursement against hospitals' characteristics and influential forces (Robinson, Pritts, Hanseman, Wilson, & Abbott, 2014).

The potential to enhance both revenue and reputation through quality improvement increases the significance for the organization and the benefits of optimal costs to accomplished quality (Ryan et al., 2014). Because the CCR includes costs, in this research, I regarded a cost element in the findings. Inherent, predictive factors allow leaders in health care to align strategies and priorities, leveraged against finite resources and external expectations (Brooks, El-Gayar, & Sarnikar, 2015; Earley, 2014; Porter-O'Grady, 2015).

The incorporation of data analysis allows leaders to implement a strategy framework from available resources and priorities (McLaughlin, Ong, Tabbush, Hagigi, & Martin, 2014). The hospitals with profitable service lines tend to invest in quality and compete for patients over unprofitable service lines along with which surgical and CV procedures benefit health care organizations by profitability and revenue generation (Anderson et al., 2012; Navathe et al., 2012). Profitability naturally precludes the investment and reinvestments into the organizational infrastructure and profitable service lines for a competitive advantage.

Implications for Social Change

Cardiovascular conditions place a burden upon health care spending, to include lost worker productivity and disability, and are the leading causes of death in the United States (Ferdinand et al., 2011; Pearson et al. 2013). The commitment to reduce costs is a commitment to serving the patient (Morris & King, 2013). Health care delivery systems have a responsibility to enhance care outcomes for communities and society (Eggleston & Finkelstein, 2014). The value provided to communities and society involves lower costs, which may allow available resources to benefit further public sectors (e.g., public health, education, transportation, and the environment) (Gordon et al., 2014). The social contract hospitals entered with society must lead to success because the past contract led to failure (Piper, 2013).

Health care systems should be accountable for providing optimal value of health care (Trastek et al., 2014). The pressure to transform from a volume-based delivery model to a value-based model is a result of consistent poor outcomes, unsustainable costs, and persistent disparities (Eggleston & Finkelstein, 2014; Krumholz, 2013). However, the concern of health care leaders toward economic consequences does benefit communities because of the resolve to enhance the cardiovascular delivery value proposition (Anderson et al., 2014).

Despite resources available through bed size, academic significance, or ownership, hospital organization must work toward enhancing the value proposition. No matter the consequence of institutional resources or external constraints, organizations may center care activities around the person over rationing finite resources by condition. Many resources contained within traditional hospital facilities may create the most value externally to the population.

Recommendations for Action

The needed transformation in health care industry may result from the expanding role data and analytics play in data generation, extraction, analysis; and the subsequent presentation and reporting (Ward, Marsolo, & Froehle, 2014). Integration of analytics, similar to the quantitative method integrated in research, may effectively reduce costs, enhance the customer experience, and improve outcomes, while exceeding ongoing health care reform expectations (Hripcsak, Forrest, Brennan, & Stead, 2015). Inferences of administrative data, preferably prospectively or predictably, enable leaders to make complex decisions on diverse reimbursement methodologies and different delivery models across the continuum of care (Brooks et al., 2015).

This study suggested the need to pay attention to the resources of health care organizations despite specific hospital characteristics. An outcome of mortality, representative of value-based expectations of health care reform, did not have a significant effect in this study. Hospitals within health care systems may allocate resources differently dependent upon the characteristics of size because other elements may keep constant (i.e., academic, ownership type) (Rosko & Mutter, 2011).

Recommendations for Further Research

The scope of this study excluded health care outside the United States and several States. Excluded from this study include outpatient stings and services, including other care delivered outside of hospitals, which contributes to a comprehensive health care delivery model. Additional research including a global perspective or varying datasets may aid researchers in the assessment of other health conditions or resources. Available incentive and actual payment data include period, time, term differences remains limited to specific audiences, yet will broaden in its availability and scope. As administrative data and clinical data become more relevant and applicable, the dependency of its integrity relies on varying factors. The data provided and used in resources made available from the HCUP continues to prove valuable and comprehensive for researchers and the public.

Quality outcomes remain underreported, and involve limited conditions (Farmer et al., 2013). Mortality is one of many outcomes that yield varying results because of the many underlying conditions that may influence its end value. Researchers may wish to investigate statewide reporting datasets or agencies with specific focuses to reveal underserved conditions and populations (Meltzer & Chung, 2014). Additional modeling approaches may improve the statistical precision of outcome metrics with adjustments for reliability, which the scope of one study is inherently limited (Shih & Dimick, 2014).

Reflections

The difficult portion of the Doctoral Study process involved the selection of content that reflected a true business problem. In the realm of health care, clinical issues or care delivery challenges continue to the focus of decision-makers. However, understanding the financial components of health care delivery is every bit as important as the care provided because each precipitate the other. The transformation and analysis of large datasets holds much value, yet remains challenging to have the right technology to support its use.

A profession in health care is a calling, and delving into the research of people being care for involves a sense of respect and humility (Gruppen, 2014; Jacobovitz, 2014; Piper, 2013). Any preconceived notions before conducting research involved the eye test for organizations that apparently *have it all* to include academic, and large hospitals and systems; and previously supported by the literature (Fareed & Mick, 2011; Rosko & Mutter, 2011; Shortell et al., 2014). Competition for resources and external forces do less damage to the *haves* versus the *have-nots*, yet remain convinced leadership bears its own valuable resource. The micro effects occur in profitable service lines, and only enhance the regional competitiveness and influence of RDT.

Summary and Study Conclusions

The results of this study replicate the findings of previous research and published literature on the relationship between the predictive ability of hospital characteristics and service line profitability (Curry et al., 2011; Dupree et al., 2014; Joynt & Jha, 2013; Navathe et al., 2012; Rosko & Mutter, 2011). Costs remain important for hospitals needing to employ strategy to resource utilization (Bloom, Markovitz, Silverman, & Yost, 2015). The results also include identification of the relationships between the various hospital characteristics and profitability with large, academic, and private (i.e., for-profit) hospitals with an inverse, profitable relationship to the outcome variable established by the previous academic and research literature (Erdem et al., 2014a; Leleu et al., 2014; McCue, 2011; Robinson et al., 2014; Washington et al., 2013).

Although each modeling procedure has its limitations for finite, subpopulation data, the combination of a GLM and multiple regression provided an appropriate sample, established standard errors, answered regression assumptions, and provided analyses relevant to the research question. An important limitation of this study is the reliance on claims data and the consequent risks of non-reconciliation of case mix across hospitals.

Both models identified mortality as non-significant in the multiple regression, $\beta = .005$, $p = .882$; and non-significant in a GLM with Bonferroni correction, $p = .490$ to the regression model, yet this factor may warrant additional investigation in future modeling. Outcome variables including mortality, readmissions, and hospital-acquired conditions for process of care may merit further research leveraged against hospital resources to profits (Ding, 2015). Specific conditions suited by service lines of varying hospital characteristics useful to explore potential gaps or processes in care could validate predictive models. Established in a predictive model for this study, large, for-profit, and academic centers warrant further investigation behind quantifying and qualifying various internal and external resources. A RDT perspective places the strategic management of hospitals to leverage resources effectively and efficiently to gain positive, financial influence (Kuntz, Pulm, & Wittland, 2015; Mannion et al., 2015).

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Appendix A: HCUP Data Use Agreement for Nationwide Databases and Indemnification Clause

H·CUP
HEALTHCARE COST AND UTILIZATION PROJECT

DATA USE AGREEMENT for the Nationwide Databases from the Healthcare Cost and Utilization Project Agency for Healthcare Research and Quality

This Data Use Agreement ("Agreement") governs the disclosure and use of data in the HCUP Nationwide Databases from the Healthcare Cost and Utilization Project (HCUP) which are maintained by the Center for Delivery, Organization, and Markets (CDOM) within the Agency for Healthcare Research and Quality (AHRQ). The HCUP Nationwide databases include the National (Nationwide) Inpatient Sample (NIS), Nationwide Emergency Department Sample (NEDS), and Kids' Inpatient Database (KID). Any person ("the data recipient") seeking permission from AHRQ to access HCUP Nationwide Databases data must sign and submit this Agreement to AHRQ or its agent, and complete the online Data Use Agreement Training Course at http://www.hcup-us.ahrq.gov, as a precondition to the granting of such permission.

Section 944(c) of the Public Health Service Act (42 U.S.C. 299c-3(c)) ("the AHRQ Confidentiality Statute"), requires that data collected by AHRQ that identify individuals or establishments be used only for the purpose for which they were supplied. Pursuant to this Agreement, data released to AHRQ for the HCUP Databases are subject to the data standards and protections established by the Health Insurance Portability and Accountability Act of 1996 (HIPAA) (P.L. 104-191) and implementing regulations ("the Privacy Rule"). Accordingly, HCUP Databases data may only be released in "limited data set" form, as that term is defined by the Privacy Rule, 45 C.F.R. § 164.514(e). HCUP data may only be used by the data recipient for research which may include analysis and aggregate statistical reporting. AHRQ classifies HCUP data as protected health information under the HIPAA Privacy Rule, 45 C.F.R. § 160.103. By executing this Agreement, the data recipient understands and affirms that HCUP data may only be used for the prescribed purposes, and consistent with the following standards:

No Identification of Persons–The AHRQ Confidentiality Statute prohibits the use of HCUP data to identify any person (including but not limited to patients, physicians, and other health care providers). The use of HCUP Databases data to identify any person constitutes a violation of this Agreement and may constitute a violation of the AHRQ Confidentiality Statute and the HIPAA Privacy Rule. This Agreement prohibits data recipients from releasing, disclosing, publishing, or presenting any individually identifying information obtained under its terms. AHRQ omits from the data set all direct identifiers that are required to be excluded from limited data sets as consistent with the HIPAA Privacy Rule. AHRQ and the data recipient(s) acknowledge that it may be possible for a data recipient, through deliberate technical analysis of the data sets and with outside information, to attempt to ascertain the identity of particular persons. Risk of individual identification of persons is increased when observations (i.e., individual discharge records) in any given cell of tabulated data is less than or equal to 10. This Agreement expressly prohibits any attempt to identify individuals, and information that could be used to identify individuals directly or indirectly shall not be disclosed, released, or published. Data recipients shall not attempt to contact individuals for any purpose whatsoever, including verifying information supplied in the data set. Any questions about the data must be referred exclusively to AHRQ. By executing this Agreement, the data recipient understands and agrees that actual and considerable harm will ensue if he or she attempts to identify individuals. The data recipient also understands and agrees that actual and considerable harm will ensue if he or she intentionally or negligently discloses, releases, or publishes information that identifies individuals or can be used to identify individuals.

Use of Establishment Identifiers–The AHRQ Confidentiality Statute prohibits the use of HCUP data to identify establishments unless the individual establishment has consented. Permission is obtained from the HCUP data sources (i.e., state data organizations, hospital associations, and data consortia) to use the identification of hospital establishments (when such identification appears in the data sets) for research, analysis, and aggregate statistical reporting. This may include linking institutional information from outside data sets for these purposes. Such purpose does *not* include the use of information in the data sets concerning individual establishments for commercial or competitive purposes involving those individual establishments, or to determine the rights, benefits, or privileges of establishments. Data recipients are prohibited from identifying establishments directly or by inference in disseminated material. In addition, users of the data are prohibited from contacting establishments for the purpose of verifying information supplied in the data set. Any questions about the data must be referred exclusively to AHRQ. Misuse of identifiable HCUP data about hospitals or any other establishment constitutes a violation of this Agreement and may constitute a violation of the AHRQ Confidentiality Statute.

The undersigned data recipients provide the following affirmations concerning HCUP data:

Protection of Individuals

- I will not release or disclose, and will take all necessary and reasonable precautions to prohibit others from releasing or disclosing, any information that directly or indirectly identifies persons. I acknowledge that the release or disclosure of information where the number of observations (i.e., individual discharge records) in any given cell of tabulated data is less than or equal to 10 can increase the risk for identification of persons. I will consider this risk and avoid publication of cell sizes less than or equal to 10.

- I will not attempt to link, and will prohibit others from attempting to link, the discharge records of persons in the data set with individually identifiable records from any other source.

- I will not attempt to use and will take all necessary and reasonable precautions to prohibit others from using the data set to contact any persons in the data for any purpose.

Protection of Establishments

- I will not publish or report, through any medium, data that could identify individual establishments directly or by inference.

- When the identities of establishments are not provided in the data sets, I will not attempt to use and will take all necessary and reasonable precautions to prohibit others from using the data set to learn the identity of any establishment.

- In accordance with the AHRQ Confidentiality Statute, I will not use and will take all necessary and reasonable precautions to prohibit others from using the data set concerning individual establishments: (1) for commercial or competitive purposes involving those individual establishments; or (2) to determine the rights, benefits, or privileges of individual establishments.

- I will not contact and will take all necessary and reasonable precautions to prohibit others from contacting establishments identified in the data set to question, verify, or discuss data in the HCUP databases.

- I acknowledge that the HCUP NIS and KID may contain data elements from proprietary restricted computer software (3M APR-DRGs, OptumInsight APS-DRGs, and Medstat Disease Staging) supplied by private vendors to AHRQ for the sole purpose of supporting research and analysis with the HCUP NIS and KID. While I may freely use these data elements in my research work using the HCUP NIS and KID, I agree that I will not use and will prohibit others from using these proprietary data elements for any commercial purpose. In addition, I will enter into a separate agreement with the appropriate organization or firm for the right to use such proprietary data elements for commercial purposes. In particular, I agree not to disassemble, decompile, or otherwise reverse-engineer the proprietary software, and I will prohibit others from doing so.

Limitations on the Disclosure of Data and Safeguards

- I, the undersigned data recipient, acknowledge and affirm that I am personally responsible for compliance with the terms of this Agreement, to the exclusion of any other party, regardless of such party's role in sponsoring or funding the research that is the subject of this Agreement.

- I will not release or disclose, and will prohibit others from releasing or disclosing, the data set or any part to any person who is not an employee, member, or contractor of the organization (specified below), except with the express written approval of AHRQ. I acknowledge that when releasing or disclosing the data set or any part to others in my organization, I retain full responsibility for the privacy and security of the data and will prohibit others from further release or disclosure of the data.

- I will require others employed in my organization who will use or will have access to HCUP data to become authorized users of the data set by signing a copy of this data use agreement and completing the online Data Use Agreement Training Course at http://www.hcup-us.ahrq.gov. Before granting any individual access to the data set, I will submit the signed data use agreements to the address at the end of this Agreement.

- I will ensure that the data are kept in a secured environment and that only authorized users will have access to the data.

- I will not use or disclose and I will prohibit others from using or disclosing the data set, or any part thereof, except for research, analysis, and aggregate statistical reporting, and only as permitted by this Agreement.

- I acknowledge and affirm that interpretations, conclusions, and/or opinions that I reach as a result of my analyses of the data sets are my interpretations, conclusions, and/or opinions, and do not constitute the findings, policies, or recommendations of the U.S. Government, the U.S. Department of Health and Human Services, or AHRQ.

- I will indemnify, defend, and hold harmless AHRQ and the data organizations that provide data to AHRQ for HCUP from any or all claims and losses accruing to any person, organizations, or other legal entity as a result of violation of this agreement. This provision applies only to the extent permitted by Federal and State law.

- I agree to acknowledge in all reports based on these data that the source of the data is the "National Inpatient Sample (NIS), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality." Substitute Nationwide Inpatient Sample (if using data prior to 2012), Nationwide Emergency Department Sample (NEDS) or Kids' Inpatient Database (KID), as appropriate.

- I agree to report the violation or apparent violation of any term of this Agreement to AHRQ without unreasonable delay and in no case later than 30 calendar days of becoming aware of the violation or apparent violation.

Terms, Breach, and Compliance

Any violation of the terms of this Agreement shall be grounds for immediate termination of this Agreement. AHRQ shall determine whether a data recipient has violated any term of the Agreement. AHRQ shall determine what actions, if any, are necessary to remedy a violation of this Agreement, and the data recipient(s) shall comply with pertinent instructions from AHRQ. Actions taken by AHRQ may include but not be limited to providing notice of the termination or violation to affected parties and prohibiting data recipient(s) from accessing HCUP data in the future.

In the event AHRQ terminates this Agreement due to a violation, or finds the data recipient(s) to be in violation of this Agreement, AHRQ may direct that the undersigned data recipient(s) immediately return all copies of the HCUP Nationwide Databases to AHRQ or its designee without refund of purchase fees.

Acknowledgment

I understand that this Agreement is requested by the United States Agency for Healthcare Research and Quality to ensure compliance with the AHRQ Confidentiality Statute. My signature indicates that I understand the terms of this Agreement and that I agree to comply with its terms. I understand that a violation of the AHRQ Confidentiality Statute may be subject to a civil penalty of up to $10,000 under 42 U.S.C. 299c-3(d), and that deliberately making a false statement about this or any matter within the jurisdiction of any department or agency of the Federal Government violates 18 U.S.C. § 1001 and is punishable by a fine of up to $10,000 or up to five years in prison. Violators of this Agreement may also be subject to penalties under state confidentiality statutes that apply to these data for particular states.

Signed: G Wesley Date: 4-25-2015

Print or Type Name: Gordon Wesley

Title: Student

Organization: Walden University

Address:

Address:

City: State: ZIP Code:

Phone: Fax:

E-mail:

The information above is maintained by AHRQ only for the purpose of enforcement of this Agreement.

Note to Purchaser: Shipment of the requested data product will only be made to the person who signs this Agreement, unless special arrangements that safeguard the data are made with AHRQ or its agent.

Submission Information

Please send signed HCUP Data Use Agreements and proof of online training to:

HCUP Central Distributor
Social & Scientific Systems, Inc.
8757 Georgia Avenue, 12th Floor
Silver Spring, MD 20910
E-mail: HCUPDistributor@AHRQ.gov
Fax: (866) 792-5313

According to the Paperwork Reduction Act of 1995, no persons are required to respond to a collection of information unless it displays a valid OMB control number. The valid OMB control number for this information collection is 0935-0206. The time required to complete this information collection is estimated to average 30 minutes per response, including the time to review instructions, search existing data resources, gather the data needed, and complete and review the information collection. If you have any comments concerning the accuracy of the time estimate(s) or suggestions for improving this form, please write to: AHRQ, 540 Gaither Road, Attn: Reports Clearance Officer, Rockville, Maryland 20850.

OMB Control No. 0935-0206 expires 12/31/2015.

HCUP-CDOW-OrderID: 042515001WESLEYGORD902 Applicant's Name: Gordon Wesley

Indemnification Clause

The Data Recipient ("Recipient") shall, to the extent permitted by Federal and State law, indemnify and hold Truven Health Analytics Inc. and its directors, officers, employees, agents, affiliates and subsidiaries harmless from any and all losses, claims, damages, liabilities, costs andexpenses (including, without limitation, reasonable attorney's fees and costs) arising out of any claim arising from any third parties, including but not limited to any or some combination of the several States comprising the United States of America and/or the Government of the United States of America, concerning Recipient's use of the NIS, NEDS, KID, SID, SASD, or SEDD data ("HCUP Data") provided by Truven Health Analytics Inc. Further, Recipient agrees that Truven Health Analytics Inc. shall not be liable to Recipient for any reason whatsoever arising out of the HCUP Data or the Recipient's use of the HCUP Data.

The Data Recipient ("Recipient") shall, to the extent permitted by Federal and State law, indemnify and hold Social & Scientific Systems, Inc. (SSS) and its affiliates and their respective officers, directors, employees and agents harmless from any and all losses, claims, damages, liabilities, costs and expenses (including, withoutlimitation, reasonable attorney's fees and costs) arising out of any claim arising from any third parties, including but not limited to any or some combination of the several States comprising the United States of America and/or the Government of the United States of America, concerning Recipient's use of the HCUP Data provided by SSS. Further, Recipient agrees that SSS shall not be liable to Recipient for any reason whatsoever arising out of the HCUP Data or the Recipient's use of the HCUP Data.

Name: Gordon Wesley Application ID: 042515001WESLEYGORD902

Signed: GWesley Date 4-25-2015

Appendix B: Certificate of Completion of National Institutes of Health Care

Certificate of Completion

The National Institutes of Health (NIH) Office of Extramural Research certifies that **Gordon Wesley** successfully completed the NIH Web-based training course “Protecting Human Research Participants”.

Date of completion: 01/18/2014

Certification Number: 1362084

Appendix C: SPSS Outputs

Table C1

Recoded Variables Into Dummy and Reference Variables

Independent Variables	Values		
	Small	Medium	Large
Old: HOSP_BEDSIZE	1	2	3
New: SMALL_BEDSIZE	1	Reference Category	0
New: LARGE_BEDSIZE	0	Reference Category	1
	Rural/Non-Teaching	Urban/Non-Teaching	Urban/Teaching
Old: HOSP_LOCTEACH	1	2	3
New: NON_ACADEMIC	1	1	0
New: ACADEMIC	0	0	1
	Government/Nonfederal	Private/Non-Profit	Private/For-Profit
Old: H_CONTROL	1	2	3
New: GOVERNMENT_ NON_FEDERAL	1	Reference Category	0
New: PRIVATE_FOR_PROFIT	0	Reference Category	1

Note. MORTALITY variable coded under original HCUP 2012 NIS data as 0 = no mortality in-hospital and 1 = mortality in hospital.

Table C2

Frequencies and Cumulative Percentages of Old Independent Variables

Old Variables		Frequency	Percent	Valid Percent	Cumulative Percent
HOSP_ BEDSIZE	small <150beds	1005	39.1	39.1	39.1
	medium 151 - 449beds	695	27.0	27.0	66.1
	large 450+beds	870	33.9	33.9	100.0
	Total	2570	100.0	100.0	
H_ CONTROL	government, nonfederal	415	16.1	16.1	16.1
	private, non-profit	1730	67.3	67.3	83.5
	private, for-profit	425	16.5	16.5	100.0
	Total	2570	100.0	100.0	
HOSP_LOC TEACH	government, nonfederal	415	16.1	16.1	16.1
	private, non-profit	1730	67.3	67.3	83.5
	private, for-profit	425	16.5	16.5	100.0

Total	2570	100.0	100.0

Figure C1

Variable			Estimate	Standard Error	Unweighted Count
Small_BEDSIZE					
% of Total		0	60.90%	2.00%	313
		1	39.10%	2.00%	201
	Total		100.00%	0.00%	514
Large_BEDSIZE					
			Estimate	Standard Error	Unweighted Count
% of Total		0	66.10%	1.90%	340
		1	33.90%	1.90%	174
	Total		100.00%	0.00%	514
NON_ACADEMIC					
			Estimate	Standard Error	Unweighted Count
% of Total		0	23.90%	1.80%	123
		1	76.10%	1.80%	391
	Total		100.00%	0.00%	514
ACADEMIC					
			Estimate	Standard Error	Unweighted Count
% of Total		0	76.10%	1.80%	391
		1	23.90%	1.80%	123
	Total		100.00%	0.00%	514
GOVERNMENT_NON_FEDERAL					
			Estimate	Standard Error	Unweighted Count
% of Total		0	83.90%	1.50%	431
		1	16.10%	1.50%	83
	Total		100.00%	0.00%	514
PRIVATE_FOR_PROFIT					
			Estimate	Standard Error	Unweighted Count
% of Total		0	83.50%	1.50%	429
		1	16.50%	1.50%	85
	Total		100.00%	0.00%	514
DIED					
			Estimate	Standard Error	Unweighted Count
% of Total	no mortality in-hospital		98.10%	0.60%	504
	mortality in-hospital		1.90%	0.60%	10
	Total		100.00%	0.00%	514

Figure C2

Bootstrap Specifications	
Sampling Method	Simple
Number of Samples	2000
Confidence Interval Level	95.0%
Confidence Interval Type	Percentile

Figure C3

Grand Mean[a]

Dependent Variable: Cost-to-charge ratio

		99% Confidence Interval		Bootstrap for Mean[c]			
						99% Confidence Interval	
Mean	Std. Error	Lower Bound	Upper Bound	Bias	Std. Error	Lower	Upper
.392[b]	.022	.335	.449	.000	.005	.380	.406

a. Weighted Least Squares Regression - Weighted by Normalized Weight

b. Based on modified population marginal mean.

c. Unless otherwise noted, bootstrap results are based on 2000 stratified bootstrap samples

Figure C4

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	DIED, NON_ACADEMIC, ACADEMIC, GOVERNMENT_NON_FEDERAL, PRIVATE_FOR_PROFIT, LARGE_BEDSIZE, SMALL_BEDSIZE[b]	.	Enter

a. Dependent Variable: Cost-to-charge ratio

b. All requested variables entered.

Figure C5

Variables Entered/Removed[a,b]

Model	Variables Entered	Variables Removed	Method
1	DIED, Control/ownership of hospital (STRATA), Bed size of hospital (STRATA), Location/teaching status of hospital (STRATA)[c]	.	Enter

a. Dependent Variable: Cost-to-charge ratio

b. Weighted Least Squares Regression - Weighted by normal_weight

c. All requested variables entered.

Figure C6

Small_BEDSIZE[a]

		Estimate	Standard Error	Unweighted Count
Population Size	.00	1565.001	82.228	313
	1.00	1004.996	67.057	201
	Total	2569.997	106.104	514
% of Total	.00	60.9%	2.0%	313
	1.00	39.1%	2.0%	201
	Total	100.0%	0.0%	514

a. MDC5 = 1

Large_BEDSIZE[a]

		Estimate	Standard Error	Unweighted Count
Population Size	.00	1699.997	86.619	340
	1.00	870.000	61.279	174
	Total	2569.997	106.104	514
% of Total	.00	66.1%	1.9%	340
	1.00	33.9%	1.9%	174
	Total	100.0%	0.0%	514

a. MDC5 = 1

NON_ACADEMIC[a]

		Estimate	Standard Error	Unweighted Count
Population Size	.00	615.001	51.628	123
	1.00	1954.996	92.696	391
	Total	2569.997	106.104	514
% of Total	.00	23.9%	1.8%	123
	1.00	76.1%	1.8%	391
	Total	100.0%	0.0%	514

a. MDC5 = 1

ACADEMIC[a]

		Estimate	Standard Error	Unweighted Count
Population Size	.00	1954.996	92.696	391
	1.00	615.001	51.628	123
	Total	2569.997	106.104	514
% of Total	.00	76.1%	1.8%	391
	1.00	23.9%	1.8%	123
	Total	100.0%	0.0%	514

a. MDC5 = 1

GOVT_NON_FEDERAL[a]

		Estimate	Standard Error	Unweighted Count
Population Size	.00	2154.995	96.921	431
	1.00	415.001	43.179	83
	Total	2569.997	106.104	514
% of Total	.00	83.9%	1.5%	431
	1.00	16.1%	1.5%	83
	Total	100.0%	0.0%	514

a. MDC5 = 1

DIED[a]

		Estimate	Standard Error	Unweighted Count
Population Size	no mortality in-hospital	2519.997	105.274	504
	mortality in-hospital	50.000	15.811	10
	Total	2569.997	106.104	514
% of Total	no mortality in-hospital	98.1%	0.6%	504
	mortality in-hospital	1.9%	0.6%	10
	Total	100.0%	0.0%	514

a. MDC5 = 1

Figure C7

Model Summary[a]

R Square	.434

Subpopulation: MDC in effect on discharge date = 5

a. Model: Cost-to-charge ratio = (Intercept) + SMALL_BEDSIZE + LARGE_BEDSIZE + NON_ACADEMIC + ACADEMIC + GOVERNMENT_NON_FEDERAL + PRIVATE_FOR_PROFIT + MORTALITY

Figure C8

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
NIS discharge weight	36484846	4.9975124	5.0029028	5.00000082	.000081837
Valid N (listwise)	36484846				

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
NIS discharge weight	4789020	4.9989970	5.0029028	5.00000045	.000075730
Valid N (listwise)	4789020				

Descriptive Statistics

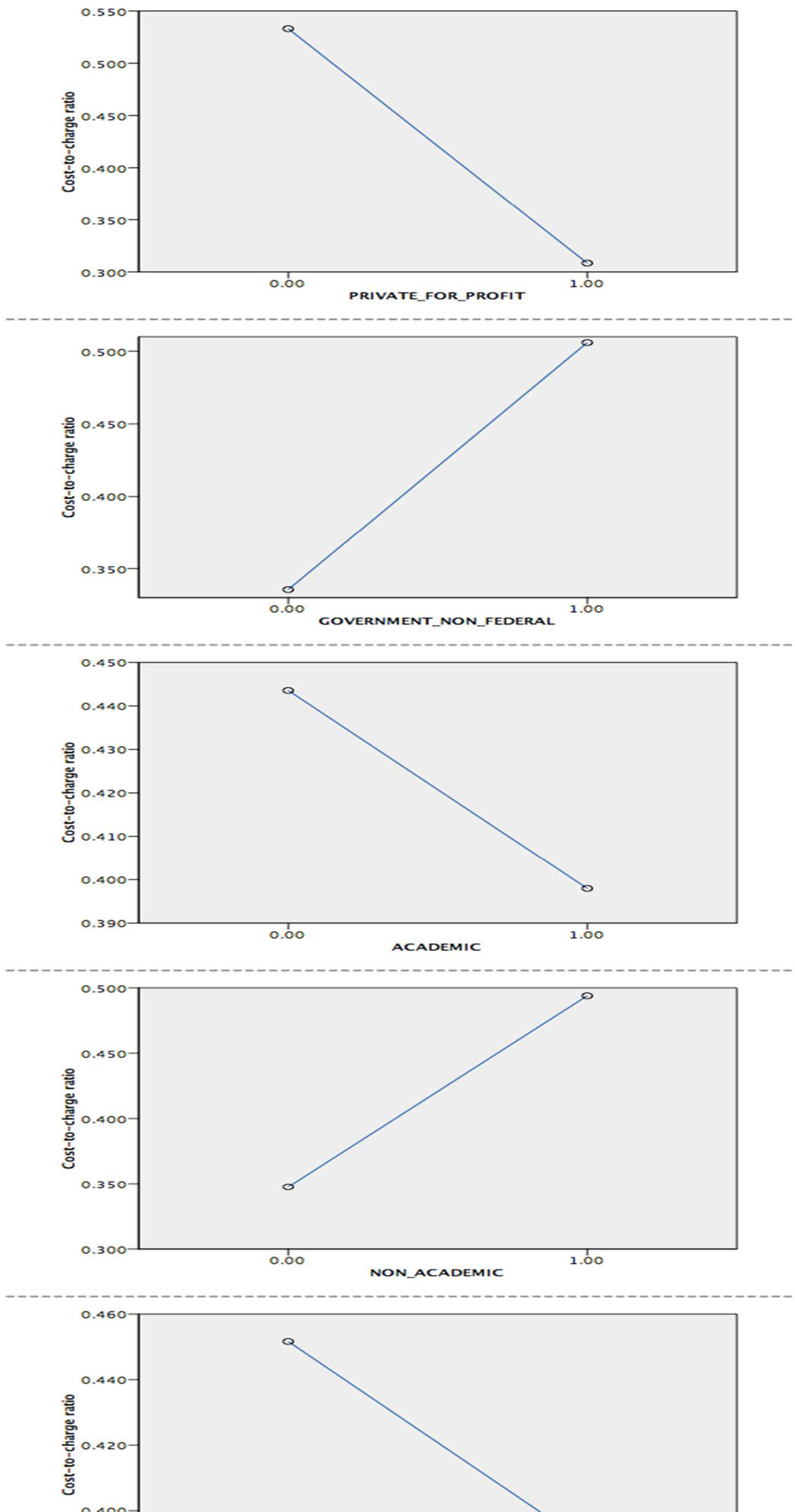
	N	Minimum	Maximum	Mean	Std. Deviation
NIS discharge weight	36484846	5	5	5.00	.000
Valid N (listwise)	36484846				

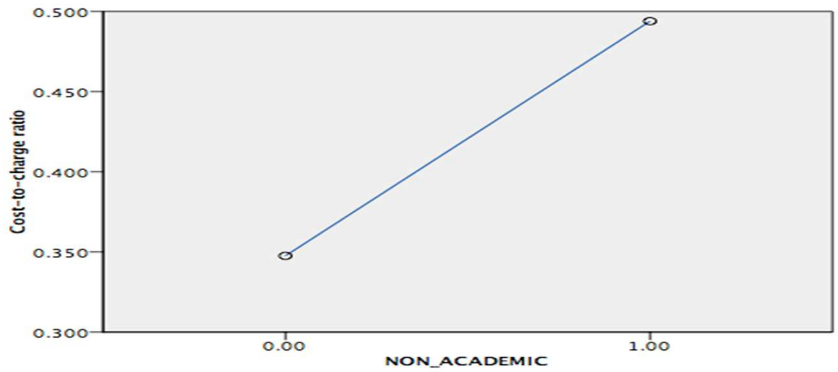
Figure C9

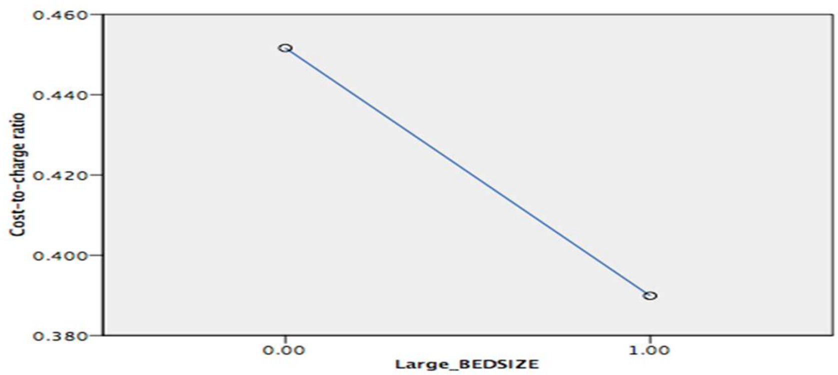
Estimated Means

Target: Cost-to-charge ratio

Estimated means charts for the top ten significant effects (p<.01) are displayed.




0.500
0.450
0.400
0.350
0.300
Cost-to-charge ratio
0.00
1.00
NON_ACADEMIC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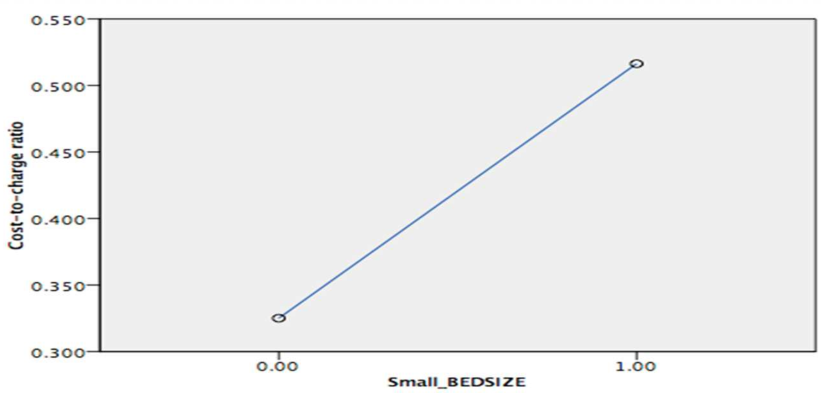
0.440
0.420
0.400
0.380
Cost-to-charge ratio
0.00
1.00
Large_BEDSIZE


0.550
0.500
0.450
0.400
0.350
0.300
Cost-to-charge ratio
0.00
1.00
Small_BEDSIZE