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INPATIENT UTILIZATION OF COMPUTED TOMOGRAPHY: THE INFLUENCE OF
MARKET, HOSPITAL, AND PATIENT CHARACTERISTICS

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of
Philosophy in Health Related Sciences

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Abstract

INPATIENT UTILIZATION OF COMPUTED TOMOGRAPHY: THE INFLUENCE OF MARKET, HOSPITAL, AND PATIENT CHARACTERISTICS

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A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Health Related Sciences—Health Administration at Virginia Commonwealth University.

Virginia Commonwealth University, 2017

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The use of computed tomography (CT) in the care of patients has grown dramatically since its introduction over 30 years ago. The vast majority of the utilization research has focused on factors associated with the variable use in the outpatient and emergency department settings. This has left much of the inpatient use and variation understudied. This study has multiple aims. The first is to characterize the inpatient variation across multiple states and markets. The second is to evaluate the relationship between inpatient CT use and commercial payers across these areas. The third is to develop a model to evaluate the relationship between inpatient CT use and the characteristics of markets, hospitals, and patients.

The study uses a four-state convenience sample of cross-sectional data for hospitals. It included non-Federal, acute care hospitals that reported the performance of inpatient CT exams during 2015 ($N=181$). The literature review was used to justify the inclusion of variables in the

study. The descriptive analyses were used to justify the appropriateness of the variables and methodology for testing.

A comparison of means demonstrated the significant differences for inpatient utilization between states. A univariate general linear model demonstrated a negative relationship with a hospital's proportion of commercially insured patients and the inpatient utilization rate. An ordinary least squares multivariate linear regression was used to test for variable significance within each of three constructs: markets, hospitals, and patients. The results indicated that inpatient CT rates were positively associated with higher level of insurer concentration (market), positively associated with system centralization (hospitals), and negatively associated with a hospital's increasing proportion of minority patient discharges (patients).

The study serves an important function in identifying varying patterns of CT utilization across the full spectrum of inpatients across multiple states, regardless of payer. It also creates new knowledge about how the characteristics of these markets, hospitals, and patients are related to inpatient use. It also provides implications for administrators, researchers, and policy makers. The additional knowledge and understanding provided by this research have the potential to lead to improvements in the appropriate and equitable use of inpatient CT exams.

Chapter 1: Introduction

Overview

This study is designed to understand the relationship between varying inpatient computed tomography (CT) utilization rates and the characteristics of markets, hospitals, and patients. The CT scan uses radiation-emitting technology to render and combine multiple, refined cross-sectional images of organs and body parts to diagnose diseases, monitor disease progression, plan treatments, and guide procedures.

The study uses a conceptual framework to better develop and shape the variable relationships. This research will address a gap in the literature specific to inpatient CT use and how it varies across multiple institutions and markets. This study is non-experimental, conducted from a cross-section of 2015 data, and without repeated measures to provide a snapshot of performance.

This first chapter provides the introduction and rationale for the research. It does so by framing the situational issues surrounding the observed increases in CT utilization as background. This framework includes introducing the recent evolution of markets and observed relationships with hospitals and patients. Chapter 1 also introduces the literature gap and the aligned aims of the study. A summary of the study significance, an introduction to the conceptual framework, a summary of the data sources, and an overview of the remaining chapters follow this section.

Background

Over the last several decades, the rapid expansion in the use of CT exams has led to healthcare advances but also to increasing financial costs and increasing radiation exposure. Over 80 million CT scans were performed annually as of 2010 (Levin, Rao, & Parker, 2012). An extension of their work showed that even the most recent growth has occurred across all settings: emergency department, outpatient, and inpatient (Levin, Rao, Parker, & Frangos, 2013). The medical imaging expenditures surpassed the \$100 billion threshold for all payers in 2004, and doubled for Medicare between 2000 and 2006 (Iglehart, 2006, 2009). Between 1980 and 2006 there was a seven-fold increase in the annual cumulative ionizing radiation dose attributable in large part to CT use (Rumack, 2010). Per the National Council on Radiation Protection & Measurement (NCRP), this increase meant that ionizing medical radiation in the U.S. equaled the annual all-source environmental exposure (Schauer & Linton, 2009).

During the same period of rapid proliferation of CTs, the healthcare marketplace evolved dramatically in ways that shape resource access and utilization. Both hospitals and insurers underwent a dramatic amount of consolidation. Market consolidation lends itself to opportunities for controlling and coordinating the provision of inpatient and outpatient services (Luke, Luke, & Muller, 2011; Sikka, Luke, & Ozcan, 2009). For example, consolidated systems may share information systems that improve the transfer, continuity, and efficiency of care. In 1989, 38% of US acute care general hospitals were in systems (Luke, 2010). The 2014 update of the American Hospital Association (AHA) annual survey data revealed this had increased to 65% being in systems (American Hospital Association, 2016). Insurers likewise consolidated and negotiated competitively with hospitals over payment and utilization terms. The American Medical Association (AMA) reported that, as of 2014, 71% of insurer markets in the 388 largest

Metropolitan Statistical Areas (MSAs) were regarded as highly concentrated based on Department of Justice / Federal Trade Commission standards (AMA, 2016). This was an increase from less than 50% in the first AMA report in 2001 (AMA, 2001). This decreasing competition between commercial insurers and the countervailing negotiations with consolidated hospitals stands to compound the access to and utilization of services (Trish & Herring, 2014). This study takes these market forces into consideration as they interact to influence inpatient CT use.

Prior work has shown that hospital characteristics are associated with health resource consumption and CT use. Consumption is shaped by hospital indicators of complexity such as system membership, size, teaching status, and ownership type. Each of these uniquely contribute to a hospital's resource utilization. Systems have been shown to explicitly direct patients to specific hospitals based upon patient complexity (Luke et al., 2011; Sikka et al., 2009). CT use in particular has been noted to increase along with hospital size and complexity (Kirsch et al., 2010; Shafrin, 2006). Likewise, teaching hospitals regularly have higher utilization rates for CT exams, particularly in the emergency department (Korley, Pham, & Kirsch, 2010; Larson, Johnson, Schnell, Salisbury, & Forman, 2011). Larson et al. (2011) found increased CT use in the emergency departments (ED) of not-for-profit hospitals.

CT utilization has also been reported to vary significantly with patient characteristics. Not surprisingly, increasing patient acuity leads to increasing CT use (Kirsch et al., 2010). However, Kirsch et al. (2010) also found that women were more likely than men to receive a CT scan in the ED. This showed that gender may be a factor along with observed increases that correlated with patient age (Broder & Warshauer, 2006). Dramatic differences have been noted based on race, with nonwhite patients having only 72% the utilization rate of white patients

(Larson et al., 2011). Collectively, these underscore the importance of taking patient characteristics into consideration when assessing CT utilization rates, as this study does.

Literature Gap

This study demonstrates that there is a literature gap involving the inpatient use of CT exams across multiple markets. Broder and Warshauer (2006) explicitly looked at inpatient usage; however, their work was limited to a single hospital. Many studies have looked beyond a single institution but have been limited to CT use in the emergency room and not the inpatient setting (Kirsch et al., 2010; Korley et al., 2010; Larson et al., 2011). Medicare data addresses the challenge of multiple markets and can be the source of inpatient data. However, this excludes the majority of inpatients who are not Medicare enrolled and is compromised by the fact that Medicare does not negotiate with hospitals (Bhargavan & Sunshine, 2005). The challenge of filling this literature gap will be addressed in the forthcoming summary of data sources.

Purpose and Aims

The purpose of this study is to determine if there is a relationship between inpatient CT utilization and the characteristics of markets, hospitals, and patients. By doing so, this study will contribute to the limited body of research related to inpatient CT use. The novel application of data will help identify which aspects of markets, hospitals, and patients are interacting to shape the variability observed in utilization rates. The following objectives will achieve this purpose:

- Objective 1: To characterize the degree of variation in inpatient CT utilization rates across multiple hospitals, states, and markets.
- Objective 2: To evaluate the relationship between inpatient CT performance and the proportion of commercial payers across multiple markets and institutions.

- Objective 3: To evaluate the relationship between inpatient CT use and the characteristics of markets, hospitals, and patients.

Study Significance

This study is acutely relevant given the increasing prevalence of CT utilization, the rising financial costs, the current public concern with potential health consequences, and the gap in knowledge related to drivers of inpatient use. Stakeholders affected by the implications of the study extend beyond academic researchers to include hospital administrators, policy makers, and industry regulators. Consumption patterns affect strategic planning and healthcare costs, and have the potential to create inadvertent health consequences such as adverse reactions to contrast or increased exposure to ionizing radiation. The results of this research will specifically be relevant in:

- a) providing insight into the variability of inpatient CT use;
- b) helping in understanding the characteristics of markets, hospitals, and patients that may influence inpatient CT utilization;
- c) providing a cross-sectional snapshot of baseline information to address how future industry consolidations may alter resource consumption; and,
- d) adding to the limited body of research about the full spectrum of inpatient CT use.

The literature review will expand upon the inpatient use of CT resources that have been understudied despite becoming increasingly prevalent (Levin et al., 2013). Research into the use of CT scans has largely focused on emergency and outpatient settings, or exclusively on Medicare patients, using only descriptive techniques. In this case, the addition of a conceptual framework to anticipate relationships adds rigor to the contribution to fill the literature void.

Conceptual Framework Overview

This study uses a conceptual framework to explain general relationships and to develop specific hypotheses between CT resource utilization and the characteristics of markets, hospitals, and patients. Using a framework in lieu of ad hoc methods to postulate variables and hypotheses is the ideal for reliable and robust outcomes (Bacharach, 1989; Breyer, 1987). The framework supports the use of independent variables that are chosen based upon their conceptual association with or effect upon the dependent variables.

The framework suggests that demand for services will balance against supply to form an equilibrium point that may shift as external factors influence observed utilization (Allen, 2013; Mick & Wytttenbach, 2003). In complex markets, like healthcare, demand is particularly sensitive to external forces (Allen, 2013). External forces intercede and alter healthcare consumption patterns by changing the context within which the decision to consume is made (Mick & Wytttenbach, 2003).

The external forces included as part of this study are variables aligned with the characteristics of markets, hospitals, or patients mentioned previously. These characteristics are discussed in greater detail in Chapter 4, along with the rationale for controlling for each hospital's primary state of operation. This careful consideration of variables is important in the evaluation of secondary administrative data (Breyer, 1987). Beyer (1987) elaborates on this idea as the method by which one maximizes the explanatory power of a model by minimizing the explanatory variables. Chapter 3 provides greater details on the consideration given to and the prior application of conceptual frameworks to health services research.

Summary of Data Sources

Medicare inpatient data and National Hospital Ambulatory Medical Care Survey (NHAMCS) data are well represented in the prior imaging utilization studies referenced above. However, this study leverages other available resources to triangulate the full spectrum of inpatient CT utilization and address the literature gap. To do this requires the use of five data sources from three different entities. The first is Intellimed, Inc., a third-party aggregator of hospital discharge data, which is the source of the CT utilization data. The four states of Nevada, Maryland, Virginia, and Washington require reporting of discharge-level data that includes the performance of a CT exam during an inpatient stay. Intellimed collects this data and makes it available commercially and to researchers. Intellimed is also the source of the majority of hospital data as well as half of the market and patient characteristic data.

The second entity is the American Medical Association (AMA). The AMA is the source of private payer health insurance information through its annual report of insurer market concentrations. This annual report is used in the preparation of market data for the study. The AMA report (2016) is based upon 2014 market data representing all 50 states and the 388 largest markets, specifically.

The third entity is the Centers for Medicare and Medicaid Services (CMS). CMS is the source of three different data files and routinely makes available data for research and public use. CMS data are used in the preparation data to characterize hospitals and patients. The data from each source are linked by common variables into a single master file for analysis. A complete review of each data source and derived variables will be provided in Chapter 4. The convenience sample of data includes 219 acute care hospitals across this four-state sample that reported CT

scan utilization in 2015. The population sample, as well as inclusion and exclusion criteria, will also be discussed in greater detail in Chapter 4.

Chapter Summary and Preview of Remaining Chapters

This chapter provided an overview of the need for better understanding of the drivers of inpatient CT utilization, an increasingly prevalent technology. It demonstrated how this increasing utilization of the technology is occurring within the context of an evolving marketplace. It also highlighted the need to consider hospital and patient factors in any investigation. The chapter provided an overview of how the framework will be applied to formulate and hypothesize robust variable relationships. It also explained how the investigation of CT use across multiple markets will help to fill a literature gap specific to inpatient settings. Chapter 2 expands on the presence and significance of the gap in the literature.

There are five additional chapters to the study in which are provided a detailed literature review, the rationale of the framework, the methodology employed to test the hypothesized relationships, the analytical results, and the conclusions. Chapter 2 reviews the relevant literature, including a review of the observed increases in CT utilization and drivers associated with the increased use. It also presents the potential inadvertent consequences of CT use and prior attempts to curb utilization.

The remaining chapters structurally prescribe a method for addressing the identified literature gap and sharing the results. Chapter 3 explains the conceptual framework and uses it to structure the study within the context of market, hospital, and patient characteristics. Chapter 4 details the methods used in the research design. These include a discussion of validities, data sources, data management, measurement variables, and an analytical plan including the selection

of a statistical technique. The analytical findings are reported in Chapter 5, with their implications and significance discussed in Chapter 6.

Chapter 2: Literature Review

Overview

There is a great deal of literature on the use of and expenditures for CT scans. However, it is incomplete. Studies that address utilization and expenditures for all age groups are typically limited either to the outpatient setting or to studies within a single institution. Studies that do examine inpatient (IP) CT use and expenditures typically use Medicare data and so are limited to examining the population mostly age 65 and over. This chapter reviews this literature for insights that can guide this study of inpatient use of CT scans among a broad cross section of the population.

Growth of Computed Tomography and Medical Imaging

The focus of this study is IP use. However, this section of the literature review is largely dedicated to reporting on the overall prevalence of CT use in health care largely through the limitation of an outpatient (OP), emergency department (ED), or a Medicare perspective. It reviews suggested drivers of these increases and the associate variables. There is also a summary of the reported implications of increasing CT use and attempts made to curb those increases.

Increases in imaging utilization.

The use of medical imaging for both the diagnosis and monitoring of disease progress has become a matter of routine in health care. The technology permits many minimally invasive procedures via CT-guidance, which compete directly with traditional open procedures (Chien & Abbas, 2009). Routine CT and medical imaging use is commonplace in both the OP and IP

world. Increasing CT technology applications have benefited the early diagnosis, monitoring, and even the treatment of diseases.

The dissemination of the CT device itself has been rapid. Roemer observed in 1961 that in areas with higher hospital beds per capita, hospital length of stay was longer (Shafrin, 2006). This became known as Roemer's Law and is synonymous with supply inducing demand when a third party essentially guarantees payment. An application of such a law to CT devices suggests that the dissemination of CT devices would result in even faster increases in utilization. Accordingly, Shafrin (2006) reported that a CT installed is a CT device used. This occurs at least in part to recover the significant capital expense and upkeep of the device. CT device dissemination increased more than 50% during the 10 years preceding a 2004 census (Baker, Atlas, & Afendulis, 2008). Without regard to causation, others reported in a more recent study that the greater availability of CT in an area correlated to more frequent use of each device (Berdahl, Vermeulen, Larson, & Schull, 2013).

Multiple reports and studies demonstrate the escalating rates of CT use (Baker et al., 2008; Bhargavan & Sunshine, 2005; Boone & Brunberg, 2008; Brenner & Hall, 2007; Larson et al., 2011). CT use increased 20 fold from 3 million performed in 1980 to 60-62 million in 2005 and 2006 (Amis et al., 2007; Rumack, 2010). Rumack (2010) points out that the growth through 2007 was an average of 10% annually. More recent data is difficult to locate, however a November 2014 study reports that the ED Medicare beneficiary portion of CT growth continued unabated from 2002 through at least 2012 (Levin, Rao, Parker, & Frangos, 2014). Levin et al. (2014) reports this is despite the suggestion of flattening CT growth in other areas. These studies have primarily focused on increases in some aspect of OP, ED, or Medicare patient utilization. This leaves the implications of IP use still largely unaddressed and relevant.

For Medicare beneficiaries, the rate of all physician-billed CT interpretations (both IP and OP) increased more than 100% per 1000 enrollees between 1995 and 2005 to a rate of 547 CT scans per 1000 enrollees. This again increased to over 600 CTs per 1000 enrollees by 2008. Fewer than half of these were performed in the OP setting with the balance being performed on IPs and ED patients (Levin, Rao, Parker, Frangos, & Sunshine, 2011) Rate increases were also found across the entire patient population of one large tertiary care academic hospital from 2000 to 2004 (Boone & Brunberg, 2008). They observed an association between CT increases and patient characteristics such as age, sex, and patient status (IP, OP, or ED). Utilization rates increased 27% in OP areas. IP rates increased at an even higher rate, 48%. And they found that CT use rate in the ED more than doubled by 131% over the same time. Boone and Brunberg (2008) reported that though ED patients accounted for only 9.6% of the 2004 visits, they were nearly half of all CT scans performed. The CT use rate of 558.6 CT scans per 1000 ED visits was nearly quadruple the rate of 121.2 CT scans per 1000 IP days (Boone & Brunberg, 2008). Larson et al. (2011) found that admitted ED patients had higher utilization rates than those patients who were discharged home. This is a logical finding given the likely higher acuity and complexity of patients ultimately admitted from the ED. However, these findings underscore the prevalence of CT use in the care and decision making process.

The increases consistently reported throughout the literature have each been provided from only a few perspectives of the varying patient care environment. Many have used some version of the National Hospital Ambulatory Medical Care Survey (NHAMCS) to observe significant ED increases (Berdahl et al., 2013; Coco & O’Gurek, 2012; Feng, Pines, Yusuf, & Grosse, 2013; Korley et al., 2010; Larson et al., 2011; Mullins, Goyal, & Pines, 2013). Some have reported upon CT increases across the ED, OP, as well as the IP health spectrum selectively

using either Medicare data or private payer data (Bhargavan & Sunshine, 2005; Korley et al., 2010; Levin et al., 2014). Neither set of data accurately represents a cross section of the entire IP population. This is because the vast majority of Medicare patients are elderly (>65 years), but private payer patients are children or working age adults. It follows that much of the information available on CT utilization relates to use in the ED, the OP setting, or Medicare populations given the availability of data. A few investigators have studied CT use across a complete cross-section of the IP population, but these studies have been limited to using a single market and institution's in-house data (Boone & Brunberg, 2008; Broder & Warshauer, 2006). A list of relevant studies addressing CT utilization can be found in Table 1. To date there has been no evidence of a multi-market or multi-institution study that investigates the full spectrum of the IP population.

Literature findings of less appropriate utilization.

The literature suggests that CT increases have occurred for both appropriate and less appropriate reasons. Usually the increased rates are appropriate, justified, and replace more invasive and costly procedures. These reasons, like patient complexity, are discussed in another section. There is also a common belief in “inappropriate utilization” as a driver (Duszak & Berlin, 2012, p. 695). Inappropriate utilization was the focus of a 2009 summit in Washington, DC entitled “Medical Imaging: Addressing Overutilization in an Era of Healthcare Reform” sponsored in part by the American Board of Radiology (ABR) focusing on the “identification of the key forces driving overutilization” (Hendee et al., 2010, p. 241). Research identified multiple contributing factors to this inappropriate use. These are self-referral and the fee-for-service (FFS) payment methodology, litigation and defensive medicine, changing practice patterns, and duplicate studies (Bernardy et al., 2009; Chordas, 2009; Hendee et al., 2010).

Table 1

Relevant Studies of CT Utilization

Author(s)	Dataset	Population	Key Findings	Gap/Limitation
Berdahl et al., 2013	National Hospital Ambulatory Medical Care Survey (NHAMCS) 2003-08 and Canadian sources	Stratified survey ED visits in the U.S. and Canada	1. CT scanners were more prevalent in the U.S. 2. U.S. clinicians used CT more frequently.	Included ED utilization of all ages and payers, but does not include IP studies.
Boone & Brunberg, 2008	Single tertiary care hospital used from 2000-2004	CT scans performed at a single large level I trauma center	1. OP increased 27%, ED increased by 131% & IP increased 48%. 2. Differences existed by age group.	Included ED, OP, and IP CT scans but only for a single institution.
Bhargavan & Sunshine, 2005	1. Medicare's Medical Expenditure Panel Survey (MEPS) 2001; 2. MedSolutions OP private pay imaging, 2000.	Nationwide utilization of all medical imaging	1. Rapid increases in high-technology modalities (MR, CT). 2. Substantial variation among states and census regions.	Included ED, OP, and IP studies, but IP portion of study considers only Medicare enrollees.
Broder & Warshauer, 2006	CT Utilization 2000-2005 in the ED of a single institution	Observed practice patterns in the single large, tertiary referral center ED	1. ED CT utilization far exceeded ED patient volumes. 2. Increases ranged from 51% to 463% by anatomy.	Included only CT from the ED and at a single institution
Coco & O'Gurek, 2012	NHAMCS 1997-99 and 2005-07	Stratified nationwide survey of ED CTs performed for chest symptoms	1. CT rates increased dramatically without improving clinically significant diagnoses. 2. Clinically nonsignificant diagnoses increased	Included ED utilization of all ages and payers, but does not include IP studies and only for chest symptoms

Table 1: *Continued*

Author(s)	Dataset	Population	Key Findings	Gap/Limitation
Feng et al., 2013	NHAMCS 2001-2009	Stratified nationwide survey of CT studies performed in the ED for chest symptoms	1. Nonurban hospitals had highest growth rate for ED CT for chest symptoms at 43%. 2. Low frequency of PE diagnosis warrants better evidence-bases use of CT for chest symptoms.	Included ED utilization of all ages and payers, but does not include IP studies and only for chest symptoms.
Kirsch et al., 2010	Data received from a third party billing company for calendar year 2006	A 41 state sample of CT utilization in the ED	1. ED CT was used for 27% of admitted patients. 2. Emergency-boarded physicians ordered more CTs.	Multi-state study of CT use in the ED including all payers and hospital types, but does not consider IP studies.
Korley et al., 2010	NHAMCS 1998-2007	Stratified nationwide survey of CTs and MRs from the ED for injuries	CT and MR increases were not explained by an increase in patient acuity or life-threatening injuries.	Included only ED trauma, but did not consider IP studies
Larson et al., 2011	NHAMCS 1995-2007	Stratified nationwide survey CT use in the ED	1. A 5.9 fold increase in CT use (2.7M to 16.2M) during the study period. 2. CT use increased at a higher rates in the ED.	Included ED utilization of all ages and payers, but does not include IP studies
Levin et al., 2014	Medicare Part B databases, 2002-2012	CT ED use for Medicare patients	1. ED CT use increased steadily from 2002-2012. 2. This was despite flattening growth of CT in other areas.	Included ED CT utilization but for only Medicare beneficiaries.
Mullins et al., 2013	NHAMCS 2002-09	Stratified nationwide survey ED disposition	Patients admitted to the ICU had ED CTs performed 37% of the time	Included ED utilization of all ages and payers, but does not include IP studies and only for ICU admissions.

Self-referral and fee-for-service.

Imaging self-referral and FFS payments work together to increase utilization. Hendee et al. (2010) describe self-referral as “the referral for a procedure in which the referring physician is also the service provider or has an ownership interest and benefits financially by providing the service” (p. 242). In 2001, the FFS reimbursement of “unnecessary imaging” (p. 171) component of self-referred studies was estimated to be \$16 billion annually (Levin & Rao, 2004). Levin and Rao (2008) updated their earlier work and reinforced the roll of self-referral and fee-for-service in increasing utilization. Further the U.S. Government Accountability Office points out that though some growth “may represent appropriate increases” (p. 5), “payment policies (may) embody financial incentives for physicians to overuse imaging services” (Government Accountability Office, 2008, p. 5).

Litigation and defensive medicine.

The threat of malpractice liability has been reported to compel physicians to use imaging in the practice of defensive medicine. Hendee et al. (2010) define defensive medicine as “diagnostic or therapeutic measures applied principally to safeguard against possible accusations of malpractice rather than to benefit the patient” (p. 241). Such practice results in the exhaustive imaging of patients though the cost may be high and a marginal benefit that may be small or nonexistent. At best defensive medicine extracts the maximum medical benefit out of a medical imaging series. At worst it results in non-clinically significant follow up with additional complications and far-ranging costs for patients and health systems. An example of this is evident in the controversy surrounding the National Lung Screening Trial and patient complications resulting from what were benign, incidental findings on CT (American Cancer

Society, 2011). A Massachusetts Medical Society (2008) survey of members found that 28% of CTs were ordered in response to the perceived threat of litigation.

Public policy can also encourage increased use. An example is the Emergency Treatment and Labor Act (EMTALA) of 1987. EMTALA compelled hospitals and providers to provide a screening evaluation to assess the validity of a patient's emergency visit. A quick and simple way of demonstrating such an evaluation became ordering a CT scan even if its appropriateness was poor, based on patient indications. Amis et al. (2007) pointed out that the speed, reliability, and general efficacy of a CT allowed rapid disposition of ED patients. This speed helps to decrease the direct risk of litigation to the ED physician by sharing it with an interpreting physician. The performance of a CT, even if poorly indicated or done for defensive purposes, became a means of objectively demonstrating treatment.

Changing practice patterns.

Some have pointed to changing practice and referral patterns of some physicians and groups as a driver of increasing utilization. It has become common to place CT scanner in or adjacent to the ED. Some have suggested that this simple immediacy, despite its benefits, may have contributed to less appropriate use (Boone & Brunberg, 2008). This work suggests that the utility of and increased preference for CT is believed have shifted some of the diagnostic imaging away from lower and non-radiation alternatives. It also suggests that sometimes a CT is ordered simply because it is quick and easy, though it may be poorly indicated based on the patient's presentation.

Broder and Warshauer's (2006) findings largely support the idea of changing practice standards and patterns. They found that within the ED population from 2000 to 2005, the rate of utilization increase varied greatly between different types of CT exams. Many types of CT

exams increased over that time due to a change in practice standards and diagnostic indications. For example, they observed a 500% increase for CT of cervical spine for indications of trauma due to evolving trauma standards. However, they found comparable increases in the use of head CT, despite neither discernable changes in actual clinical indications nor changes in neurology standards. Others reinforced this by observing that increases occurred despite no significant change in patient acuity (Korley et al., 2010; Mullins et al., 2013). Together these suggest factors beyond practice standards are associated with increases. One suggestion has been the increasing sub-specialization of medicine as a driving force behind such increases (Kirsch et al., 2010; Pitts, Morgan, Schrager, & Berger, 2014). Ultimately, usage has increased even when the patient population has not changed.

Research on data from Medicare enrollees suggests that market penetration of CT devices is associated with the rate of increasing utilization (Bhargavan & Sunshine, 2005). Utilization of novel imaging technologies increases the fastest at the time of introduction, but begins to plateau as the market saturates with devices and providers. Novel therapies, increased device speed, and study precision can help to sustain growth in a particular modality. Other factors found to be positively associated with higher utilization include an increased number of general providers and radiology providers in a state (Bhargavan & Sunshine, 2005). While causation has not been demonstrated in such a complex system, either the presence of radiologists drives increasing utilization or the increased utilization seems to lure a greater number of radiologists per capita. Bhargavan and Sunshine (2005) observed that markets approaching radiologist saturation have diminishing rates of increase, as they reach their capacity limits, and these markets show reduced geographic variation.

Duplicate studies.

When an ordering clinician is unaware of or unable to access a previously performed exam or results, the speed and efficiency of the CT has “a lower threshold for using it” (Smith-Bindman, Miglioretti, & Larson, 2008, p. 1491). It is very quick and easy to order and perform a repeat study to often answer the same clinical question. Such a scenario may occur when a patient is transferred between facilities, but his or her studies do not transfer successfully or quickly due to interoperability problems. The result is what Bernardy et al. (2009) describes as the “incomplete availability of patients’ imaging histories, leading to duplicate studies” (p. 844). Reported rates vary, but America’s Health Insurance Plans (AHIP) reports that “about 20% of hospital radiology tests are duplicates” (p. 2), and that a “full third of imaging procedures may be inappropriate” (AHIP, 2008, p. 2).

Factors influencing CT and health resource utilization.

There are specific factors frequently reported in the literature that are associated with variation in CT and health resources uses. The following subsections review these factors, which largely reflect hospital, patient, and market factors. The findings are often limited in general applicability due to the previously described data limitations. These studies have often been restricted in scope to ED patients, outpatients, Medicare patients, or a single institution’s proprietary data

System centralization.

Many hospitals have now joined into a multihospital system (MHS), and membership in these systems has been shown to impact resource consumption though CT use has not been explicitly reported in many studies. Studies have explored the role of centralization with MHSs in coordinating services and shifting procedures to different facilities within systems

(Chukmaitov et al., 2009; Luke et al., 2011). Luke et al. (2011) investigated a multistate sample of 404 hospitals in 117 urban MHSs and concluded that systems appear to explicitly direct high-risk procedures to specific facilities. These high-risk procedures require greater resources and were found to often be directed to higher capacity facilities. This conclusion demonstrates that the intensity of service utilization within an individual hospital may be explicitly controlled by the greater system for those in a MHS. This opportunity to better coordinate and share previously performed CT studies between institutions is most accessible to hospitals engaged in formal MHSs. These observations complement the work of others to demonstrate the relationship between the increasing system centralization and coordination of services to improved quality outcomes (A. S. Chukmaitov et al., 2009).

Ownership type.

For-profit and not-for-profit ownership has been associated with the way in which CT and health care resources are consumed. However the directionality has been mixed. Most years of the NHAMCS data demonstrated CT utilization rates for ED patients that were slightly higher in not-for-profit hospitals than in proprietary, for-profit hospitals (Larson et al., 2011). This analysis did not explore why for-profit ownership would be associated with lower CT use in the ED. Somewhat conversely, others have shown an association between for-profit ownership and an increase in the outpatient volume of health resource utilization (Chukmaitov, Devers, Harless, Menachemi, & Brooks, 2011). These authors suggest the difference may be dependent upon whether the service generates or loses revenue for the hospital in the outpatient fee-for-service setting. It is prudent to recall that the diagnosis-related prospective payment system for inpatient admissions fixes the reimbursement. This system makes any additional inpatient CT exams

function as a cost to the hospital, especially if the same scanner timer is competing with fee-for-service outpatients.

Payers.

Historically the source and amount of payment for health care has affected the rate of resource utilization. The classic RAND Health Insurance Experiment from 1973 to 1982 demonstrated the marginal cost sensitivities of consumers to using health care resources (Brook et al., 2006). It did so by varying the share of the consumer cost burden against the observed amount of services consumed. Resource consumption remains associated with the cost borne by the patient via the payer mix present in a market. Within the nationwide sample of ED visits reviewed by Larson et al. (2011), CT use was again associated with payer type. In 2007, patients with private commercial insurers demonstrated the highest rates at 14.7%. Those with Medicare or Medicaid had marginally lower rates (14.3%). Those with the lowest use identified as self-paying (12.9%). The odds of receiving a CT as a privately insured patient were statistically significantly higher than any other class of payer.

Kirsch et al.'s (2010) billing data study had similar CT use patterns but more dramatic differences related to the payer. Their non-random, nationwide sampling of patients found that commercially insured patients had a CT scan used during their ED visit 15.1% of the time. The uninsured self-paying had a CT scan performed during 12.7% of ED visits. Kirsch et al. (2010) also differentiated Medicare and Medicaid as payers. Though Medicaid represented a large portion of all scans performed, Medicaid patients had CT utilization rates at one-third that of Medicare patients (22.5% vs. 7.8%). A weighted average of this study's Medicare and Medicaid patients puts the proportion of publicly funded patients receiving a scan at 14.4%. This is consistent with the Larson et al. (2011) combined NHAMCS findings of 14.3%.

The control a payer has over modulating access to care and the cost burden placed on patients and employers is acutely relevant given the consolidation that has occurred in the insurer market. Employer-sponsored insurance (ESI) remains the largest segment of commercial health insurance. ESI covered 149 million non-elderly people in the U.S. as of May 2014 (Claxton et al., 2014). Further, the American Medical Association (AMA) reported that as of 2014, 72% of insurer markets in the 388 largest Metropolitan Statistical Areas (MSAs) were regarded as highly concentrated based on Department of Justice and Federal Trade Commission standards (AMA, 2016). This was an increase from less than 50% of the largest U.S. markets in the first AMA report in 2001 (AMA, 2001).

Within a given market the insurer concentration has ramifications, since hospitals and insurers negotiate for favorable contract terms. It has been shown that insurers exercise the power of their market concentration in negotiating premiums and preferential hospital contracts (L. S. Dafny, 2010). He noted that markets with more concentrated insurer power (i.e. less competition) had higher premiums and suggested that insurers were engaging in monopolistic price discrimination. In related work, Dafny, Duggan, and Ramanarayanan (2012) reported that at least 7 percentage points of the observed 60% increase in inflation-adjusted premiums between 1998 and 2006 were associated with decreasing competition. Guardado, Emmons, and Kane (2013) studied the merger of two insurers in a natural experiment and assigned a causal association between the increasing market share and a 13.7% single-year increase.

Hospital size.

There are other hospital characteristics shown to be associated with resource utilization. One multi-institutional study of 2006 payer data for ED visits showed that CT rates increased along with the annual patient volume (Kirsch et al., 2010). High-volume EDs exceeding 40,000

annual visits had nearly twice the CT utilization rate (17.8%) as the low-volume EDs (9.3%) having fewer than 20,000 annual visits. Kirsch et al. (2010) offered possible explanations. The volume of the ED would likely correlate strongly with the patient complexity and hospital size. Also, the most severe patients are ultimately expected to be admitted to the largest hospitals able to provide tertiary or quaternary care. In addition, they report high ED volumes may be related to increased accessibility of both a scanner and rapid results. This access, as previously described, has at times been observed to further enhance resource use (Shafrin, 2006).

Teaching status.

EDs with training programs have been shown to have higher scan rates. Larson et al. (2011) observed a modest increase in the frequency of CT use in settings considered academic. They used a less restrictive definition of an academic ED requiring only 10% of ED visits were attended by residents. However, Korley et al. (2010) found that applying a more restrictive 50% visit threshold to define academic EDs resulted in more dramatic differences. They found that patients in an academic ED were 52% more likely to receive a CT scan than those at a nonacademic ED. They attributed this to trainee inexperience, the ready availability of CT, and the acuity of academic patients. Both studies used multiple years of the National Hospital Ambulatory Medical Care Survey (NHAMCS) data to look at ED patterns.

Kirsch et al. (2010) also reported an association between the type of board certification and the likelihood of ordering a CT on ED patients. Board-certified emergency medicine physicians were significantly more likely to order a CT study on a patient than those who were not board certified (16.3% vs. 11.3%). These observations persisted after controlling for the patient age, sex, physician age, and the ED volume. Interestingly, Kirsch et al. (2010) found that the age of the provider was negatively related to the likelihood of ordering a CT study for a

patient. The oldest clinicians were significantly less likely to order a CT study than the youngest physicians (11.8% vs. 16.0%). These large utilization studies suggest some combination of physician training and the teaching aspect of the academic environment may relate to the likelihood of ordering a CT study on their patients.

Case mix.

Increasing patient acuity has been shown to increase the likelihood of receiving a CT exam while in the ED. This is evident by the finding that the most ill patients receiving care in the ED (i.e., those ultimately admitted to the hospital from the ED) have been found to have the highest utilization rates of CT in the entire hospital (Kirsch et al., 2010). This study showed that these patients are 2.5 times as likely to have a CT as those who are discharged (Kirsch et al., 2010). Once admitted, the CT use continues in the inpatient setting, and has been observed to increase over time as well. One single institution study observed a 48% increase in CT use for inpatients between 2000 and 2005 (Boone & Brunberg, 2008).

Patient demographics.

Patient demographics have been associated with CT and resource utilization across multiple health care settings. CT utilization has been found to vary with statistical significance between genders (Kirsch et al., 2010). Kirsch et al. (2010) found that women were found to be more likely than males to receive a CT scan at 14.3% as compared to 13.8%. They observe that though this difference is statistically significant, it may not be clinically relevant in spite of the additional cost and radiation considerations. The authors also found that a patient's age is related to CT use. ED CT use increased with each adult decade of life from 11.3% to 24.6%. At another large tertiary medical center, CT rates from 2000-2005 increased with each adult age group suggesting increasing needs with age and that a large elderly population may affect overall rates

(Broder & Warshauer, 2006). Another patient demographic observed to differentiate rates has been race. Larson et al. (2011) reported that in the later years of their study, white patients had a significantly higher rate of CT utilization than nonwhite patients. They observed 38% higher CT utilization rates for white than black patients in the ED (14.9% vs. 10.8%).

Implications of increasing CT utilization.

The American College of Radiology (ACR) reports (2009) that CT technology has undoubtedly saved many lives, reduced many hospital stays, improved disease detection, and improved ED throughput. However, these benefits have not come without costs, associated risks, and unintended consequences. Evaluating the clinical merit of the CT exam is beyond the scope of this study but deserves acknowledgement. The purpose of this section is to explore the costs and risks associated with CT use to underscore the importance of developing a comprehensive understanding of utilization patterns. This is part of the “need to focus on the potential side effects of these advanced imaging techniques” (p. 837) for which Dr. Rumack (2010) advocated as the President of the ACR. The technology has both financial costs to the U.S. health system and potential inadvertent health costs to those receiving scans given the technology’s use of upon ionizing radiation.

Financial costs.

Not surprisingly, as utilization has increased so has the financial cost dedicated to medical imaging. For example, the cost of medical imaging has increased at approximately twice the rate of other medical technologies (Hendee et al., 2010). The \$100 billion threshold for medical imaging payments by all combined payers was surpassed in 2004 (Iglehart, 2006). Medicare’s MedPAC report (Government Accountability Office, 2008) revealed that its portion of medical imaging costs remained one of its fastest growing areas from 2000-2006. More recent

data suggest a modest curbing of Medicare's expenditure growth rate in the wake of the Deficit Reduction Act of 2005 that targeted advanced imaging, like CT (Lee, Duszak, & Hughes, 2013). However, Lee et al. (2013) found that though Medicare expenditures per CT decreased, the absolute spending figures did not, due to the volume increases that more than offset savings. The continued high costs and rapid growth have resulted in continued payer scrutiny in an attempt to justify the public value. Attempts to curb utilization will be reviewed later in this chapter.

Population health costs.

Though there are significant benefits to the use of CT, it is not without risk. The use of CTs creates costs beyond those easily measured as a direct financial cost. The frequent use of contrast in CT studies can induce nephropathy and sometimes rare life-threatening contrast reactions (Korley et al., 2010). Concern over ionizing radiation has attracted the interest of researchers and the mainstream press alike (Bogdanich W., 2010; Park, 2012; Redberg & Smith-bindman, 2014). Study results are often repeated in lay publications and heighten public awareness of the potential harm of ionizing radiation. Public discourse prompted the ACR to publish a statement in response to the studies associating CT scans and increased cancer risk. In it they stated, “Medical imaging exams have been directly linked to greater life expectancy, declines in cancer mortality rates, and are generally less expensive than the invasive procedures that they replace” (ACR, 2009, para. 1). However, the ACR conceded, “widespread use has resulted in increased radiation exposure for Americans.” (para. 1). Reports indicate a more than seven-fold increase in the cumulative ionizing radiation dose attributable to health care received annually in the U.S. between 1980 and 2006 (Hendee et al., 2010; Rumack, 2010). Per the National Council on Radiation Protection & Measurement (NCRP) this increase has gone from 124,000 to 880,000 person-Sieverts during that time (Schauer & Linton, 2009). This seven-fold

increase means that as of 2006, ionizing medical radiation equaled the annual all-source environmental exposure to ionizing radiation in the U.S. (Hendee et al., 2010; Schauer & Linton, 2009).

Elevated radiation doses were again addressed in a 2011 single-institution study of 500 transfer patients. It showed that 52.8% of patients transferred to the facility with an outside scan had phases of the study that were unindicated based upon ACR Appropriateness Criteria (Guite, Hinshaw, Ranallo, Lindstrom, & Lee, 2011). This meant that “33.3% of the total effective radiation dose to the patient population was due to unindicated phases” (Guite et al., 2011, pg. 758). Applying the 50 milliSievert annual safety threshold for health care workers, as a frame of reference for safety, indicates that 21.2% of these patients were above it. Guite et al. (2011) also found that 25% of the phases were unindicated on transfer patients less than 10 years of age. This is concerning because children are at an elevated risk; at such a young age they have more years to accumulate dosage, and their bodies and cells are more sensitive to radiation while dividing and growing rapidly (Brenner & Hall, 2007). This is potentially compounded by the fact that they are also the most likely to be overdosed in the setting of a protocol that has not been customized to their smaller body sizes (Paterson, Frush, & Donnelly, 2001). Benner and Hall (2007) concluded that at 2007 CT utilization rates, the radiation from those scans will account for 1.5-2.0% of lifetime cancers. It was reported that while only 26% of imaging studies are considered advanced imaging, the vast majority of the ionizing radiation in medicine (89%) is attributed to advanced imaging techniques like CT (Rumack, 2010). For these reasons, Smith-Bindman et al. (2009) advocated for the evaluation of CT scan benefit within the context of additional radiation risk including the reduction of any unnecessary studies.

The challenge of patients being exposed to increasing amounts of ionizing radiation has led to large national efforts to educate both the public and providers to curb dosing. The U.S. Food and Drug Administration launched a national campaign in 2010 to reduce unnecessary exposure to CT, fluoroscopy, and nuclear medicine studies (U.S. Food and Drug Administration, 2010). This included improving devices, and also followed the 2007 efforts of the Alliance for Radiation Safety in Pediatric Imaging's *Image Gently* initiative to improve the quality and reduce the radiation exposure to pediatric patients through medical imaging (Goske et al., 2008). Also in 2007, the ACR commissioned a blue ribbon panel to assess dangers and develop recommendations for reducing excess utilization (Amis et al., 2007). Thirty-seven recommendations were created by the panel in 2007 and then revisited in 2010 to assess their progress (Amis & Butler, 2010). Health concerns have resulted in a partnership between the ACR and the Radiology Society of North America to create the RadiologyInfo.org website (American College of Radiology, 2009). It serves as a portal to educate both the public and providers about the potential risks and benefits of imaging that uses ionizing radiation. While all CT exams use radiation, some modalities that do not may be adequate for the clinical question at hand. Others have advocated for a movement beyond purely radiation safety and quality to one of advocacy and the installment of a culture of "patient-focused radiology" (Rumack, 2010). Rumack explains that patient-focused radiology extends to include the consideration of advanced imaging's potential side effects as part of the value function of risk-benefit assessment. However, significant challenges exist when attempting to alter practice models that are engrained in an organization's culture (Dugan, Mick, Scholle, Steidle, & Goldberg, 2011). The combined increases in CT utilization with the observed financial costs and population health concerns have led many payers and policymakers alike to explore ways to curb the growth of CT use.

Attempts to curb utilization.

Multiple efforts have been made to curb the perceived overutilization of CT. Within institutions, this has usually involved improving study selection methods. One such tool is a computerized physician order entry (CPOE) system augmented by imaging decision support to assist in the appropriate ordering of a CT. The mismatched pairing of a study to a given patient's clinical indications has been identified as a source of less appropriate studies (Chordas, 2009). Decision support stands to indirectly limit growth by guiding providers to studies that demonstrated the most value. However, only recently has decision support based upon robust imaging appropriateness criteria become readily accessible because of its dependency on widespread adoption of electronic medical records (EMRs). When appropriateness criteria did exist in the past, these were often without much evidence basis and not integrated into CPOE systems (Hendee et al., 2010).

Easy and timely access to evidence-based standards helps to guide clinicians in their CT ordering choices (Feng et al., 2013). The ACR has established and regularly updates its consensus and evidence-based "Appropriateness Criteria" to assist clinicians in ordering the best study for the clinical question at hand (Levin et al., 2012; Rumack, 2010). However, the ACR's Appropriateness Criteria are often not easily accessible at the point of care for ordering physicians. Even for those institutions that have a CPOE system, the system often does not incorporate appropriateness criteria into any associated decision support. Institutions that have successfully incorporated appropriateness criteria into the decision support of their CPOE report as much as a 20% decrease in CT utilization (Raja et al., 2012; Rosenthal et al., 2006). Overall this represents a cost savings for health care, decreased radiation for patients, and decreased professional services revenue for interpreting physicians.

External entities have attempted to impose controls over the use of CT and imaging resources too. Payers use benchmarking for providers ordering scans in an attempt to identify and isolate outlying physicians. A more common technique is the use of preauthorization for high-tech studies (Hendee et al., 2010). Preauthorization curbs the growth in utilization rates by ensuring the threshold for appropriateness of study fit. It also works by simply creating a cumbersome process to get payer approval for many CT and other advanced imaging studies. Similarly, federal mandates for the use of EMRs are in part an effort to reduce inappropriate utilization by eliminating duplicate studies (Health and Human Services, 2013). Likewise, imaging facility accreditation became required per the Medicare Improvements for Patients and Providers Act (2008) for CT imaging Medicare reimbursement (Government Printing Office, 2008). One aspect of accreditation is continuous quality control intended to reduce inadequate studies that require repeat.

The Omnibus Budget Reconciliation Act of 1993 (Sabo, 1993) contained legislation intended to prevent OP imaging referrals to imaging facilities where the referring physician holds a significant financial interest. The goal was to remove any physician financial incentive for having the study performed. However, this legislation did not regulate ordering in the IP setting, the subject of this project. Nor did it limit interpreting physicians from recommending additional imaging, over watchful watching, when an otherwise equivocal study initially resulted. Such ambiguity and latitude in the scope of practices can result in further utilization increases.

Gaps in the Literature

This review demonstrates that while much is known about CT utilization and expenditure and the factors that have driven increases in them over the last decade, much of the evidence

comes from the outpatient and emergency department settings. Literature that examines inpatient data is limited to Medicare data and therefore the 65 and over population. Single institutions may maintain their own repositories of data that differentiate between ED, OP, and IP scans but will be limited to only that one organization. OP survey data, even large multi-market sets such as the NHAMCS data, have been used to characterize use patterns but are limited to the ED and OP setting. Lastly, private payer studies have demonstrated utility in looking across both ED and OP settings as well as markets, but have excluded Medicare patients and IPs. It appears that there is no published study that has captured a multi-market perspective of the factors potentially influencing the performance of IP CT studies.

Chapter Summary

This chapter reviewed the literature for observations about the growth of CT utilization across the continuum of care. It also reviewed factors that are associated with CT and health resource use. IP use of CT exams has been largely under-investigated, and there is an urgent need for a better understanding of their utilization. This exploratory study provides a single-year snapshot of the multi-market, multi-state IP utilization of CT exams to aid in closing the existing gap in the literature. IP CT use is not only an issue for administrators, academics, and payers but also remains a significant health risk to patients when used inappropriately. As previously discussed, hospital and insurer consolidation occurred concurrently with the growth in CT use. Many hospitals consolidated into MHSs, and many markets are now highly concentrated and dominated by only a few hospitals and insurers. It is conceivable that the interplay between markets, hospitals, and patient factors may influence IP CT utilization. The economic principles suggesting this will be discussed in greater detail in Chapter 3.

Chapter 3: Conceptual Framework

Overview

The purpose of this chapter is to provide the conceptual basis for the organization of this study and the rationale for the selection of variables, their relationships, and derived hypotheses. This rationale will be used to explain the relationships between the various hospital, patient, and market inputs affecting the supply of CT resources and the subsequent demand for inpatient utilization of these exams as an output measure. That will be followed by a review of assumptions and limitations, the conceptual framework, and proposed hypotheses. These hypotheses, derived from the framework, will address the study objective to test the relationship between inpatient CT use and characteristics of markets, hospitals, and patients. The hypotheses will be tested against a purposefully developed secondary set of convenience data.

Structured Research

Bacharach (1989) wrote of social science research and published on the criticality of research rooted in and aligned with theoretical concepts and structures. He contended that basing hypotheses in frameworks offers a perspective that frequently results in a simultaneously more rigorous and more contemplative rationale. Further, he asserted that theory is intended to go beyond simply the minimal purpose of description. Theory helps investigators to hone questions that they expect to ask while also reminding investigators of constructs and other perspectives that may have not been considered. Bacharach (1989) writes that such a framework is “a statement of relationships between units observed or approximated in the empirical world” (pg.

498). In practice, the genuine measure of a framework’s utility is not the accurate representation of reality, but the ability to accurately predict outcomes.

Bacharach (1989) provides a framework for organizing the constructs, related variables, and hypotheses (Figure 1). This framework includes methods to guide evaluation of the framework for adequacy and considers the essential falsifiability and utility of variables, constructs, and relationships. This includes both empirical and logical adequacy. Empirical adequacy is an assessment of whether observations are simply true or false. Logical adequacy requires that relationships must be non-tautological and that the antecedent must specify the consequence.

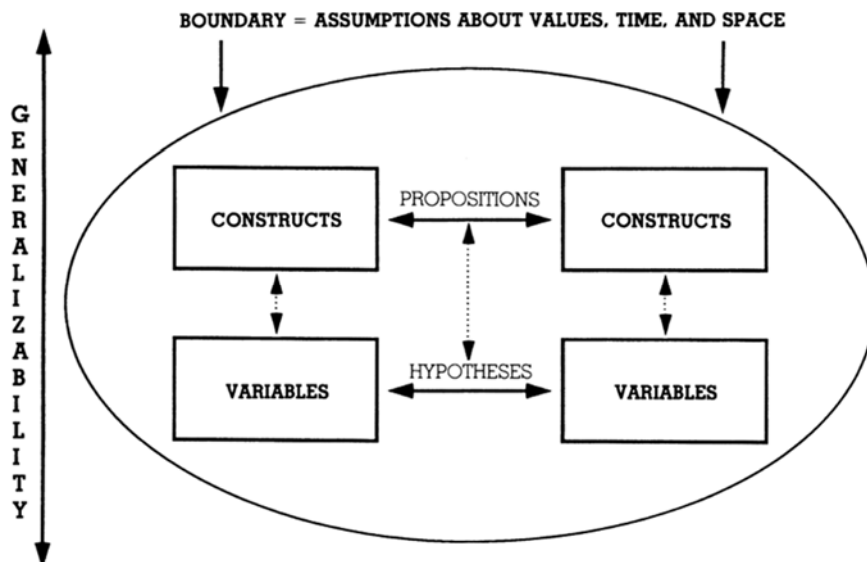


Figure 1. Framework Components (Bacharach, 1989)

Mick and Wyttenbach (2003, pg. 34) explain how “the ‘demand’ for a doctor’s services is never a direct function of physician supply, insurance coverage, and disease pattern.” The concepts of supply and demand are most often interpreted within the context of an assumed perfectly competitive market for a particular service or product (Mankiw, 2007). The marginal benefits gained from an activity, with respect to the marginal costs incurred by the rational

consumer, directly relate to the willingness of the market to supply or permit a particular product or activity as output (Mankiw, 2007). However, the lessons learned are often more broadly applicable to more complex markets as well, since the observed demand in more complex markets is often determined by more factors than simply cost. Demand is often altered by externalities that either increase or decrease demand as a consequence (Mankiw, 2007).

Healthcare is an especially complex marketplace that is subject to external influences. These may include regulation, accreditation, health insurance coverage, preferred partnerships, and increasing copayments that alter utilization. One particular example is Certificate of Need (CON) programs, which are administered by select states. They require applicants to demonstrate patient need before regulators will approve the expansion of many healthcare resources, including new hospitals and bed expansion projects along with large capital purchases such as MRI or CT devices. These externalities and assumptions of the supply and demand model lead to a partial equilibrium within the context of all other things being equal.

Healthcare Applications

Aggregate healthcare resource demand and utilization were explored extensively in the classic RAND health insurance study (HIS) of the 1970s (Brook et al., 2006). The RAND study demonstrated the sensitivities of groups to cost and the resultant changes in consumption of healthcare resources. These changes reflect the elasticity of resource demand. As the cost burden increased on the insured, they consumed fewer resources. Increasing cost burden decreased the demand for services. Not all resources varied equally. Acute care hospital needs were the most inelastic and varied the least, whereas wellness care varied the most and was most likely to be deferred. The cost sharing of the RAND HIS experiment demonstrated the relationship between supply inputs, such as cost, and the subsequent demands for services.

The RAND HIS also demonstrated that OP and IP services are often complementary from the consumer perspective and not substitutes (Brook et al., 2006). This is a critically important distinction when studying IP utilization of any service to ensure that services are not simply being performed as an OP in lieu of being performed while an IP. The opportunity to transfer revenues to different cost centers reflects a potentially large driver of health resource utilization. Market-based reforms and principles have been applied routinely in the United States and abroad in attempts to broaden coverage, control costs, and improve quality (Allen, 2013). Such was the intention with The Patient Protection and Affordable Care Act of 2010 (Claxton et al., 2014).

Assumptions

The finite limits of knowledge are the boundaries beyond which all other possibilities are considered equal (Lawson, 2013). There is an accepted limit beyond measurable knowledge, which may still have a quantifiable impact on behavior. This limit is defined by the conceptual framework and exists because it is not possible for every individual to fully comprehend, process, or understand every iterative possibility. Still, individuals are expected to make decisions from which gained benefit is expected. The cognitive ability of an individual to make a decision within these constraints represents a fundamental assumption of the framework.

The provision and consumption of healthcare resources is assumed to be at stable equilibrium. At one extreme is the monopolistic seller who can very often set prices above what would be most efficient at equilibrium-level prices. The inverse situation is monopsony. Monopsony occurs when there is a single dominant purchaser that can drive down prices. In both scenarios, there is a disequilibrium in the market for goods that compromises equitability and efficiency. This can exacerbate the concept of information symmetry, which is needed to make

informed decisions. Healthcare is extremely complex and often requires a level of expertise attained only after years of training to make an informed utilization decision. Patients often lack this knowledge and are insulated from the financial cost. Physician decisions are often removed from financial implications by design. The result is that the decision to use a healthcare resource is often subsidized or completely paid for by another entity with few negative financial implications for the patient or the provider. Despite these required assumptions and understood limitations balancing the supply of and demand for services remains a popular and viable conceptual system of constructs by which to frame research questions.

Conceptual Framework

This study's conceptual framework is diagramed and summarized in Figure 2. It summarizes the various relationships between the input and output constructs. The framework attempts to demonstrate graphically the probable mechanisms by which the various input measures directly associate with the output measures.

The input measures correspond to those previously observed in the literature review as representative of markets, hospitals, and patients and have been shown to have a probable relationship to the use of CT exams. They are the a) insurer market share, b) hospital market share, c) system centralization, d) payer mix, e) hospital bed count, f) teaching status, g) ownership type, h) case mix index, and i) minority mix. The first two input measures (a & b) represent indicators of the market that are anticipated to alter the demand for inpatient CT use. The next five variables (c through g) are hospital characteristics expected to alter the demand for inpatient CT use. The patient factors influencing demand (h & i) consist of case mix and minority mix. The input and output variables are summarized in Table 2.

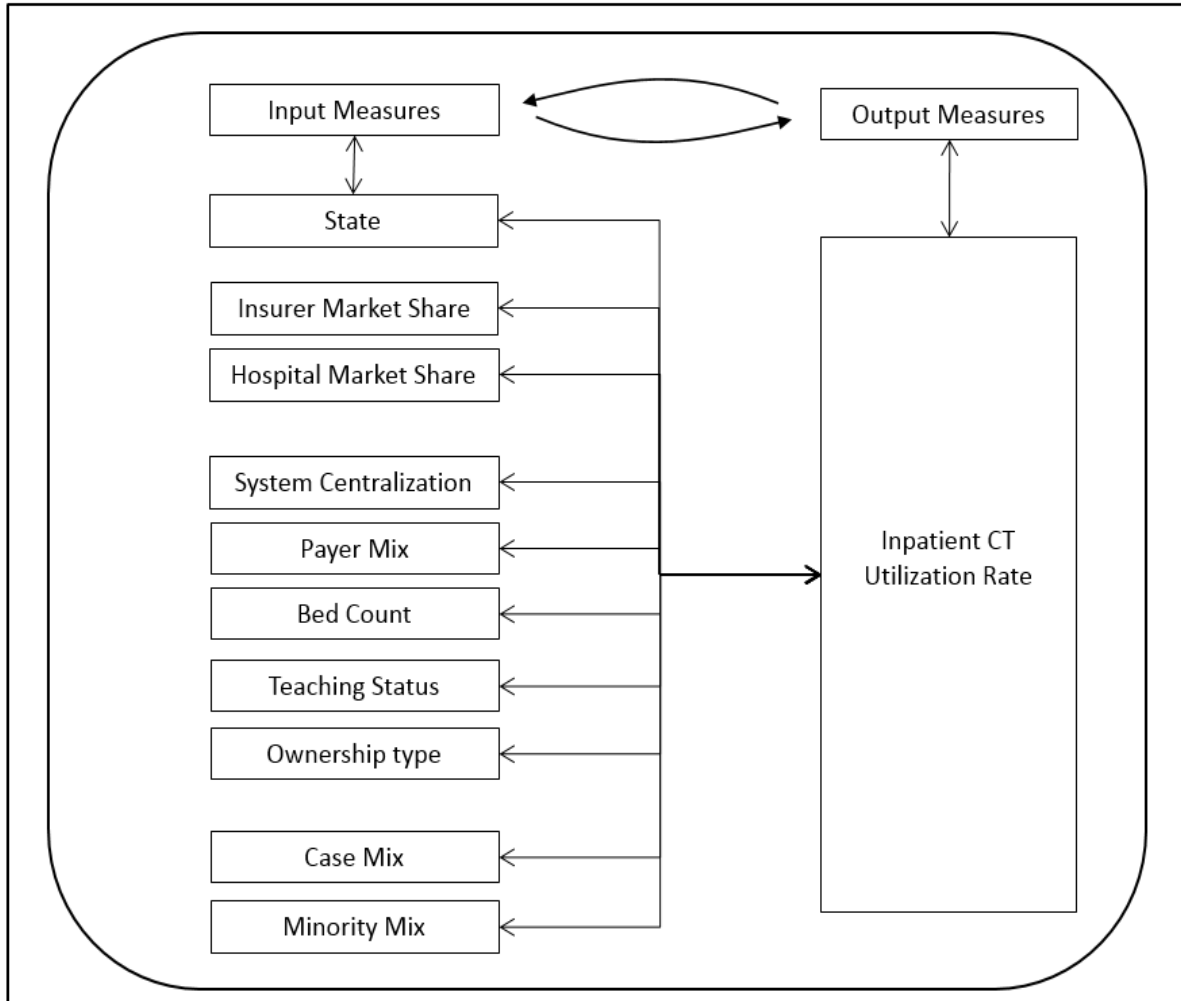


Figure 2. Conceptual Relationship of Variables to Inpatient CT Use

Table 2
Input and Output Measures

Characteristics	Input Measures	Output Measures
State	State	
Markets	a) Insurer market share b) Hospital market share	
Hospitals	c) System centralization d) Payer mix e) Bed count f) Teaching status g) Ownership type	Inpatient CT Utilization Rate
Patients	h) Case mix index i) Minority mix	

Given the prior healthcare resource work showing significant healthcare resource use variation across even small geographic areas, the state input variable is anticipated to have a strong influence on the demand for inpatient CT services (Bhargavan & Sunshine, 2005; Zhang, Baik, Fendrick, & Baicker, 2012). For this reason, this project suggests the use of state as a control variable.

Study Hypotheses

H₁: Characteristics of markets will be associated with inpatient CT utilization.

Insurer market share. The Herfindahl–Hirschman Index (HHI) is an econometric measure of control over a given market (ACA, 2014). It originated in production industries but was later applied to healthcare. In healthcare, it is a measure of an insurer’s control over its market. Increasing insurer control of a local market is expected to be associated with the demand for inpatient CT services.

Hospital market share. The hospital HHI is also a measure of control and concentration of a hospital’s local market (Zwanziger & Mooney, 2005). With domination of the local market, a hospital faces decreased threats of competition and substitute, alternative choices by consumers. Also, hospitals with a high market HHI measure can more often negotiate preferential contracts with the commercial insurers. Therefore hospitals with higher market HHI measures (i.e., less competitive markets) are expected to be have associated changes in their inpatient CT rates.

H₂: Characteristics of hospitals will be associated with inpatient CT utilization rates.

System centralization. The literature review suggest that belonging to a centralized system may result in associated changes in CT utilization rates. Membership provides better opportunities to coordinate care resources and share previously performed studies, thus reducing clinician demand for the repetition of prior studies. Membership also decreases the likelihood of

local competitors providing an adequate substitute good. Becoming a system member stands to increase both the local and regional market control and negotiating power. A summary of objectives, research questions and hypotheses is presented in Table 3.

Table 3
Summary of Objectives, Research Questions, and Hypotheses

Objective	
Objective 1: To characterize the degree of variation in inpatient CT rates across the hospitals of multiple states and markets.	
Objective 2: To evaluate the relationship between inpatient CT performance and the proportion of commercial payers across multiple markets and institutions.	
Objective 3: To evaluate the relationship between inpatient CT use and the characteristics of markets, hospitals, and patients	
Research Questions	Hypotheses
Are the market characteristics related to inpatient CT utilization?	Hypothesis 1: Characteristics of markets will be associated with inpatient CT utilization rates.
Are hospital characteristics related to the rate of inpatient CT utilization?	Hypothesis 2: Characteristics of hospitals will be associated with inpatient CT utilization rates.
Are patient characteristics related to inpatient CT utilization?	Hypothesis 3: Characteristics of patients will be associated with inpatient CT utilization rates.

Payer mix. The literature review showed that commercial payers tend to observe higher rates of CT utilization than government payers such as Medicare and Medicaid. The addition of payers above and beyond the fixed reimbursements for Medicare and Medicaid add to organizational complexity. This suggests that the superior reimbursement and increased margin for commercially insured patients results in a disincentive to limit or restrict the higher margin care in any way. Therefore it is expected that hospitals with increasing proportions of

commercially insured inpatients are predicted to observe changes in the use of inpatient CT utilization.

Bed count. The literature review showed that bed count has been frequently used in health services utilization research, and that larger hospitals tend to have more complex patients. In many cases, the very largest hospitals in regional systems are often tertiary referral centers where the highest acuity patients are cared for by multiple specialty teams. This increasing organizational complexity frequently demands a CT examination as the standard of care. History suggests that a larger hospital size will be associated with increased CT utilization.

Teaching status. The literature review demonstrated that academic hospitals, with both training programs and more specialized faculty care, have higher CT rates in the ED. This duality exists because less experienced physician trainees, who may be less knowledgeable about the appropriateness of a study, may order them more frequently. Also, their more advanced specialist supervising physicians may have more knowledge about potential study applications. These factors compound with the observation that academic hospitals are shown to be organizationally complex with many layers of care frequently resulting in higher CT utilization rates. This demand for services at academic centers suggests that teaching hospitals will observe higher rates of inpatient CT utilization.

Ownership type. For-profit hospitals have been previously observed in the literature to engage focus more explicitly on revenue and costs. An unnecessarily performed inpatient CT exam is costly lost revenue opportunity. For-profit hospitals therefore have a greater financial incentive to engage in centralization and coordination of services. This focus is expected to result in associated changes to the inpatient CT utilization rates. Therefore, it is expected that not-for-profit ownership will be associated with increased inpatient CT utilization.

H₃: Characteristics of patients will be associated with inpatient CT utilization rates.

Case mix. As presented in the literature review, the overall acuity of a hospital's inpatient case mix is likely associated directly with its CT utilization patterns. Increasing case mix reflects increasing patient acuity. The overall patient population presents as sicker and in need of more comprehensive care, driving an increase in demand. The increased demand from a higher hospital case mix index is expected to be associated with increased inpatient CT utilization rates. Therefore, it is hypothesized that a decreasing case mix index will be associated with a decreased the patient need and demand for inpatient CT scans.

Minority mix. It was demonstrated in the literature review that nonwhite patients both elect to use fewer medical imaging services and have physicians who tend to be less likely to use medical imaging in their delivery of care. The ascribed reasons included socioeconomic status, a decreased likelihood to seek medical care, suspicion of healthcare providers, health insurance coverage, and some instances of discrimination. Regardless of the reason, as the discharged proportion of patients who are nonwhite increases, the demand for inpatient CT services is expected to decline. Therefore as the proportion of patients identified as white decreases, the rate of inpatient CT utilization is anticipated to decrease.

Chapter Summary

This chapter provided the rationale for explaining the probable relationships between the input and output variables of the conceptual framework. The framework is dynamic and flexible within its assumptions and limitations, allowing adequate assessment of these relationships between market, hospital, and patient factors. The multi-institutional analysis of CT exam utilization across the entire inpatient population is novel and may have direct, pragmatic implications for administrators, policy analysts, and institutional planners.

Chapter 4: Methodology

Overview

This chapter provides greater detail into the methodological techniques used to conduct the study. It also details the research design, data sources, and analytical techniques to be employed in answering the research questions and testing the hypotheses. This chapter will discuss data validity, data management techniques for reliability, and variable selection. This study will be submitted to the Virginia Commonwealth University Institutional Review Board (IRB) for approval as an exempted study per Title 45 Part 46 of the Code of Federal Regulations. No human subjects will be involved in this study, nor is there any individually identifiable information obtained, stored, or accessible during the conduct of this study.

Research Design

The study is designed to determine if inpatient CT utilization is associated with the characteristics of 1) markets, 2) hospitals, and 3) the hospitals' patient populations. The study is a retrospective, non-experimental study of secondary data collected for administrative purposes (Polit & Beck, 2008). It is a correlational study design. The term "correlational study" is traditionally applied to studies that are purely observational or descriptive, but a statistical analysis is performed (Cook & Campbell, 1979). To accomplish the study aims, the design needs to permit an exploration of the potential correlations between the constructs of interest and their representative variables.

The study uses a four-state sample of convenience data. The data represent a complete cross-section of hospitals, both within systems and independent, for the entirety of the calendar year 2015. This data has been made available through Intellimed Inc., a commercial vendor of aggregated of hospital discharge data. The study design examines the relative magnitude and the directionality of variable relationships as they are underpinned by the conceptual framework described in Chapter 3 (Cook & Campbell, 1979; Polit & Beck, 2008). A more robust experimental design would require interventions to assess the causal factors of inpatient CT utilization, which is not within the scope of this project. An intervention specific to and exclusive to radiology resource utilization would be ideal. The single cross-sectional snapshot provided by this retrospective study of an evolving system proves appropriate for an initial evaluation of market forces, hospital characteristics, and patient characteristics on multi-market inpatient CT utilization.

Research Design Validity

The validity of the research design is critical to the successful and accurate completion of the study. This section reviews four major types of validity that have been identified as key to the research design process of non-experimental studies. These validities are statistical conclusion, internal, construct, and external (Polit & Beck, 2008, p. 291). These concepts are summarized in Table 4, along with the threats they may pose and how those are being addressed in this study.

Statistical conclusion validity.

Statistical conclusion validity is the assessment of the actual existence of an empirical relationship between study variables. The primary way to support statistical conclusion validity in a retrospective, cross-sectional study is to maintain adequate sample size. This requires the

Table 4
Summary of Validity Types, Threats, and Mitigation Techniques

Validity	Threats	Mitigation Technique
Statistical Conclusion	Power Range	Maintain adequate sample size / delimit included variables. Operationalize variables based upon prior literature.
Internal	Temporal ambiguity Selection Instrumentation Endogeneity Maturation	Assess logical adequacy. Use instrumental variable analysis. Sample a full calendar year cross-section.
Construct	Inadequate preoperational explication of constructs	Use qualitative description. Operationalize based on prior literature.
External	Poor sample representativeness	Sample multiple states and locations. Demonstrate varying sample dimensions. Use comparison data

careful inclusion of literature-supported variables. The maintenance of an adequate sample size will be discussed in greater detail later in the Power Analysis section. Also, this study will operationalize variables in a manner consistent with prior examples from the literature so as to help ensure adequate range and statistical power to detect differences.

Internal validity.

Internal validity is an assessment that the relationships proposed by the research design are in fact a true representation of reality. Internal validity threats are of particular concern in correlation studies due to the risk of spurious, extraneous, uncontrolled relationships in correlational studies (Polit & Beck, 2008, p. 295). These competing causal explanations are delimited during the design process by controlling for the available characteristics of markets, hospitals, and patients that may be associated with or related to CT utilization rates. If possible,

an instrumental variable analysis will be performed to assess endogeneity, the effects of uncharacterized variables, and the validity of relationship (Baiocchi, Cheng, & Small, 2014). Internal validity is also supported through an assessment of the temporal cause and effect of variables (Polit & Beck, 2008, p. 291). Independent variables must be the logical antecedent of dependent variables for the maintenance of internally valid relationships. To delimit any complications of selection or self-selection bias, the cross-sectional nature of this study is intended to include as many hospitals as possible within the four-state sample. Selection bias is a legitimate threat to internal validity in many studies given the investigator's ability to potentially bias the study sample (Polit & Beck, 2008, p. 295). The only selection that occurs in this study, the determination of a hospital to participate in a system, is outside of the investigator's control. Hospitals may remain independent or join systems for any number of reasons (Alexander, Halpern, & Lee, 1996; Keeler, Melnick, & Zwanziger, 1999). As discussed in detail in Chapter 2, drivers include but are not limited to a desire for autonomy, protection of resources, access to capital, economies of scale, or financial undesirability. An indication of system membership is to be featured in the model and will have great implications on generalizability. Generalizability will be discussed in greater detail below, and will be aided by descriptive statistics.

Maturation is relevant to any change that occurs as a function of the passage of time (Polit & Beck, 2008) Institutions may have continually evolving and variable rates of CT utilization as a result of varying factors. Economic conditions and incentives/disincentives may change over the course of time. New physicians, new devices and techniques, changing patient demographics, new technology applications, or industry consolidation have all been previously noted to alter health service utilization rates (see Chapter 2). Likewise, changes may be observed and adopted at varying rates across different markets or states. This risk will be mitigated by

making the cross-sectional term of this study a full calendar year. Year-over-year trends and changes will not be observed with this design, but seasonal variations will be delimited to provide a snapshot of the current status of utilization.

Construct validity.

Construct validity is an assessment of how well the research design operationalizes the construct given the use of selected measures or variables. Polit and Beck (2008, p. 300) assert that this is the key to “translating the resultant evidence into practice.” They go on to report that secondary data studies are susceptible to the propensity of researchers to identify patterns in data when there may be none. This susceptibility increases when there is an “inadequate preoperational explication of constructs” (Cook & Campbell, 1979, p. 64). This is mitigated by qualitative description. Adequate qualitative description is achieved in part by offering the explanation with the greatest “clarity & parsimony” (Bacharach, 1989, p. 510). This project design takes careful consideration in the selection of variables from higher-level input and output constructs only after ensuring their logical adequacy. Furthermore, they are operationalized as indicated from the literature. Prior literature use is summarized in a later section dedicated to variables.

External validity.

External validity concerns how well the observed relationships and findings of the study generalize to other contexts, settings, and conditions (Polit & Beck, 2008, p. 302). It is dependent upon the representativeness of the sample being used as it relates to the general populations of hospitals, market, and insurers. Therefore representativeness is the primary threat to external validity. A broad, heterogeneous sample is anticipated to improve the representation of construct exemplars. Along with careful adherence to the study design, adequate construct representation

enhances the external validity of any findings (Polit & Beck, 2008, p. 302). Descriptive statistics will be provided for each variable as part of the results to more fully understand the limitations of any generalizations. The results of the four-state convenience sample of non-Federal, acute care hospitals will be interpreted cautiously given their exploratory nature.

Data Sources

This study uses secondary data to evaluate the existence of relationships between hospitals, markets, their patient characteristics, and the likelihood of inpatient CT utilization. The six data sources that are used come from four different entities: Intellimed, Inc., the AMA, the American Hospital Association (AHA), and the Centers for Medicare and Medicaid Services (CMS). CMS is the provider of Hospital Compare, case mix, and Open Payment data. Table 5 provides a summary of data variables, their sources, linking variables, and related characteristics. The sources all contain de-identified patient information. Data from each source are linked by common variables into a single file for analysis.

Intellimed, Inc. is a healthcare data company that specializes in market analytics. Intellimed provides data associated with a patient origin, hospital market position, service line information, and physician resource utilization (Intellimed, 2016). Intellimed makes available to clients Healthcare Cost Utilization Project (HCUP) data from the Agency for Healthcare Research and Quality (AHRQ) on the hospitals and providers associated with each inpatient care episode (AHRQ, 2017). This data is aggregated from the National Uniform Billing Committee UB-04 form that is associated with each patient episode billed to CMS or to a private payer (National Uniform Billing Committee, 2017). Inpatient care episodes have ancillary service indicators for the use of computed tomography services.

Table 5

Summary of Data Sources, Variables, and Key Characteristics

Data Source	Linking Variable(s)	Variable	Key Characteristics
Intellimed, Inc.	CMS hospital number; Zip code	Inpatient CT utilization	Volume of cases reported to have had a CT performed while an inpatient based upon Intellimed ancillary revenue database for CY2015.
		Discharge volume	Intellimed data includes inpatient discharge-level detail collected from the UB-04 form for calendar year 2015.
		Payer mix	Payer mix is calculated based upon the payer group from the discharge volume.
		Hospital market share	Calculated based upon Intellimed discharge volume per zip code for each hospital.
		State	Hospital addresses are provided by Intellimed systems.
		Bed count	Reported number of licensed beds for each hospital. (Gresenz, Rogowski, & Escarce, 2004)
		Minority mix	Hospital service mix of minority patients as calculated based upon counts of patient race.
	Core Based Statistical Area	Reported for each hospital location.	
AMA, Competition in Health Insurance (2016)	CBSA & Zip code	Insurer Market Share	HealthLeaders-InterStudy 2014 data reported private payer insurance market concentrations based upon CBSA, available and published by the AMA (AMA, 2016).
AHA Annual Survey (2016)	CMS hospital number	System Centralization	The AHA 2016 annual survey results showing system centralization categorization.
CMS Hospital Compare Data (CMS, 2015)	CMS hospital number	Ownership type FY2015	CMS Hospital Compare data reports ownership type (e.g. Government, Non-profit, Proprietary, etc.).
CMS, FY 2015 (CMS, 2017)	CMS hospital number	Case Mix FY2015	The adjusted case mix index (CMI) for 2017 payments is based on the billed MS-DRGs for Medicare claims during FY2015 and excludes transfers.
CMS Open Payments Data (CMS, 2014)	CMS hospital number	Teaching Status FY2015	CMS updates and reports every October, through the Open Payments system, hospitals that receive payment(s) under Medicare direct graduate medical education (GME), indirect medical education (IME), or psychiatric hospital IME programs for the upcoming fiscal year. Ref: (Ayanian & Weissman, 2002; CMS, 2014)

The American Medical Association provides an annual report of private payer health insurer market concentrations across the country (AMA, 2016). The 2016 AMA report is based upon 2014 market data from all 50 states and the 388 largest Core Based Statistical Areas (CBSA), a geographic area delineated for use by Federal statistical agencies (U.S. Census Bureau, 2017). The private payer market concentration is reported as a Hefindahl-Hirschman Index (HHI) measure. These HHI measures will be linked to each hospital's corresponding CBSA. If the hospital is located in an area without a reported insurer HHI, i.e. an area with a smaller population, then the corresponding state HHI will be linked.

The AHA annual survey results (2016) provide details related to hospitals, the services, they provide, facilities they operate, staffing, and physician arrangements, along with other institutional measures. Of particular interest is the information related to system affiliation and cluster taxonomy as a measure of centralization (Bazzoli, Shortell, Dubbs, Chan, & Kralovec, 1999). The AHA categorizes hospitals in systems as follows: centralized health system, centralized physician/insurance health system, a moderately centralized health system, a decentralized health system, or an independent hospital system. These are consolidated into three categories for this study: centralized (centralized and physician/insurance systems), moderately centralized, and decentralized (decentralized and independent hospital systems).

The Centers for Medicare & Medicare Services publicly report a case mix index file each year, "Hospital Compare" data and "Open Payment" information. The 2017 case mix index (CMI) file reports the non-transfer CMI that is based upon the Medicare patient severity reported by each hospital for the fiscal year 2015 (CMS, 2017). The 2017 CMI is used to adjust the CMS payments to hospitals to reflect the level of inpatient acuity observed at that hospital. The CMI reflects the average diagnosis-related group relative weight for each hospital. CMS also provides

basic hospital characteristic data on its “Hospital Compare” site (CMS, 2015). The CMS “Open Payments” program directory is the source of teaching hospital information for forthcoming fiscal year (CMS, 2014). For this program CMS defines a teaching hospital as any hospital receiving direct or indirect graduate medical education payments in the prior year (CMS, 2014).

Working with secondary data.

Working with secondary data for a retrospective, non-experimental study presents its own set of advantages and challenges. Though convenient, secondary data does not afford the opportunity to customize the data collected to maximize sensitivity and discriminatory ability. The manner, content, and time frame for data are all predetermined and collected for other purposes (Hulley, Cummings, Browner, Grady, & Newman, 2007). As such, the validity of secondary administrative data has been previously brought into question given the discordant purposes between the compilation of data and the goals of the research (Dismuke, 2005; Sarrazin & Rosenthal, 2012). For example, Dismuke (2005) reported that nonrandom systematic underreporting of ICD-9-CM codes for CT in administrative does occur. However, in these studies the gold standard truth is the revenue coding of the universal billing forms, such as those collected from the UB-04 for remuneration given the financial incentive to accurately report the completion of imaging studies on the UB-04 (Dismuke, 2005).

As a commercial vendor of hospital discharge data, Intellimed has a vested financial interest in the validity, accuracy, and consistency of the data it provides. Intellimed collects and makes commercially available HCUP discharge data from the State Inpatient Database (SID) project (AHRQ, 2017). And like HCUP, Intellimed routinely and systematically defines and applies terms across states. This uniformity is a benefit of using a sole provider of SID data and ensures that the same calendar years and type of data detail are pulled for each state and treated

similarly. The Intellimed staff also performs checks to confirm, and edits to correct when necessary, data for consistency across all fields and states. When possible, they also use tools to help ensure validity by confirming that things such as gender codes are aligned with the logically plausible procedures. Also included are tests for temporally logical dates and patient age appropriateness. These conform to HCUP quality controls that include processing and performance of standard quality checks to “confirm that data values are valid, internally consistent, and consistent with established norms” (AHRQ, 2016).

The AMA (2016) provides detailed information regarding their annual methodology. Included are data collection methods, HHI calculation techniques, background information, and rationale. The annually recurring report is deliberately produced in the same manner to allow reproducibility and year-over-year comparisons in support of valid and internally consistent results.

Data collection and management.

Data have been managed using IBM SPSS version 22 (IBM, 2016). The Intellimed revenue module was queried for the discharge data detailing inpatient CT encounters and hospital details. CMS Hospital Compare, Open Payment, and CMI data were each downloaded from their respective locations previously cited. The presence and then accuracy of the CMS provider number was then verified for each dataset and used to merge the multiple data fields. Each hospital’s zip code will be used to crosswalk it to a CBSA congruent with AMA health insurer market data to create the final dataset. These data and their sources were reflected previously in Table 5.

Unmatched, absent, or null values will be identified and quality checked after each merge. Doing so promotes data integrity. This method allows the investigator to readily identify

and preempt the loss of any missing information between unmatched data. It also preserves sample size, power, and the nonrandom removal of cases. This technique will be used during any derivation, grouping, or categorization of non-native variables from within the same dataset. With each iterative check of derived variables, it will also be possible to evaluate the data for patterns that may suggest spurious relationships between variables. Simple cross-tabulations and graphical arrays can reveal the frequency of two or more measures of interest. It also allows the investigator to make necessary adjustments to maintain reliable data (e.g. low categorical counts and low signal strength).

Institutional Review Board.

The secondary and administrative data collected for this study contain no protected health information. The researcher has no access to the primary data or to any patient identifiers. As such, the study does not constitute human subjects research and is except from review by the VCU Institutional Review Board.

Study Sample

The four-state sample represents a total of 181 acute care hospitals that reported performing inpatient CT scans during the calendar year 2015. Of the 181 hospitals, 30 (16.6%) are independent and 151 (83.4%) belong to MHSs (Table 6). These MHSs are spread across 16 different CBSA-defined markets. Included hospitals may be either for- or not-for-profit organizations. Acute care hospitals are more appropriate for this study because they must compete with one another in markets in ways that other hospitals do not. This study excludes Veterans Administration hospitals and long-term care facilities. These operate under a different mandate, are centrally controlled, and do not have to compete in the common marketplace given their unique population of patients and conditions. Similarly, long-term acute care hospitals

Table 6
Included Hospitals by State and MHS Membership, 2015

State	Independent	MHS Member	Total
MD	13	30	43
NV	3	18	21
VA	4	67	71
WA	10	36	46
Total	30	151	181

(LTACH) are licensed and identified as such in Intellimed data. These may be associated with a larger network of hospitals or referral centers, but they do not compete with acute care hospitals for patients. Instead LTACHs typically receive patients from an associated acute care hospital prior to discharging patients to a rehabilitation facility, skilled nursing facility, or home. Hence LTACHs have a distinct function apart from but complementary to acute care hospitals and are also excluded for the purposes of this study.

Power Analysis

Studies conducted with small samples run the risk of failing to detect an actual, real difference, a Type II error (Polit & Beck, 2008). This error is the failure to reject the null hypothesis when it is incorrect. When using previously collected secondary data, the power analysis is performed after data collection to assess the limits of the variable parameters. This helps establish confidence in the findings.

Using multivariate regression techniques to analyze the data allows the application of a rule-of-thumb technique for determining power with a given sample size. Tabachnick & Fidell (2007) suggest a $50+8x$ rule-of-thumb, where x is the number of predictive variables, for multiple regression techniques. This study proposes the use of 11 independent variables plus

three binary covariates in a generalized linear model. With 14 total predictive variables and the resultant power calculation to exceed the 80% threshold, this requires a minimum of 162 cases. This is the generally supported threshold and goal for research power, and represents a four-to-one probability of accurately rejecting a null hypothesis. With 181 cases, this study is adequately powered.

This rule is adjusted for a goal of 80% power with an alpha of 0.05 and an anticipated moderate effect size of approximately 30%. The effect size is a quantification of actual difference between groups. *A priori* sample size calculation for multiple regression finds that given a 30% anticipated effect size, 80% desired power, 14 independent variables, and an alpha probability of 0.05, only 74 cases are needed to detect a difference (Soper, 2016). Should the effect size be halved to only 15%, then this increases to a minimum of 135 cases. The alpha of 0.05 indicates a 5% chance threshold that any differences are simply the result of random variation. The sample size allows for an effect size of approximately 10% without committing a Type 1 error. Type 1 error is common in regression and correlation studies with large sample sizes. Such studies may observe a statistically significant finding when in fact there is no relevant clinical difference, for example. This situation represents the challenge of interpretive value and will be assessed as part of the results and conclusions.

Model, Variables, and Measurements

Variables for this study are used as independent, dependent, and control variables in the regression model. The model evaluates associations between control, market, hospital, and patient variables to the observed inpatient CT utilization rates. This section provides greater detail about how variables are operationalized and measured, how they are associated with the hypotheses, and how they relate to the dependent variables of the model.

Model formulation.

The model aligns with the conceptual framework principles that predict a functional relationship between CT utilization rates and the independent characteristics of markets, hospitals, and patients. The model is as follows:

$(\text{CT count} / \text{discharges}) = f(\text{insurer market share, hospital market share, system centralization, payer mix, bed count, teaching status, ownership type, case mix, minority mix}).$

In addition to the state covariates, there are ten independent variables hypothesized to relate to the frequency of CT utilization. Two describe characteristics of the market, six describe hospital characteristics, and the remaining two reflect the local patient population. Those describing the market are the insurer market share and hospital market share. Those describing the hospital characteristics largely reflect the characteristics of an increasingly complex organization. They are system centralization, payer mix, bed count, teaching status, and ownership type. The remaining two patient characteristic variables are case mix and minority mix. Each variable aligns with a hypothesis described in Chapter 3, as is summarized in Table 7.

Table 7
Summary of Hypotheses and Variables

Hypotheses	Independent Variables
Hypothesis 1: Characteristics of markets will be associated with inpatient CT utilization rates.	<ul style="list-style-type: none">• Insurer market concentration• Hospital market share
Hypothesis 2: Characteristics of hospitals will be associated with inpatient CT utilization rates.	<ul style="list-style-type: none">• System centralization• Payer mix• Bed count• Teaching status• Ownership type
Hypothesis 3: Characteristics of patients will be associated with inpatient CT utilization rates.	<ul style="list-style-type: none">• Case mix index• Minority mix

Dependent variable selection.

The dependent variable, inpatient CT utilization rate, for this study is derived by the combination of two Intellimed-provided measures: the annual count of inpatient CTs performed as an institution and the annual number of discharges. CT utilization has been extensively investigated and reported in the literature and previously in Chapter 2 (Baker et al., 2008; Bhargavan & Sunshine, 2005; Boone & Brunberg, 2008; Brenner & Hall, 2007; Larson et al., 2011). Discharge counts have also been applied to multiple prior studies. Alexander et al, (2009) did use the raw discharge volumes as a control variable in their study of community benefit and uncompensated care as they related to hospital characteristics. However, discharges are more commonly used as a means of adjusting or weighting other variables as is done in this study. Investigators have used hospital-level discharge volumes to calculate variables such as gross and net revenues per discharge (Alexander et al., 2009; Melnick & Keeler, 2007; Trinh, Begun, & Luke, 2010). Others have used the count of discharges to calculate HHI market share concentration in the same way as is proposed for this study and has been previously discussed (Zwanziger & Mooney, 2005). Patient discharge volumes have also been used when testing and comparing other models of market share concentration as well, such as those derived from bed counts or inpatient days (Trish & Herring, 2014). For this study, the inpatient CT utilization rate serves as the dependent variable in the regression analyses against state control variables and the market, hospital, and patient independent variables.

State control variables.

The control variables are derived based upon the sample state. The four states represented in the sample (MD, NV, VA, and WA) require three binary, numerical dummy variables to accurately represent the four states as regression input. The literature review previously

demonstrated the existence of, and hence importance of controlling for, variations across geographic areas. Small area variation in health resource utilization can be sizeable between geographic areas (Bhargavan & Sunshine, 2005; Zhang et al., 2012). This is true of imaging utilization in the Dartmouth Atlas's Health Referral Regions (HRR), which are based upon cardiovascular and neurosurgical referral patterns. Significant differences in imaging utilization have been observed between both large regions and the smaller HRRs (Larson et al., 2011; Onega et al., 2012; Zhang et al., 2012).

Regional and state-level distinctions have been applied to published studies of imaging utilization. One nationwide study placed states into regions for practical purposes and observed significant variation in CT use specifically within the emergency department (Larson et al., 2011). Another observed state-to-state variation in CT use within the Medicare population as well (Bhargavan & Sunshine, 2005). Others include state-level granularity in their analyses (Kirsch et al., 2010; Luke et al., 2011). These observations underscore the importance of including some provision for the control of location. Without controlling for the location, it is conceivable that the shared statistical variation could outsize or may dilute other associations with clinical variation.

For the purposes and scale of this study, treating the state as a covariate remains a necessity to help permit the control of other extraneous political and regulatory differences that may affect utilization rates from state to state, as employed by Alexander et al. (2009). States become the legal frame of reference for many healthcare resource determinants within the output/input market (e.g. Certificates of Need, health insurer licensure, ACA Exchanges, Medicaid determination, etc.). As such, state legislatures can impact the access and utilization of health resources within their borders. Within the four-state sample, only two states are

proximate; the Washington, DC market will straddle two states, VA and MD. In this case, the state covariates will effectively force the model to treat the market as two sub-distinct markets. The statistical control of state-level variables helps protect against extraneous variables and improve the design and internal validity by reducing the likelihood of spurious correlations.

Market variables.

This study makes use of two variables that describe markets and have been previously shown to be associated with healthcare resource consumption. They are detailed and operationalized in the following sections about insurer and hospital market shares.

Insurer market share.

The insurer market concentration is represented by an HHI measure and is another independent variable measure in the model. The literature review showed the commercial insurer consolidation over the years. As an index, HHI can be presented on a scale of 0.0 to 1.0. The Department of Justice and Federal Trade Commission measure of “highly concentrated” is an HHI exceeding 0.25. HealthLeaders-InterStudy (HLIS) produces the leading available data for commercial insurer concentration, which is used annually as a source of data for the AMA (AMA, 2016; Bates, Hilliard, & Santerre, 2012; Trish & Herring, 2014). The HLIS data, as presented in the AMA work, provides market share and insurer concentration as a function of the insurer-reported persons covered in an MSA region (AMA, 2016). This is somewhat limited in precision and discrimination, as it does not adjust for actual days admitted to reflect a hospital and area’s actual hospital discharge market. However, others have similarly used insurer market concentration at the level of the MSA in their study of how insurers drive systems to explicitly coordinate and share services (Trinh et al., 2010; Trish & Herring, 2014). The benefit of the CBSA-level method is that it provides the most granular market data available. Others have

evaluated insurer market power between states by using HHI at the state level but noted limitations in the absence of more granular data (Bates et al., 2012).

The input market interface between insurers and hospitals is where an insurer's pooled collection of covered persons is reflected in their negotiating power with providers. It is an important distinction recognized and utilized by others in their works (AMA, 2016; Trish & Herring, 2014). Trish & Herring (2014), using data from the HLIS consortium, evaluated the collective bargaining power of insurers' complete portfolios of business as it appears to the hospital input market. This includes fully-insured risk-based coverage as well as administrative services sold to self-insured businesses. They found that insurance premiums fluctuated in response to interplay between the insurer concentration and the hospital market concentration. Premiums were found to be highest when both hospital and insurer concentrations were high, and the least when both concentrations were low and competitive (Trish & Herring, 2014). This seemingly supports the notion that these two are functionally competing forces for market dollars.

Hospital market share.

The hospital market share is a continuous variable observed from 0.0 to 1.0, where 1.0 reflects a perfect monopoly. Each hospital has a weighted market share. The weighted market shares are calculated by using the discharged patient zip code, the smallest unit of area available (Zwanziger & Mooney, 2005). Such weighted market shares are calculated through a multistep process. The first step is to A) calculate the Herfindahl-Hirschman Index (HHI) for each zip code (HHI_j). A zip code's HHI is the sum of the squared proportions of each hospital servicing that zip code. The second step is to B) calculate the proportion of each hospital's discharges to each zip code (w_{ij}). The products of the multiple A) zip code HHIs and B) each hospital's zip code

proportions are then summed into a cumulative, weighted market share for each hospital (HHI_i). This is represented arithmetically as follows:

$$HHI_i = \sum_j w_{ij} HHI_j$$

where the HHI_i is the HHI for the i^{th} hospital, the w_{ij} is the proportion of discharges from the zip code j that are discharged from hospital i , and HHI_j is the HHI for the zip code (Zwanziger & Mooney, 2005). An example of how to calculate HHI is included in Appendix A. This measure of hospital market concentration ensures that hospital competition is operationalized locally by actual discharges and weighted relatively. The limitation of this method is that it does not adjust for length of stay. Other methods for calculating market share, such as relative market bed counts, have been investigated alternatively but found to be largely correlative to a discharge rate basis (Trish & Herring, 2014).

Hospitals variables.

This study makes use of five variables that describe hospitals and have been previously shown to be associated with healthcare resource consumption. They are system membership, payer mix, bed count, teaching status, and ownership type. The variables are detailed and operationalized in the following sections.

System centralization.

System centralization is identified by the AHA cluster identifier category. It has been suggested that studies focusing only on system membership may miss the impact of system type on quality outcome measures (A. S. Chukmaitov et al., 2009). The cluster type categories are reduced into three tiers for system members (centralized, moderately centralized, and decentralized), and there is a separate identifier for independent hospitals that are not in systems. These four categories are

represented by three dummy variables representing centralized, moderately centralized, and decentralized with independent as the reference category.

Payer mix.

Payer mix is a commonly used descriptor of hospitals (Larson et al., 2011; McCullough, 2008; Muller, 2010; Trinh et al., 2010; Trish & Herring, 2014). It is a numerical measure of the proportion of a facility's inpatients who are covered by a commercial payer as compared with Medicare, Medicaid, or self-pay. Having a larger share of patients who are covered by commercial payer has been shown to result in higher CT utilization rates. Larson et al. (2011) showed a significant difference in emergency department CT utilization based upon the government origin of the third-party payer. A smaller government payer mix has also been observed to have a relationship with the way in which systems allocate resources between their hospitals (Trinh et al., 2010). For example, others showed that a decreasing proportion of government payers in the payer mix relates to the diffusion and adoption of radiologic technology (McCullough, 2008; Shin, Menachemi, Diana, Kazley, & Ford, 2012). It stands to reason that this confluence of factors will result in a continued association between CT use and payer mix in the inpatient setting. The independent variable for payer mix in this model is infinitely variable and may theoretically range from 0.0 to 1.0.

Bed count.

The staffed inpatient bed count is a measure reported by hospitals for the AHA annual survey and is available via Intellimed. The variable is continuous but will never be less than 25 due to the prior decision to exclude critical access hospitals. It is a commonly used indicator for a hospital and expected to positively correlate with CT use. Multiple investigators have used the bed count to some effect in their work. Size has been positively correlated with hospital

efficiency (Sikka et al., 2009). It has also been positively associated with service sharing and efficiency (Trinh, Begun, & Luke, 2008; Trinh et al., 2010). Likewise, bed count has been used as a proxy for hospital complexity such that it defines the scale and scope of the organization (Luke et al., 2011; Muller, 2010). Interestingly, the expanded scope and improved efficiencies associated with bed count have been observed despite the association between the number of beds and uncompensated care (Alexander et al., 2009). The variable is continuous and >25 . However, variable exploration and model requirements may additionally result in the need to group similarly sized hospitals together to ensure robust, meaningful findings without sacrificing statistical power. One example includes bed size categories < 100 , $100-249$, $250-399$, and ≥ 400 (Zwanziger, Melnick, & Bamezai, 2000). Another consideration would be the adjustment of bed count by patient discharge volume, but that would impair the model discriminatory ability between the variables.

Teaching status.

Multiple investigators have evaluated the effect of residency training programs on the utilization of healthcare resources and imaging in particular. Some have found the relevancy of the academic distinction due to the prior observation that CT utilization increases along with the level of training of the ordering physician, which likewise tends to increase at teaching institutions (Kirsch et al., 2010). Larson et al. (2011) evaluated hospital teaching status and CT utilization but defined the teaching status of an institution on the basis of the percentage of patient visits involving a resident or intern. Their threshold was 10% or more for deeming an institution to be a teaching one. Others deemed emergency departments as academic when more than 50% of their patient visits involved a resident or intern physician (Korley et al., 2010).

However, this method is not prudent for this study given the scope beyond the emergency department to the inpatient care areas.

For this study, the teaching status indication is distinguished by membership in the American Association of Medical Colleges' (AAMC) Council of Teaching Hospitals (COTH). Studies have previously used COTH members as a proxy for structural complexity to reflect teaching status (Alexander, Weiner, Shortell, & Baker, 2007; Moriya, Vogt, & Gaynor, 2010). COTH membership includes almost 400 members nationwide and is limited to hospitals that have at least four active and approved residency programs (AAMC, 2015), two of which must be in the core disciplines of surgery, medicine, pediatrics, family medicine, psychiatry, or obstetrics and gynecology. This study likewise uses a binary variable for teaching status to indicate its membership in COTH.

Ownership type.

Hospital ownership type has been used to distinguish between the differences in legal, administrative, and organizational arrangements of for-profit (FP) and not-for-profit (NFP) hospitals. The distinction is important because ownership type is believed to potentially affect the structural and strategic decisions facing an organization (Sikka et al., 2009). This study uses a binary numerical system to distinguish FP and NFP hospitals. Some investigators have used a three-category indicator that further distinguishes the NFP hospitals into a local, government-owned sub-category (Larson et al., 2011; Moriya et al., 2010). However, the binary indication is more useful in this context and not uncommon (Muller, 2010; Sikka et al., 2009; Trinh et al., 2010). This is because FP hospitals have shown greater cost sensitivity to competition driven by hospital consolidation than their NFP competitors (Keeler et al., 1999). Likewise, binary ownership indicator has also been used in other works investigating organizational resource and

service coordination (Muller, 2010; Trinh et al., 2010). Similarly, FP ownership has been shown to be associated with a decrease in uncompensated care as compared to the nonprofit groups (Alexander et al., 2009). However, the model will also be tested using the three category method that distinguishes non-Federal, local government-operated hospitals despite their limited numbers in the four-state convenience sample.

Patient variables.

This study makes use of two variables that describe the patient population and have been previously shown to be associated with healthcare resource consumption and medical imaging: case mix and minority mix. These variables are detailed and operationalized in the following sections.

The independent variables available to represent patient characteristics in the model reflect varying degrees of patient complexity. Each hospital has a service population that is reflected in the characteristics of the actual patients receiving care there and not simply those representing the population of the surrounding areas. Patients may elect to receive care at different institutions around them either through self-selection or through financial incentives associated with the insurer, employer, and hospital relationships. This type of granularity allows differentiation between hospitals occupying the same census bureau areas. Two such patient characteristics are case mix and minority mix.

Case mix.

Case mix is a measure of the patient characteristics of a facility. It represents inpatient acuity and is measured by the Case Mix Index (CMI) for fiscal year 2015 from CMS (CMS, 2017). This score is determined by the complexity of the facility's Medicare patient population. The CMI value is calculated by summing the diagnosis-related group (DRG) weighting and then

dividing by the number of Medicare discharges (CMS, 2017). CMI is widely used in health services research despite its specificity to Medicare patients. One example in particular employed case mix adjustments to evaluate the performance and efficiency of large urban hospitals (Grosskopf & Valdmanis, 1993). They concluded that CMI utility is sustained even in more heterogeneous samples of patients and facilities.

Other investigators have used CMI as variables for statistical model construction (O'Neill, Rauner, Heidenberger, & Kraus, 2008; Trinh et al., 2010). CMI has been described as “capturing the variation in both the complexity and resource-intensity of inpatient cases” in using it as an ideal determinant of healthcare resource utilization (O'Neill et al., 2008, p. 178). CMI was likewise used to represent patient complexity in the evaluation of resource sharing and the efficiency of systems (Nayar & Ozcan, 2008; Trinh et al., 2010). One recent example used case mix adjustment to understand the utilization of imaging resources in particular (Shinagare et al., 2014). As an index score, CMI is measured on a continuous numerical scale and centered on 1.0.

Minority mix.

Investigators have previously represented patient characteristics with a measure of minority mix. Inpatient populations vary largely given the prior observations that race and ethnicity seem to be associated with health service utilization (Korley et al., 2010; Larson et al., 2011). Multiple researchers have used black, white, and other as categorizations for races in American research. Some have used it specifically with the all-cause CT utilization in the ED to significant effect (Larson et al., 2011). This method has likewise been used to investigate the injury-related use of medical imaging in the ED (Korley et al., 2010). Other investigators have observed significant associations between the indication of minority status and other imaging modalities. Onega et al. (2012) investigated the use of positron emission tomography, which is

closely related to CT. Schueler, Chu, and Smith-Bindman (2008) investigated the use of mammography. This has been attributed, at least in part, to a historical distrust of the medical system. The minority status of a hospital's patient population was acutely relevant in Groeneveld, Laufer, and Garber's work (2005). In it they demonstrated how minority patients were observed to have decreased access to advanced procedures. They found the diminished rate of advanced resource utilization was compounded when minority patients were treated at a hospital with relatively high minority census. They observed this pattern to be consistent across the 11-year study period. With findings suggesting the clinical significance of non-white status against all other factors, the most prudent solution to represent and preserve statistical rigor is to use the proportional measure of the non-white patients discharged. Therefore, the minority mix is the numerical proportion of all discharged patients from that facility who are reported as belonging to a minority group or being non-white. The variable is numeric and continuous on the spectrum of possible values from 0.0 to 1.0. Other combinations of categorical representations will be tested as the findings suggest.

Collectively, the ten independent variables of the model align to test the construct relationships and association between 1) market, 2) hospital, and 3) patient characteristics. The model variable summary is provided in Table 8. Model performance metrics will be presented and reviewed for normality and representativeness. Residual differences between observed and predicted values will be analyzed for symmetrical distribution, central tendency, and patterns to assess model fit. Residual analysis will include assessments for heteroscedasticity, non-linearity, and outliers. Adjustments will be made using generally accepted statistical methods to correct for problems of fit across markets, hospitals, and patient characteristics. The selection of specific data analysis methods follow in the next section.

Table 8

Model Variable Summary

Type	Variable	Description	Measure	Data Type
Control	State	The four states are coded using three dummy variables.	State = VA, MD, NV, or WA	Categorical
Dependent	CT utilization rate	The inpatient count of CTs performed annually over the number of hospital discharges in the same calendar year.	Proportion from 0 to 1	Continuous
Independent	Insurer Market Share	HHI of local insurance market based upon the summed proportions of covered lives within the CBSA commercial market.	Proportion from 0 to 1	Continuous
	Hospital Market Share	The sum of a hospital's weighted share of service zip codes based upon patient discharges	Proportion from 0 to 1	Continuous
	System Centralization	An ordinal indication of system centralization (centralized, moderately centralized, decentralized, or independent).	Four levels	Categorical
	Payer Mix	The percentage of discharged patients using a commercial payer/insurer.	Proportion from 0 to 1	Continuous
	Bed Count	An indication of the number of inpatient beds reported by a hospital for the AHA survey.	Numerical, ≥ 25	Discrete
	Teaching Status	An indication of whether a hospital has a physician residency training program.	Categorical "Y" or "N"	Categorical
	Ownership Type	An indication of For Profit / Not for Profit ownership.	Binary "For Profit" = 1	Binary
	Case Mix	An indication of the CMS DRG case mix index for the institution.	Numerical ≥ 0	Continuous
	Minority Mix	The percentage of discharged patients identifying as a minority.	Proportion from 0 to 1	Continuous

Data Analysis

The process of data analysis is stepwise and deliberate, and to ensure data reliability, it must be a continual process as well. A thorough exploration and review of all values for dependent, independent, and control variables will be performed. The data will be exported from Intellimed and merged into a single flat file representing all four states using Microsoft Excel. The data will then be analyzed using IBM SPSS Statistics Version 22 for Microsoft Windows. The dataset will be run through discrete steps consisting of data exploration, cleaning, descriptive analysis, and correlational analysis.

Data quality.

The data will be explored, evaluated, analyzed, and checked for quality using descriptive and univariate techniques. These include cross tabulation and a correlation matrix prior to multivariate statistical analysis. The results of these processes will determine any necessary value replacement or data transformation using acceptable statistical techniques. Part of the data exploration and cleaning process will be dedicated to the performance of a missing values analysis (MVA). It will be followed by the computation and derivation of model variables.

Descriptive and univariate techniques to be employed will include visual representations of the data. MVA will be used to identify and then repair, replace, or exclude any systematically missing or invalid data, as necessary. Cross-tabulation, scatterplots, and histograms will assist in evaluating for kurtosis, skewness, and heterogeneity of data. Correlational analysis between variables (i.e. zero-order correlation) will demonstrate the presence or absence of normality and the need for any subsequent transformation of the data. This will be the means by which highly correlated variables, or even tautological variables, will be assessed and identified (Tabachnick & Fidell, 2007). In addition, the degree of variation across states, markets, and cities will be

described. Frequency tabulations and the supporting distributions will be demonstrated for categorical data. Mean, median, standard deviation, and ranges of numerical data will be presented as well.

The results of the univariate analysis will dictate any necessary data transformation techniques. Variables will be binned, categorized, truncated, and transformed numerically as prescribed. Transformations are intended to help improve the fit of the model and the integrity of any subsequent statistical model. Univariate analysis and data exploration will then be followed by regression analyses, both multivariate and generalized.

Selection of statistical techniques.

The study framework outlined in Chapter 3 requires the application of a regression model suitable for the count of event frequency. This study uses a rate ratio as a measure of event incidence: the count of annual CTs performed over an exposure represented by the count of annual discharges. Given the relatively large sample size, a multivariate regression - ordinary least squares (OLS) model will be given first consideration and tested for appropriateness. A negative binomial regression model is an alternative technique should the OLS model be found to be inappropriate.

Multivariate regression.

Despite potential limitations with count-frequency data, a standard linear multiple regression that represents the relationship between utilization and multiple independent variables will be tested and used if appropriate. This will be a standard OLS regression model. With an adequate sample size, standard linear methods can be adequate for count-frequency data. The OLS regression will be used to represent and evaluate the relationship between the CT use rate per inpatient discharge and the characteristics of markets, hospitals, and patients. Regression permits

association and correlation between not only the dependent variable and the independent variables but also between the independent variables themselves in the form of shared variance (Tabachnick & Fidell, 2007). The assumptions of OLS are linearity, homoscedasticity, the absence of autocorrelation, error normality, and no multicollinearity (Borghers & Wessa, 2012). Standard regression techniques will permit the inclusion of variables contributing to the increase in R² variance. Independent variables will be converted and adjusted as necessary and appropriate.

The standard OLS model is as follows:

$$\begin{aligned} &(\text{Count of INPATIENT CT Exams})/(\text{Count of annual DISCHARGES}) = X + B_{ST} \\ &(\text{STATE as COVARIATE}) + B_{IM} (\text{INSURER MARKET}) + B_{HM} (\text{HOSPITAL} \\ &\text{MARKET}) + B_{SM} (\text{SYSTEM CENTRALIZATION}) + B_{PM} (\text{PAYER MIX}) + B_{BC} (\text{BED} \\ &\text{COUNT}) + B_{TS} (\text{TEACHING STATUS}) + B_{OT} (\text{OWNERSHIP TYPE}) + B_{CMI} (\text{CASE} \\ &\text{MIX INDEX}) + B_{MM} (\text{MINORITY MIX}) \end{aligned}$$

The value X is a constant that equals the y-intercept of (CT utilization rate) when all of the independent variables are zero (0).

Standard tests of multicollinearity, normality, and between group variances will be performed and reported.

Negative binomial regression alternative.

If the count data has unique requirements resulting from non-normality and data limits and fails the tests of OLS, then a generalized linear model (GLM) is needed to address the non-normal distributions. This is not uncommon of dependent variables (DVs) that are count data and smaller sample sizes (Gardner, Mulvey, & Shaw, 1995). This can cause some linear regression methods to predict nonsensical negative events (Gardner et al., 1995; Ver Hoef & Boveng,

2007). Together, these may suggest the Poisson distribution as the GLM of choice to address both non-normality and delimited data. Gardner et al. (1995) point out that an advantage of a Poisson distribution is that it maintains statistical power often lost when other techniques force the categorization or dichotomization of DVs to adjust for data limits.

The Poisson distribution, however, requires the mean and variance to be equal for accurate results. This equality is uncommon in biological or social science count data (Ver Hoef & Boveng, 2007). The variation often exceeds the mean, and the data are considered overdispersed when this happens. Closely related to but less stringent than the Poisson regression is the negative binomial. It will tolerate overdispersed data in addition to non-normal, delimited count data (Gardner et al., 1995; Ver Hoef & Boveng, 2007). Table 9 summarizes the appropriateness criteria for employing the negative binomial.

Table 9

Assessing the Appropriateness of the Negative Binomial Regression

Appropriate when:

- The occurrence of one DV event does not affect the likelihood of another.
 - The dependent variable is count data and may be an incidence rate ratio.
 - Negative values do not occur (and zeroes are rare).
 - The dependent variable is not normally distributed.
 - The data are likely overdispersed.
-

Given count data and the limited time and space interval, a negative binomial regression may be appropriate. The exposure in the negative binomial is the discharge volume observed during the same one-year time period. The log link function of the negative binomial ensures that predicted counts remain non-negative. The expected value of the incidence rate DV to the linear function of the independent variables is as follows:

$\ln E(Y_i | x_{i1}, \dots, x_{ik}) = \beta_0 + \beta_1 x_{i1} + \dots + \beta_k x_{ik}$; when values of $i = 1, \dots, n$. given that β represents the various independent variables.

$\ln(\text{Count of INPATIENT CT Exams})/(\text{Count of annual DISCHARGES}) = X + B_{ST}$
(STATE as COVARIATE) + B_{IM} (INSURER MARKET) + B_{HM} (HOSPITAL MARKET) + B_{SM} (SYSTEM CENTRALIZATION) + B_{PM} (PAYER MIX) + B_{BC} (BED COUNT) + B_{TS} (TEACHING STATUS) + B_{OT} (OWNERSHIP TYPE) + B_{CMI} (CASE MIX INDEX) + B_{MM} (MINORITY MIX)

The output of a negative binomial regression, assuming statistical validity, is a convenient tool for practical real world analysis. It may provide coefficients or rate ratios for estimating probabilities of different scenarios. For example, one could potentially extrapolate to determine the probability of inadequate equipment or staffing to handle the anticipated CT volumes. Likewise, the outcome could be applied to anticipate the imaging needs as institutional and market conditions change.

Analytical validation.

Tests of variable normality are necessary to confer rigor prior to executing the model. The Kolmogorov-Smirnov test will be used to test sample normality and goodness-of-fit for the OLS model (Villasenor & Estrada, 2009). A null hypothesis for this test is the normality of the sample. Therefore failure to reject the null means the sample is normally distributed; rejecting the null means the sample is not normal, but is skewed and will dictate transformation. Data transformation may necessitate removing extreme outlier values, log transformations, or square-root derivations. In addition, a Levene's test will be performed on the state and the CBSA levels. The Levene's metric will evaluate the amount of variation between the sample groups. Given the assumption of non-normality in the negative binomial model, a non-parametric Levene

generalization will be necessary to test the equality of variances between samples (Nordstokke & Zumbo, 2010).

Standard statistical tests will be conducted prior to the analysis of results to ensure analytical validity. These are tests of residuals to be performed in addition to the previously described efforts to identify highly correlated, collinear variables and even tautological effects from a singularity. Redundant variables exceeding an intra-correlation of 0.80 will be identified and removed from the analysis (Tabachnick & Fidell, 2007). Residuals will be evaluated for normality, linearity, and an absence of heteroscedasticity between the predicted values of the dependent variable and the errors from the actuals. These scatterplots will assist in determining if additional transformation of the data is necessary. Transformation techniques include log and/or square root transformations. The plots will be evaluated both visually and statistically. Residuals are ideally expected to maintain a linear relationship with the predicted dependent variable scores as well as remaining homogenous along the spectrum of predicted inpatient CT counts.

An evaluation of any analytical output and residual error should include an assessment and consideration of the possible endogeneity of independent variables with the model error. This is indicative of a statistically biased regression coefficient. This consideration is not uncommon in outcomes research and econometric studies, particularly those involving supply and demand (Newhouse & McClellan, 1998). Using a lagged independent variable is one proposed solution for controlling and mitigating endogeneity (Muller, 2010; Newhouse & McClellan, 1998). In applying this principle, this study uses insurer market concentration (HHI_i) data from 2014 as a measure in the model against the latter 2015 hospital inpatient CT count frequency. This is temporally logical given the negotiation of hospital reimbursement contracts with payers in advance of inpatient CT exam performance. However, one should expect an

interplay and a degree of bi-directionality between variables, both conceptually and in temporal arrangement. This is a fundamental challenge and limitation of any interpretation.

Study Limitations and Assumptions

This study provides a snapshot of a single year of inpatient CT studies performed. Given that it is not longitudinal, it cannot show year-over-year trends. This is a relevant limitation given the earlier evidence that found that both hospital and insurer consolidations continue to occur, especially in the wake of the ACA of 2010. As previously stated, the four-state convenience sample limits the generalizability of any findings. Also, this study does not explicitly address the hospital-physician relationship. There are multiple styles of practice arrangements in place that may affect physician autonomy and therefore influence the propensity to order an inpatient CT. Compounding the challenge is that sometimes these arrangements are mixed even within a single institution. It is also not within the purview of this study to assess the appropriateness of the individual CT exams, because individual case information is not available. Likewise, the study explicitly assesses neither institutional quality nor service arrangements that may affect how hospitals and clusters direct their patients based upon acuity or service sharing needs. It is understood that the charges reflected on the UB-04 do not necessarily reflect what was collected. Collection rates may adversely affect actual revenue. This leads to the study assumptions.

It is assumed that charge data on the UB-04 released by the individual hospitals to their state agencies is accurate and complete. It is also assumed that the states of MD, NV, VA, and WA are complete and accurate in their aggregation of the UB-04 data when collecting and subsequently transferring data to Intellimed. It is further assumed that the quality checks performed by Intellimed are adequate for the accurate receipt and compilation of data, and that in

doing so they have uniformly defined measures and applied them across the multiple states consistently.

Chapter Summary

This chapter detailed the methods to be employed during the conduct of this study. It provided detail regarding the research design, the study questions and hypotheses, and the analytical plan for addressing them. The chapter also provided further information regarding the data sources, variable construction and validity, and the statistical methodology. Equally important, it clarified the assumptions necessary to perform the study and demarcated the necessary limitations of that dataset that must be accepted.

Chapter 5: Results and Analysis

Overview

This chapter presents the results of the analytical plan that was detailed in the prior chapter on methodology. The chapter begins with data exploration and descriptive work. That work is followed by univariate results to assess normality and transformations. Finally, there is a formal assessment of multicollinearity before concluding with the results of multivariate regression.

Data Exploration

This data exploration section addresses missing values and the inspection for outliers. It also addresses the descriptive analyses of the continuous and categorical variables.

Missing values.

The four-state dataset of 181 acute care hospitals (non-critical access, non-VA) that provide inpatient CT services was reviewed for missing values. This review was achieved by confirming the presence of values while merging the data from the multiple data sources: Intellimed, CMS, the AMA, and the AHA. The variables of interest were added from the data tables described in Chapter 3 by matching each institution's CMS identification number. Health insurer data from the AMA was added manually by matching each hospital's area of service to a corresponding state and metropolitan area. As a result of this matching, there are no missing values in the final dataset.

Outliers.

An assessment of multivariate outliers was performed by calculating and reviewing Mahalanobis Distances (Tabachnick & Fidell, 2007). There were three multivariate outliers with a chi square greater than 22.458 within the dataset given 6 degrees of freedom at the 0.001 significance level (Tabachnick & Fidell, 2007). The three facilities were in three different markets across two states and in both urban and rural areas. There were no discernable gross patterns to these facilities, so they were removed from the dataset given the sensitivity of regression techniques to outliers. The dataset was left with n = 178 hospitals.

Descriptive analyses of variables.

The characteristics of the continuous variables for these remaining 178 hospitals, after the removal of outliers, are presented in Table 10. The value ranges, means, and standard deviations of these continuous variables were assessed for logical adequacy. The variable ranges were often observed to be broad, but no remaining values were found to be implausible. The variables' distributions are later assessed for normality, which is often skewed when range proportions are bound by set limits such as zero and 100%.

Table 10
Descriptive Statistics for Continuous Variables

Variables	N	Minimum	Maximum	Mean	Std. Deviation
CTs per Discharge	178	0.15	0.71	0.38	0.101
Market Insurer HHI	178	1498	5520	2717.72	844.422
Market Hospital HHI	178	1564	6922	3355.51	1173.068
Hosp. Commercial Payer %	178	0.11%	66.05%	20.07%	13.91%
Hosp. Bed Count	178	31	927	238.48	177.991
Patient Case Mix Index	178	0.826	2.637	1.586	0.289
Patient Nonwhite %	178	0.27%	88.94%	30.50%	19.75%

Categorical variables were assessed to ensure adequate representation of both possible outcomes. No proportion of observations exceeded 90% nor were any less than 10%. The

frequencies of the categorical variables are reported in Table 11. For the purposes of regression, the state and the hospital's AHA centralization variable were later converted into three dichotomous dummy variables.

Table 11
Frequencies for Categorical Variables

Variable	Value	N (%)
State	MD	43 (24.2%)
	NV	21 (11.8%)
	VA	69 (38.8%)
	WA	45 (25.3%)
	Total	178 (100%)
Hosp. Teaching Status	1 (Y)	62 (34.8%)
	0 (N)	116 (65.2%)
	Total	178 (100%)
Hosp. For-Profit Ownership	1 (Y)	34 (19.1%)
	0 (N)	144 (80.9%)
	Total	178 (100%)
Hosp. AHA Centralization	Centralized	57 (32.0%)
	Moderately Decentralized	36 (20.2%)
	Decentralized	55 (30.9%)
	Independent	30 (16.9%)
	Total	178 (100%)

Univariate Analysis

In follow-up to the descriptive analysis, this section contains a univariate analysis of the 178 hospitals after the removal of Mahalanobis outliers. The data were assessed for normality and transformed when appropriate to address skewness and kurtosis using generally accepted techniques (Tabachnick & Fidell, 2007). This section also contains the results from a comparison of means and a univariate general linear regression (GLM).

Assessing normality.

Regression is dependent upon the assumption of normality for input variables that are continuous. The independent and dependent variable distributions were assessed for normality,

skewness, and kurtosis by reviewing z scores and histograms (Tabachnick & Fidell, 2007). Gross examination revealed instances of mildly positive skewness to the right and mild kurtosis. Only one variable (Hospital Bed Count) had a skewness or kurtosis value that exceeded an absolute 1.0 value (1.629 & 3.130, respectively). The dependent variable (CTs per Discharge) was observed to have the least skewness with a z score of 0.480. Each continuous variable was tested for normality using a Kolmogorov-Smirnov (K-S) Goodness-of-Fit Test (UCLA Institute for Digital Research and Education, 2016). With the exception of CTs per Discharge (the DV), all variables significantly deviated from normal with a p value < 0.05. This suggests the need to transform each of these rightward skews by transforming the variables and retesting.

Data transformations.

Table 12 shows a summary of skewness and kurtosis both before and after transformation. Each of the seven continuous variables were transformed. Though not statistically necessary, the CTs per Discharge rate was transformed by a factor of 1000x for interpretive purposes as is not uncommon practice in health care utilization studies. Accordingly neither the skewness nor kurtosis was observed to have changed. A review of the Market Insurer HHI histogram revealed a bimodal distribution despite the relatively low skewness score. Hospitals in a market with insurer HHI greater than the 2500 threshold of "highly concentrated," set forth by the FTC (American Medical Association, 2016), were flagged with a binary indicator of 1. All other hospitals were set to 0, reflecting their lower HHI.

The two variables with the largest skew values (Market Hospital HHI and Hospital Bed Count) underwent log transformations. Each of the three remaining continuous variables (Hospital Commercial Payer Percent, Patient Case Mix Index, and Patient Nonwhite Percent) had smaller initial skew values. As such, these three underwent only square root transformations.

Table 12
Variable Assessment and Transformations

Variables	Before Transformation	Transformation	After Transformation
CTs per Discharge	Skewness z score = 0.480 Kurtosis z score = 0.529	New X = 1000(X)	Skewness z score = .480 Kurtosis z score = .529
Market Insurer HHI	Skewness z score = 0.512 Kurtosis z score = 0.456	X > 2500 = 1	1 (Y) = 97 (54.5%) 0 (N) = 81 (45.5%)
Market Hospital HHI	Skewness z score = 0.965 Kurtosis z score = 0.673	New X = Log (X)	Skewness z score = 0.165 Kurtosis z score = -0.382
Hosp. Commercial Payer %	Skewness z score = 0.955 Kurtosis z score = 0.693	New X = SQRT(X)	Skewness z score = -0.167 Kurtosis z score = 0.038
Hosp. Bed Count	Skewness z score = 1.629 Kurtosis z score = 3.130	New X = Log (X)	Skewness z score = -0.236 Kurtosis z score = -0.372
Patient Case Mix Index	Skewness z score = 0.567 Kurtosis z score = 0.819	New X = SQRT(X)	Skewness z score = -0.241 Kurtosis z score = 0.536
Patient Nonwhite %	Skewness z score = 0.707 Kurtosis z score = 0.095	New X = SQRT(X)	Skewness z score = -0.132 Kurtosis z score = 0.407

In some instances the skewness turned negative. However, in each of these five transformations the resulting skewness z scores were closer to zero in absolute terms. K-S testing was again performed for each of the remaining transformed continuous variables, and each failed to deviate from normality and had p-values > 0.05. Table 13 shows the resultant K-S significance for each continuous variable.

Table 13
Kolmogorov-Smirnov Significance

Variables	K-S Sig.	Transformed K-S Sig.
CTs per Discharge	0.200	0.200
Market Insurer HHI	0.000	n/a
Market Hospital HHI	0.000	0.200
Hosp. Commercial Payer %	0.000	0.200
Hospital Bed Count	0.000	0.200
Patient Case Mix Index	0.027	0.200
Patient Nonwhite %	0.010	0.075

Comparison of means.

In support of the first objective of the study, to characterize the degree of variation in inpatient CT rates across the hospitals of multiple states and markets, a comparison of means was performed. The mean rate of discharges with a CT was compared across each of the four states, representing 51 distinct markets. The means varied from a low rate of 340 discharges with a CT out of 1000 in the state of Washington to a high rate of just over 412 scans per 1000 discharges in Maryland. The Maryland rate represents a 21% increase over Washington rates.

Table 14 shows results of the comparison of mean CT scan rates between states. Utilization rates varied widely and were dispersed across hospitals within the states as well. This can be observed in the relatively large standard deviation values for each state. Despite this large variation around the mean, the between-groups analysis tested positive ($F_{4,4(3)}, p=0.005$).

Table 14
Mean CT Scan Rates (per 1000 discharges)

State	Mean	N	Std. Deviation
MD	412.2	43	110.6
NV	389.1	21	99.1
VA	393.5	69	89.1
WA	340.0	45	99.3
Total	384.0	178	101.2

The results of the comparison of means indicate that the observed means are statistically significant and different by more than chance alone. This is demonstrated in the between-group ANOVA which can be seen in Table 15. The ANOVA had an Eta-squared value of 0.071 indicating that 7.1% of the variance was explained by each hospital's state. This finding supports the use of state as a control variable as it was detailed in the conceptual framework.

Table 15

Analysis of CT Rate Variance Between States

		Sum of Squares	df	F	Sig.
CTs per 1000 Discharges * State	Between Groups	128355	3	4.4	0.005
	Within Groups	1683019	174		
	Total	1811374	177		

Univariate GLM.

In support of the second objective, a univariate general linear model (GLM) was performed to evaluate the relationship between inpatient CT performance and the proportions of commercial payers. The relationship between the CT rate and the proportion of commercial payers was framed conceptually in the literature review and cut across multiple institutions and markets. The model used the normal-transformed square root of the hospital commercial payer mix as a solo predictor of discharges with a CT. The results demonstrated a statistically significant negative relationship between the two continuous variables ($F_{5.5(1)}$, $p < .05$). In addition, the model suggests that the single predictor variable can explain 3.0% of the variation in the DV ($R^2 = .03$).

The results of the univariate GLM are presented in Table 16. The results suggest that the rate of having a CT as an inpatient varies negatively with an increasing proportion of commercial payers. These results support the continued inclusion of the commercial payer in the full multivariate regression model where it will be more fully vetted.

Assessing Multicollinearity

This section provides the results of a Pearson correlation test and evaluates bivariate correlation. The concern is to ensure that adequate correlation exists for statistical purposes, but that not too much correlation occurs. Too much correlation between variables can lead to

Table 16

Univariate GLM Results between Commercial Payers and CT Rates Estimates

Variable	CTs per 1000 Discharges	
	B	95% CI
Intercept	428.1**	[388.1, 468.1]
Commercial Payer Percent SqRt	-10.6*	[-19.5, -1.7]
R ²	0.03	
F	5.47*	

*p < .05. **p < .01

multicollinearity or singularity, when one variable becomes a perfect or near perfect predictor of another.

The bivariate correlation was performed to assess for collinearity prior to variable transformation. The pre-transformation bivariate correlations are presented in Table 17. As expected from the literature review and proposed by the conceptual model, multiple statistically significant correlations were observed. In total, 18 were observed. Nine were found to be statistically significant to weak levels (<0.3), six were to moderate levels (0.3 - 0.5), and three were strong correlations (>0.5) (Cohen, 1988). No bivariate correlation exceeded the very highly correlated threshold of 0.9, which would have suggested multicollinearity or singularity (Tabachnick & Fidell, 2007).

The bivariate correlation test was repeated after transformation of the continuous variables to observe for changes and for desirable effects. The results are presented in Table 18. With the improved normality of variable distributions, elevated levels of correlation were observed without creating multicollinearity. This finding is a desirable effect of variable transformation (Cohen, 1988).

Post-transformation, there were 20 statistically significant correlations. The number observed to be statistically significant to weak levels (<0.3) improved to 10, and seven were then

Table 17

Multicollinearity Testing Before Transformation

	Insurer HHI	Hospital HHI	Centralized	Moderately Centralized	Decentralized	Commercial Payer Percent	Bed Count	Teaching Status	For-profit Owner	CMI
Insurer HHI	1									
Hospital HHI	.071	1								
Centralized	.031	-.048	1							
Moderately Centralized	.178*	.056	-.346**	1						
Decentralized	-.148*	-.177*	-.459**	-.337**	1					
Commercial Payer Percent	-.090	.136	.068	-.021	-.111	1				
84 Bed Count	.103	-.024	.038	.027	.042	.134	1			
Teaching Status	.089	-.138	.130	.014	-.004	.011	.535**	1		
For-profit Owner	.034	-.053	-.211**	-.174*	.479**	-.341**	.014	-.025	1	
CMI	-.045	-.110	-.057	.016	.160*	.123	.624**	.462**	.006	1
Nonwhite Percent	-.051	-.527**	.087	-.023	-.021	.004	.253**	.194**	-.043	.182*

** Correlation is significant at the .01 level (2-tailed).

* Correlation is significant at the .05 level (2-tailed).

Table 18

Multicollinearity Testing After Transformation

	Insurer HHI >2500	Hospital HHI Log	Moderately Centralized	Moderately Centralized	Decentralized	Commercial Payer Percent SqRt	Bed Count Log	Teaching Status	For-Profit Owner	CMI SqRt
Insurer HHI >2500	1									
Hospital HHI Log	-0.126	1								
Centralized	0.095	-0.009	1							
Moderately Centralized	.151 *	0.040	-.346 **	1						
Decentralized	-0.146	-.185 *	-.459 **	-.337 **	1					
Commercial Payer Percent SqRt	-0.121	.246 **	0.076	0.000	-.155 *	1				
Bed Count Log	0.079	-0.052	0.017	0.037	0.070	.154 *	1			
Teaching Status	0.076	-0.139	0.130	0.014	-0.004	-0.014	.501 **	1		
For-Profit Owner	0.071	-0.079	-.211 **	-.174 *	.479 **	-.417 **	0.011	-0.025	1	
CMI SqRt	-0.105	-0.120	-0.054	0.014	.162 *	0.074	.635 **	.458 **	0.010	1
Nonwhite Percent SqRt	-0.002	-.556 **	0.087	-0.050	0.015	0.008	.340 **	.213 **	-0.040	.247 **

** Correlation is significant at the .01 level (2-tailed).

* Correlation is significant at the .05 level (2-tailed).

found to be at moderate levels of correlation (0.3 - 0.5). No new strong correlations (>0.5) were created, for a sustained tally of three. Again no bivariate correlation exceeded the very highly correlated threshold of 0.9.

Multivariate Analysis

To fulfill the third objective of the study, testing the relationship between inpatient CT use and the characteristics of markets, hospitals, and patients, the regression module of SPSS was used to create a multivariate linear regression as described in the earlier methodology of Chapter 4. The regression module was selected over the general linear model due to the exploratory nature of the study, which is better served by the former's key features. The regression module allows users to leverage block functionality for covariation and additional multicollinearity diagnostics. The previous variable transformations to dichotomous or normal distributions adequately satisfied a critical prerequisite for regression. Additional post-hoc testing was used to further evaluate the validity of the model. The resulting output allowed the review of the variables and constructs for statistical significance.

Multivariate linear regression.

The multivariate linear regression (ordinary least squares regression) was executed using a blocked, enter method. Block methodology was used to allow the coded state dummy variables to be entered as covariates.

Table 19 shows the regression models, summary statistics, predictors, and overall fit. Model 1 is the states-only model controlling and demonstrates that the state dummy variables collectively account for 7.1% of the variance ($R^2 = 0.071$) in the observed CT rate. This is consistent with the ANOVA results from the comparison of means. Model 2 builds on Model 1

Table 19

Multivariate Regression Predictors of CT Rates

Variable	CTs per 1000 Discharges		
	Model 1 B	Model 2	
		B	95% CI
Intercept	340.0	861.7**	[348.7, 1374.6]
Covariates			
MD	72.3	39.2	[-15.7, 94.2]
NV	49.1	0.9	[-58.7, 60.6]
VA	53.6	14.0	[-37.3, 65.2]
Market Characteristics			
Insurer HHI >2500		46.2*	[9.8, 82.7]
Hospital HHI Log		-109.3	[-242.7, 24.1]
Hospital Characteristics			
Centralized		53.4*	[8.2, 98.6]
Moderately Centralized		16.5	[-33.8, 66.8]
Decentralized		32.9	[-15.9, 81.6]
Commercial Payer Percent SqRt		-9.0	[-19.8, 1.8]
Bed Count Log		5.3	[-58.7, 69.4]
Teaching Status		2.3	[-33.1, 37.8]
For-Profit Owner		-19.6	[-68, 28.8]
Patients			
CMI SqRt		-59.4	[-243.3, 124.5]
Nonwhite Percent SqRt		-12.1*	[-22.3, -1.9]
R ²	0.071**	0.222**	
F	4.42**	7.30**	

*p < .05. **p < .01

by including the remaining 11 variables representing characteristics of markets, hospitals, and patients. Model 2 accounts for an additional 15.1% of observed variation on top of Model 1 for a total of 22.2% of observed variation ($R^2 = 0.222$). Both models were statistically significant ($p < 0.01$).

Of the market characteristic variables, the full model shows that elevated levels of insurer concentration were positively associated with the CT rate in a statistically significant way. When the insurer HHI was over 2500, the observed CT rate was significantly higher (46.2, $p = 0.013$).

There was not a statistically significant relationship seen between the hospital's HHI and the CT utilization rate. Hospitals belonging to a centralized system were positively associated with CT rate (53.4, $p = 0.021$). No other hospital variables were found to have a statistically significant relationships with the DV. Of the patient characteristic variables, the full model shows that the square root transformed percentage of nonwhite patients was negatively associated with the CT rate (-12.1, $p = 0.020$). The interpretation of B for a square root transformed variable will be discussed Chapter 6. There was not a statistically significant relationship observed for the similarly transformed patient CMI.

Table 20 shows the collinearity statistics for each variable of the models. The SPSS regression module will calculate tolerance at $1-R^2$, where R^2 is the calculated tolerance of each individual IV onto the remaining independent variables as a measure of collinearity. Tabachnick & Fidell (2007) recommend a minimum tolerance of 0.1, which corresponds to a variance inflation factor (VIF) of 10.0. These values complement their multicollinearity threshold of 0.9. No variable in the full model has a tolerance less than 0.3, and no VIF exceeds 3.0, further suggesting the absence of multicollinearity.

The full model to represent the number of discharges with a CT scan per 1000 hospital discharges is expressed by the following:

$$Y' = 861.7 + 39.2(\text{MD}) + 0.9(\text{NV}) + 14.0(\text{VA}) + 46.2(\text{Insurer HHI} > 2500) - 109.3(\text{Hospital HHI Log}) + 53.4(\text{Centralized}) + 16.5(\text{Moderately Centralized}) + 32.9(\text{Decentralized}) - 9.0(\text{Commercial Payer Percent SqRt}) + 5.3(\text{Bed Count Log}) + 2.3(\text{Teaching Status}) - 19.6(\text{For-Profit Ownership}) - 59.4(\text{CMI SqRt}) - 12.1(\text{Nonwhite Percent SqRt})$$

Table 20

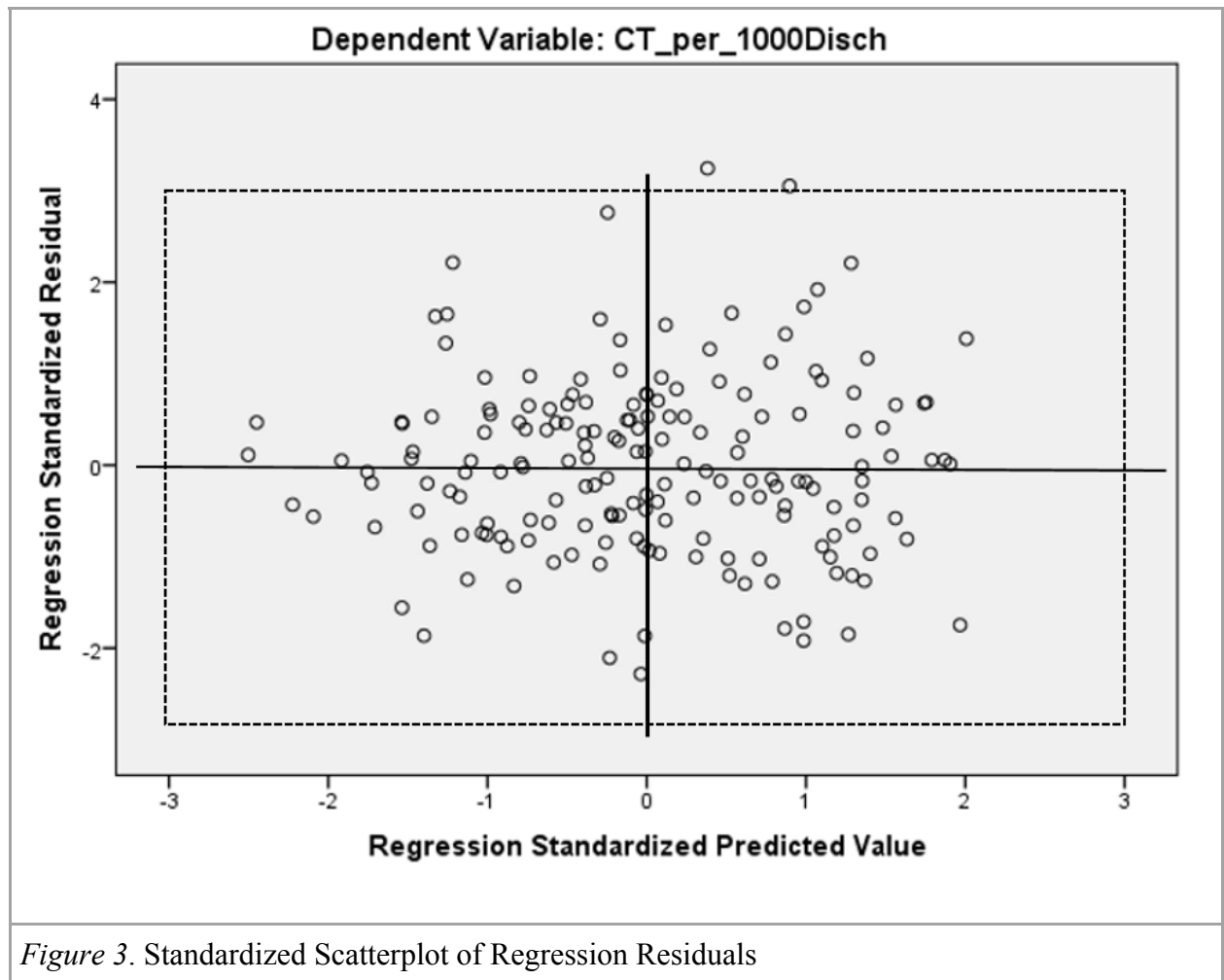
Model Collinearity Diagnostics

Variable	CTs per 1000 Discharges			
	Model 1		Model 2	
	Tolerance	VIF	Tolerance	VIF
MD	0.674	1.483	0.342	2.923
NV	0.773	1.294	0.512	1.954
VA	0.645	1.551	0.304	3.293
Insurer HHI >2500			0.574	1.743
Hospital HHI Log			0.504	1.986
Centralized			0.426	2.348
Moderately Centralized			0.464	2.156
Decentralized			0.373	2.681
Commercial Payer Percent SqRt			0.591	1.693
Bed Count Log			0.433	2.309
Teaching Status			0.663	1.507
For-Profit Owner			0.523	1.913
CMI SqRt			0.436	2.293
Nonwhite Percent SqRt			0.509	1.965

Testing residuals for normality.

One additional assumption of regression is the normality of residuals. This assumption can be tested visually and arithmetically. Figure 3 shows a scatterplot of the standardized residuals. This visual representation suggests normality given the relatively dense and uniform appearance of residuals (homoscedasticity) mostly within the confines of ± 3.0 z scores on either axis. Only two institutions have a standardized residual > 3.0 .

To confirm the normality of the residuals, the skewness (0.501) and kurtosis (0.980) of the residual plot were again calculated. Both were below 1.0 in magnitude. Additionally, a non-significant K-S statistic (0.075) was found, suggesting there was no statistically significant deviation from normality. Based upon these results, the regression model residuals appear to conform to the assumption of normality. With this support for the regression model's residual



normality, no alternative models (e.g. the negative binomial) were explored or deemed necessary for consideration.

Chapter Summary

This chapter presented descriptive summaries of the data. The analytical steps to do so included an evaluation of the first two objectives using univariate methods. The proposed model variables were presented, evaluated, and transformed for multivariate regression adequacy. An assessment of multicollinearity was performed before and after a presentation of model results. Lastly, the normality of the residuals was tested as the final assumption of multivariate regression.

Chapter 6: Conclusions

This chapter discusses the conclusions that can be inferred from the results about the possible implications for policy, planning, and health services research. It also offers a discussion of the possible limitations of the study and suggests areas for additional study. This chapter begins with a review of the key findings.

Discussion and Review of Key Findings

The primary goal of this study was to evaluate the relationship between the rate of inpatient CT utilization and the characteristics of markets, hospitals, and patients. This was accomplished through the stepwise completion of three objectives; the third objective contained three testable hypotheses.

Objective 1.

To characterize the degree of variation in inpatient hospital CT utilization rates across the hospitals of multiple states and markets.

This objective was accomplished through descriptive analysis using frequencies and comparison of inpatient CT utilization mean rates for hospitals across multiple states comprising 51 different markets. Statistically significant differences were found across the four states. By reviewing results across a multi-state sample, it is implicit that utilization also varies across markets. This inference is consistent with prior work that has shown significant state and regional variation in the utilization of imaging resources and the consumption of health services (Begun & Luke, 2001; Bhargavan & Sunshine, 2005).

Inpatient utilization was observed to vary as much as 21% from the state with the lowest incidence of inpatient CT in 2015 (Washington) to the state with the highest (Maryland). These results underscore the continued conceptual importance of including factors that account for geographic differences. The results also suggest additional inquiry into the differences between states that may influence some of these utilization patterns.

Objective 2.

To evaluate the relationship of inpatient CT performance with respect to payers across multiple markets and institutions.

This objective was met by performing a univariate general linear regression of the multi-state sample of CT rates against the payer. The results were statistically significant and suggested that 2.5% of the variation in CT utilization rates correlates with the proportion of commercial payers in the hospital's mix. Though the effects were small, the potential implications are larger since even modest shifts in utilization stand to alter cost, radiation exposure, and revenue. It was intriguing to find that the relationship between the two was negative. That is, as the proportion of commercial payers increased for the hospital's patients, the inpatient utilization seems to decrease. This persisted in spite of Maryland's all-payer program, in which all payers pay the same rates (CMS, 2018). Even Maryland, with the highest utilization rate, showed a correlational sensitivity to the proportion of commercial payers.

In the literature for outpatient and emergency department care, imaging utilization has been observed to increase for patients with commercial insurance (Bhargavan & Sunshine, 2005; Korley et al., 2010; Levin et al., 2014). This study's preliminary, exploratory findings suggest that the converse may be true for inpatients. One reason for this may be that the typically higher technical reimbursement rates for the commercially insured, paired with the outpatient fee-for-

service environment, may result in some inpatient studies being pulled to the outpatient setting. Prior multi-market inpatient work looked at utilization only for the Medicare population and did not address varying proportions of payer populations (Levin et al., 2013). Medicare studies simply do not have the full cross-section of the inpatient spectrum. This study provides some initial baseline evidence to suggest the need for additional study and inquiry.

Replicating this element of the study in future iterations and expanding it to include the array of payer types seems warranted. Additional targeted inquiry could offer a better understanding of the possible effects of the shifting coverage and reimbursement patterns. Regardless, this result underscores the utility of including payer considerations in this study and in the full model where other factors were considered as well. This work could serve as a catalyst for more detailed work directed specifically at insurer market consolidation.

Objective 3.

To use a conceptual framework to test the relationship between inpatient CT use and characteristics of markets, hospitals, and patients. There were three hypotheses related to this objective:

- H1: Characteristics of markets will be associated with inpatient CT utilization rates.
- H2: Characteristics of hospitals will be associated with inpatient CT utilization rates
- H3: Characteristics of patients will be associated with inpatient CT utilization rates.

The third and final objective of the study was met by developing and executing a multivariate regression using variables characteristic of markets, hospitals, and patients. This OLS multivariate model was regressed upon transformations of insurer HHI, hospital HHI, system membership, the proportion of commercial payers for a hospital, the hospital's bed count, the hospital's teaching status, its for-profit status, the patient case mix, and the proportion of

minority patients in its mix of discharged patients. This was done while controlling for the state in which the hospital was located.

The comparison of means for the CT utilization rate demonstrated that there were statistically significant differences between the states. Other pre-test measures were performed to ensure that the variables appropriately conformed to normality, a prerequisite of regression. Whenever possible, continuous variables were retained or transformed using generally accepted practices (e.g. Log and square root transformations) (Tabachnick & Fidell, 2007). One continuous variable had to be converted to a binary outcome. No multicollinearity was identified between the variables either before or after the transformations, which is another prerequisite of regression. Results were generated for the relationships between the CT utilization rate and each independent variable.

Results were generated and reviewed for each independent variable. From the market variables, the binary indicator of a highly concentrated insurer market with an HHI > 2500 was found to be statistically significant ($\beta = 46.236$, Beta = 0.228, $p = 0.013$). This finding suggests that hospitals in markets with these highly concentrated insurers, when all other factors are constant, would expect to observe a mean CT rate that is about 46 scanned patients per 1000 discharges higher than those hospitals in less competitive markets. The other market measure, hospital HHI, was not found to be statistically significant.

From the variables representing the characteristics of hospitals, the binary indicator for a hospital belonging to a centralized system was found to be statistically significant ($\beta = 53.396$, Beta = 0.247, $p = 0.021$). These results indicate there is less than a 5% chance that this observed positive relationship was the result of the natural, random variation from within the data. In practical terms, this finding suggests that the mean CT rate per 1000 discharges for a hospital

belonging to a centralized system would be approximately 53 scanned patients higher than the mean of those hospitals that were not in a centralized system.

The remaining hospital characteristic variables—teaching status, for-profit ownership, the proportion of commercial payers, and bed count—were not found to be statistically significant. Also not significant were the other indicators of hospital systemness including: moderately centralized, decentralized, or independent (reference group). The concept of system centralization may also be clinically relevant as others have found differences both in outcomes and in the explicit coordination of services (A. S. Chukmaitov et al., 2009; Sikka et al., 2009).

From the variables representing the patient characteristics, only the square root of the proportion of nonwhite patients was statistically significant ($\beta = -12.113$, Beta = -0.227, $p = 0.020$). The magnitude of the Beta, a standardized figure, suggests that this characteristic is the strongest predictor, corroborated by the smallest p value. The variable was also negative, suggesting that an increasing proportion of minority patients seen by a hospital correlates with a decreasing likelihood for that hospital's patients to have received a CT while an inpatient. The practical interpretation of this variable means that, all other things being equal, the mean of hospitals with a minority patient population of 64% will have nearly 24 fewer patients with a CT performed per 1000 discharges than the mean of hospitals with only a 36% minority population.

It is not possible to discern from this data precisely how the variance manifests within the hospitals' population based upon race. That is, it cannot be determined if all patients at hospitals with larger minority populations have a decreased likelihood of having a CT performed on them, or if there is in fact a difference between the hospital's minority and nonminority populations' rates of CT. The other patient characteristic variable, case mix, was not found to be statistically significant.

Post-test measures were unremarkable for the identification of multicollinearity. Variable tolerance levels were well above minimum thresholds. The final tested assumption of regression requires homoscedasticity of the residuals around the predicted values and normality of the residuals. The distribution of the residuals tested as normal using a K-S test for goodness-of-fit.

These results support the study's three hypotheses, rejecting the null hypotheses that there are no statistically significant differences within the market variables, the hospital variables, or within the patient characteristic variables. Each construct had a variable that contributed significantly to the regression model. Table 21 shows a summary of the hypotheses, variables, and their related significance.

Table 21

Hypothesis Testing Results

Hypotheses and Variables	Variable relationship & significance	Hypothesis Results
H1: Characteristics of markets will be associated with inpatient CT utilization rates.		Significant
Insurer HHI	+ / significant	
Hospital HHI	- / not significant	
H2: Characteristics of hospitals will be associated with inpatient CT utilization rates.		Significant
Centralized system	+ / significant	
Moderately centralized	+ / not significant	
Decentralized	+ / not significant	
Commercial Payer Proportion	- / not significant	
For-Profit Ownership	- / not significant	
Teaching Status	+ / not significant	
Bed Count	+ / not significant	
H3 Characteristics of patients will be associated with inpatient CT utilization rates.		Significant
Minority Mix Proportion	- / significant	
Case Mix	- / not significant	

Conceptual and Methodological Implications

The results support the study's proposed conceptual framework. It demonstrates how factors that may be conceptually associated with the constructs of the market, hospital, and patient may also be logically associated with inpatient utilization of resources. Each of the constructs contributed a statistically significant variable. Collectively, the study's variables explained just over 22% of the unadjusted variation in the observed inpatient CT rate. This is a small, approaching medium, effect size based upon the 0.12 threshold for small and 0.26 threshold for medium (Cohen, 1992). The relative robustness of statistical outcomes and the outcome's congruence with the prescribed constructs seems to suggest overall adequacy and appropriateness of the framework.

This study's results demonstrate the possibility of using linear regression methods for health services inquiry when the variable of interest is count data representing numbers of events. It is frequently necessary to use a different statistical method or design (e.g. the negative binomial) when regressing this type of data due to the data fundamentally being skewed (i.e. cannot be less than zero). If count data can be converted to a rate through an exposure variables, such as the number of annual discharges in this case, then a multivariate regression can suffice assuming all the assumptions of normality and non-multicollinearity are met.

Implications for Stakeholders

This study has potential implications for many. That a significant portion of the inpatient CT rate variation can be explained by knowing a) the state a hospital is in, b) what the local insurance market is like, c) whether it is in a centralized system, and d) the hospital's mix of minority patients should be of interest to numerous stakeholders. Administrators, health sciences

researchers, and health policy makers each stand to benefit from having a better understanding of some fundamental determinants of inpatient CT utilization.

Hospital administrators may be keenly interested in knowing that system centralization is associated with increasing inpatient CT use. Some have suggested that the centralization of large systems perhaps makes them unwieldy and inefficient (A. S. Chukmaitov et al., 2009).

Administrators of such institutions may see this as an opportunity to leverage appropriateness criteria, reduce scan redundancies, and reduce system net costs by reducing the inpatient use of exams. Likewise, administrators in highly concentrated insurance markets could use such initiatives in negotiation with insurers.

Health sciences researchers have the laudable goal of better understanding resource utilization. Because of the prospective payment methodology and bundling of payments, inpatient utilization is often more challenging to assess than outpatient. This study serves as a demonstration project for a way in which researchers may want to consider assessing the inpatient use of scarce ancillary services resources using administrative data. It even suggests to researchers that market factors extrinsic to the hospital may affect inpatient utilization in ways that extend beyond the characteristics of the hospital system and even the actual patient population.

Similarly, researchers may have an interest in better understanding the association of a hospital's increasing minority patient population and decreasing inpatient CT use. The potential implications are multifaceted. An increasing minority population may be serving as a proxy for numerous socioeconomic or cultural factors that are not measured. For example, such hospitals may be in a more impoverished area. Minority patients may bring language or cultural barriers with them into the hospital that limit the performance of studies or the communication of

symptoms, even after they are admitted. Providers themselves may also experience an unconscious bias leaving them less likely to perform an exhaustive battery of studies on a minority patient.

Health policy makers in general have the desire to align incentives to improve the overall efficiency, safety, and coordination of patient care. Reducing the absolute number of inappropriate scans helps in that regard by freeing up the resource for more appropriate life-saving interventions (Rumack, 2010). Understanding the drivers of utilization is key to this. Policy makers may be interested to note that the state of Maryland, with the transparency of its all-payer system, actually has the highest observed rates of inpatient CT utilization. This could be completely spurious and coincidental to the all-payer system, or an unintended consequence. From the public health policy perspective, even if reducing inpatient utilization had no impact on the cost of imaging, there remains a public health argument to be made for reducing the impact of cumulative radiation dose and repeated contrast administration.

Study Limitations

Mick and Wyttenbach (2003) expressed that the demand for health care services is "never a direct function of physician supply, insurance coverage, and disease pattern" (pg. 34). They proceeded to explain that external forces intercede to direct choices, preferences, and constraints. This affects both patient behavior and physician behavior. Physician agency and quantity of care provided can be affected by their training and their possession of asymmetric information (Mcguire, 2000). How well a study models these behaviors, and what meaning can be taken from the results, is based upon a set of assumptions and limitations. Retrospective correlational studies with large sample sizes and many variables are at significant risk of spurious correlation, so any inferences must be caveated with this awareness.

Cross-sectional studies of administrative data such as this are also susceptible to aggregation bias (Zellner, 1962). The aggregation of all patient discharges for a year to make up a profile of a hospital masks the individual patient variability within that hospital's patient population. Inferences from this study cannot be reduced to units more granular than the hospital-level. And, inferences upon individual hospitals risk ecological fallacy (Robinson, 2011). Data containing individual patient parameters, and a study design appropriate for such an evaluation, could help address such concerns.

For the purposes of this study, it was not feasible to perform explicit endogeneity testing. The conceptual model allowed for the inclusion and exclusion of variables under consideration when constructing the dataset, but does risk omitting endogenous variables. This method leads to a lack of instrumental variables for testing purposes. Consideration was given for the lead and lag of variables to avoid simultaneity when possible during the conceptual formation of the study. The challenge of evaluating endogeneity is not uncommon in cross-sectional studies when neither controlled experimentation nor longitudinal data are available. However, possible endogeneity should be viewed accordingly as a possible limitation when considering or generalizing the results of the study.

The four-state sample also limits the making of generalizations. With the broad range of utilization rates observed between the four states and the known geographic variability of health resource consumption, extrapolating this study's results to other states should be done with extreme caution without first replicating the work. All four states have certificate of need (CON) programs that serve as potential barriers to the deployment of advanced imaging modalities, affecting access that may not apply to non-CON states. Also, other advanced imaging modalities (e.g. MRI) may not follow the same patterns of utilization as CT. Some imaging modalities serve

as complementary alternatives to one another especially if the access to devices and modalities is limited.

Another limitation of the study is the fact that this is a single year snapshot representing 2015. Trended data over time is not possible with such a snapshot. This study used the most recent data available; however, this is a potentially significant limitation considering that insurers and hospitals continue to consolidate. It is conceivable that evolving market trends or even legislative agendas can alter local landscapes rapidly and unpredictably (e.g. Medicaid expansion).

Acknowledgment of a study's limitations, however, does not discredit the findings. The methods for operationalizing the measured variables in this study have been previously utilized and detailed in the methodology. Additionally, the body of research using cross-sectional administrative data is sizeable. The recognition of limitations ultimately serves to strengthen the interpretation of results.

Future Research

This study identifies multiple opportunities for additional research and numerous questions for future investigation. Given the observed variation explained by states, future work could be designed to look inside states for differences. For example, are there variations within Maryland that account for the observed elevated rates of CT utilization? Are these rates isolated at a few hospitals or are they more pervasive? Does the all-payer program inadvertently limit alternatives to CT? Do the results extrapolate to states without CON laws?

Future research is needed to help isolate causation between variables and to look inside the organization of hospital systems. The ability to trend variables over time would be helpful.

The literature review reported on multiple trends in the factors of interest, but to isolate them in a

study would help to augment or refute causality. Are two variables trending together over time and in the same degree of magnitude? The cross-sectional snapshot does not allow for this to occur. Future work within hospital systems to better understand the relationship between centralization and inpatient CT use seems to be warranted. Are there specific determinants of centralization that drive increased inpatient use? And if they exist, how do they relate to outcomes?

The study also lays the foundation for additional outcomes research. Once increased CT utilization has been observed, does it translate to improved outcomes or shortened lengths of stay? This is left unanswered as outcomes are beyond the scope of this study, but the benefits of CT are well documented in the literature (Rumack, 2010; Smith-Bindman et al., 2009). And if there are improvements in outcomes related to increased use, are they shared equitably? It was observed that hospitals with more minority patients have overall lower rates of inpatient CT use. Can it be determined within these hospitals that minority populations have equal treatment and shared outcomes?

This study and its findings lay a beneficial groundwork for multiple avenues of additional research. It creates questions about policy implications, questions about public health and outcomes, and questions of equity.

Conclusions

This study serves an important function in identifying varying patterns of CT utilization across multiple hospitals, markets, and states. It also serves an important role in identifying variables associated with its increasingly prevalent use.

This study creates new knowledge about how the characteristics of these markets, hospitals, and patients are related to inpatient use. The study demonstrates associations between

insurer control of markets, hospital system centralization of services, the minority proportion of patients, and the use of inpatient CT services. A better understanding of these relationships by administrators, policy makers, and researchers would be desirable. Through additional knowledge and understanding, this study may ultimately lead to improvements in the appropriate and equitable use of inpatient CT exams.

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Appendix A

Herfindahl-Hirschman Index (HHI)

Step 1

ZCA	Hosp.	Zip Code Discharges by Hospital	HHIj
00001	Hosp A	1500	0.320
00001	Hosp B	800	0.090
00001	Hosp C	350	0.020
Totals ZCA 00001		2650	0.430
00002	Hosp A	700	0.080
00002	Hosp B	600	0.060
00002	Hosp C	1250	0.240
Totals ZCA 00002		2550	0.370

Step 2

Hosp. - ZCA	Total ZCA discharges	Proportion of discharged patients	HHIj	weighted HHIi
Hosp A - 00001 HHI	1500	0.680	0.430	0.290
Hosp A - 00002 HHI	700	0.320	0.370	0.120
			Hosp A - HHIi	0.410
Hosp B - 00001 HHI	800	0.570	0.430	0.250
Hosp B - 00002 HHI	600	0.430	0.370	0.160
			Hosp B - HHIi	0.400
Hosp C - 00001 HHI	350	0.220	0.430	0.090
Hosp C - 00002 HHI	1250	0.780	0.370	0.290
			Hosp C - HHIi	0.380

Vita

Michael D. Hanshew was born on January 5, 1977 in West Virginia. After moving to Virginia with his family, he graduated from Prince George County High School in Prince George, Virginia in 1995. He graduated in 1999 from the University of Virginia (Charlottesville) as an Echol's Scholar with a Bachelor of Arts in Interdisciplinary Studies. He received a Master of Science in Health Evaluations Sciences from the University of Virginia in 2005. He presently works for the University of Virginia Health System as the Director of the Office of the Chief Medical Officer.