

2016

Investigating The Role Of Internal Hospital Factors And The External Environment On Healthcare Quality Outcomes And Patient Choice

Deepa Wani

University of South Carolina

Follow this and additional works at: <http://scholarcommons.sc.edu/etd>



Part of the [Business Administration, Management, and Operations Commons](#)

Recommended Citation

Wani, D.(2016). *Investigating The Role Of Internal Hospital Factors And The External Environment On Healthcare Quality Outcomes And Patient Choice*. (Doctoral dissertation). Retrieved from <http://scholarcommons.sc.edu/etd/3816>

This Open Access Dissertation is brought to you for free and open access by Scholar Commons. It has been accepted for inclusion in Theses and Dissertations by an authorized administrator of Scholar Commons. For more information, please contact SCHOLARC@mailbox.sc.edu.

INVESTIGATING THE ROLE OF INTERNAL HOSPITAL FACTORS AND THE
EXTERNAL ENVIRONMENT ON HEALTHCARE QUALITY OUTCOMES AND
PATIENT CHOICE

by

Deepa Wani

Bachelor of Engineering
University of Mumbai, 2000

Master of Science
University of South Carolina, 2008

Submitted in Partial Fulfillment of the Requirements

For the Degree of Doctor of Philosophy in

Business Administration

Darla Moore School of Business

University of South Carolina

2016

Accepted by:

Manoj Malhotra, Major Professor

Sriram Venkataraman, Committee Member

Yan Dong, Committee Member

Paul Bliese, Committee Member

Lacy Ford, Senior Vice Provost and Dean of Graduate Studies

© Copyright by Deepa Wani, 2016
All Rights Reserved.

DEDICATION

To my husband, Hrishikesh and our twin daughters, Shruti and Aarushi

ACKNOWLEDGEMENTS

My dissertation would not have been possible without the guidance, critical insight, and encouragement from my advisor Dr. Manoj Malhotra. I would also like to thank Dr. Yan Dong for his immense support and advice on a variety of research topics. My interactions with both of them have broadened my horizons and allowed me to see things from different perspectives. In addition, I greatly value their wisdom in various aspects of life and I will continue to seek their advice in the future.

I thank Dr. Sriram Venkataraman for his constant support with one of my dissertation essays and on various econometric topics. I also thank Dr. Paul Bliese for serving as a member on my committee and taking the time to clarify statistical concepts using simulations and graphs. I thank Dr. Mark Ferguson for his support and advice throughout my PhD program and all other faculty members of the Moore School of Business for having equipped me with the tools and techniques to finish my PhD program successfully. I am grateful to Dr. Aravind Chandrasekaran and Luv Sharma for providing useful feedback on my paper drafts. Julia Witherspoon and Scott Ranges have been excellent resources for all my administrative needs. I also acknowledge the support of fellow PhD students who helped make the tough task of finishing a PhD more bearable.

I would also like to thank my parents and my in-laws for their constant inspiration. Finally, I cannot truly express how grateful I am to my husband, Hrishikesh, for his patience, love and encouragement, and to our twin daughters Shruti and Aarushi, for putting up with the limited amount of time that I was able to devote to them.

ABSTRACT

The healthcare landscape has been changing rapidly with changes in the reimbursement system, financial incentives for using information technologies, pay for performance programs for quality improvements and increased demand for hospital services from millions of newly insured patients. Understanding the impact of these policy changes in an operations management context has been an understudied area. We contribute to the literature by incorporating research streams from healthcare, economics, marketing and quality management. This dissertation consists of three studies. The first study examines the impact of the mandated use of electronic health records, and finds that such records not only improve the efficiency with which hospitals treat patients, but also that the benefits are higher for patients with greater disease, comorbidity, and coordination complexities. The second study examines the role of process improvement factors in improving processes of care. We find that that operational slack, nursing skill mix and focused strategy improve the quality of care in both more and less competitive markets, with the greatest benefits accruing in less competitive markets. Finally, the third study examines the role of infrastructural and structural investments, patient satisfaction, and hospital reputation generated by third parties in influencing patient demand for hospitals for elective surgeries. Patient choice based on hospital attributes is heterogeneous in nature, and depends on the complexity of comorbidities and type of surgery. Collectively our three studies provide inputs to hospital managers on how to best manage their scarce financial resources in the new pay for performance health care environment.

TABLE OF CONTENTS

DEDICATION	iii
ACKNOWLEDGEMENTS.....	iv
ABSTRACT	v
LIST OF TABLES	viii
LIST OF FIGURES	ix
CHAPTER 1 INTRODUCTION	1
CHAPTER 2 DOES THE MEANINGFUL USE OF ELECTRONIC HEALTH RECORDS IMPROVE PATIENT OUTCOMES?	8
2.1 MOTIVATION	9
2.2 MEANINGFUL USE OF ELECTRONIC HEALTH RECORDS	12
2.3 LITERATURE REVIEW	14
2.4 HYPOTHESIS DEVELOPMENT	17
2.5 DATA DESCRIPTION.....	24
2.6 ECONOMETRIC MODEL.....	31
2.7 RESULTS.....	34
2.8 CONCLUSIONS AND DISCUSSION.....	38
CHAPTER 3 LONGITUDINAL IMPACT OF PROCESS IMPROVEMENT ON PATIENT CARE UNDER COMPETITION AND ACA	44
3.1 INTRODUCTION	45
3.2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT	47

3.3 DATA SOURCES, VARIABLES AND ECONOMETRIC MODEL	58
3.4 RESULTS	65
3.5 IMPACT OF ACA ON PROCESS OF CARE AND THE ROLE OF PROCESS IMPROVEMENT FACTORS	73
3.6 CONCLUSIONS AND LIMITATIONS	75
CHAPTER 4 IMPACT OF HOSPITAL CHARACTERISTICS ON PATIENT CHOICE BEHAVIOR FOR ELECTIVE SURGERIES	83
4.1 INTRODUCTION	84
4.2 LITERATURE REVIEW	89
4.3 HYPOTHESIS DEVELOPMENT	95
4.4 DATA DESCRIPTION AND ECONOMETRIC MODEL	103
4.5 EMPIRICAL SPECIFICATION OF THE DEMAND MODEL	109
4.6 RESULTS	113
4.7 ROBUSTNESS TEST	119
4.8 STUDY CONTRIBUTIONS AND CONCLUSION	120
CHAPTER 5 CONCLUSION	125
REFERENCES	129
APPENDIX A – SUMMARY OF KEY PAPERS ON THE IMPACT OF EHRs AND INFORMATION TECHNOLOGY	145
APPENDIX B – PROCESS OF CARE COMPONENTS.....	147

LIST OF TABLES

Table 1.1 List of Variables used in different studies within the Dissertation.....	7
Table 2.1 Descriptive Statistics of Variables used in main analysis.....	28
Table 2.2 Hospital Level Characteristics used in selection model	29
Table 2.3 Comparative Statistics for MU_EHR and non MU_EHR certified hospitals ...	30
Table 2.4 Main Results	35
Table 2.5 Choice Model Results.....	36
Table 2.6 Post-Hoc Results for Readmissions.....	37
Table 3.1 Descriptive Statistics.....	62
Table 3.2 Correlations.....	63
Table 3.3 Regression Results for Process of Care Dependent Variable	67
Table 3.4 Robustness Test for Process of Care Dependent Variable	72
Table 3.5 Joint Simultaneous Impact of Competition and ACA on Process of Care	74
Table 4.1 Summary of papers on Revealed Patient Choice.....	90
Table 4.2 Descriptive Statistics for Elective Hip-Knee Surgeries.....	114
Table 4.3 Conditional Logit Estimates of Hospital Choice	118
Table 4.4 Robustness Check.....	119

LIST OF FIGURES

Figure 1.1 Schematic of Factors impacting Quality of Care and Patient Choice in Healthcare	2
Figure 1.2 Schematic for Study 1	4
Figure 1.3 Schematic for Study 2	5
Figure 1.4 Schematic for Study 3	7
Figure 3.1 Theoretical Model	57
Figure 3.2 Impact of Process Design Factors on Process of Care in Low and High Competitive Markets.....	68

CHAPTER 1

INTRODUCTION

The national healthcare expenditure in the US reached \$3.0 trillion in 2014, growing by 5.3% over the previous year (CMS.gov, A). Despite increases in healthcare spending over many decades, the Institute of Medicine (IOM) reported that US healthcare system fails at providing safe and effective care, and does not make the best use of its resources (Richardson et al. 2001). Thus there is an urgent need to seek effective ways to reduce spending while improving the quality of care. In addition, there has been an upheaval in the way hospitals are reimbursed for their services. The traditional pay for service model which focused on paying providers based on the volume and complexity of services was replaced by a prospective payment system which encouraged a reduction in excessive and unnecessary care by providing a fixed payment for services rendered (James, 2012). The Affordable Care Act (ACA) was signed into law in 2010 to further reduce medical errors, readmissions and mortality and at the same time promote greater coordination across providers and reduce healthcare spending costs. Financial incentives are also built into this Act through the value based purchasing program, which create competitive conditions and encourage organizations to deliver efficient and high quality medical care through appropriate investment of resources (CMS.gov, B). Hospitals also make investments in various resources to differentiate themselves from the competition to attract insurers, referring physicians, and patients to their hospitals. Hence this dissertation provides insights into the role that various internal resources and external

factors play in improving patient quality of care. On the supply side, we contribute to healthcare operations management research and practice by attempting to understand the role of structural and infrastructural investments and competition in improving both patient as well as hospital level quality outcomes. On the demand side, we contribute through this dissertation to the understanding of how these investments help inform patient choice of hospitals. Figure 1.1 schematically shows the factors that impact quality of care and how and where patients choose to consume health care services.

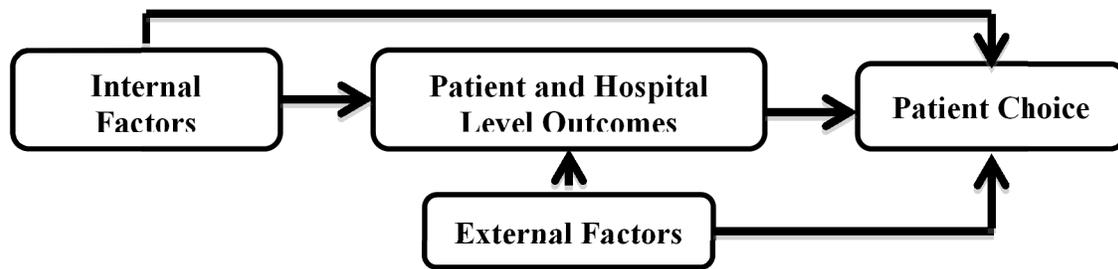


Figure 1.1: Schematic of Factors impacting Quality of Care and Patient Choice in HealthCare

Study 1

In study 1, we look at the impact of electronic health records (EHRs) on patient level outcomes. EHRs have the potential to transform healthcare delivery through the use of built-in evidence based medical guidelines, and efficient coordination of patient treatment and care. The Health Information Technology for Economic and Clinical Health (HITECH) Act was passed in in 2009 and billions of dollars were set aside in incentives to encourage meaningful use of these systems (HHS, 2009). However, past studies on adoption of such EHRs have shown mixed results (McCullough et al. 2010; Miller and Tucker 2011; Furukawa 2011; Appari et al. 2012; Dranove et al. 2012; Appari et al.

2013; McCullough et al. 2013; Jones et al. 2014; Agha 2014). In this study, we posit that hospitals that meaningfully use EHRs perform better on resource efficiency than hospitals that just adopt such systems. Further, in a knowledge-intensive industry like healthcare, diagnosing a patient's condition and treating it effectively is a complex task, considering that there are currently about 13,600 diagnoses with 6000 drugs and 4000 procedures to treat these diagnoses (The New Yorker 2011). In addition, comorbidities such as hypertension, diabetes, obesity, etc. are increasing in the United States and clinicians have to take these factors into consideration while designing effective treatment plans. Task complexity has been previously identified as an important factor in affecting performance (Payne 1976, Van de Ven and Ferry 1980, Locke et al. 1981, Culnan 1983, Campbell and Gingrich 1986, Wood 1986, Campbell 1991, Argote et al. 1995), and this argument can be extended to treatment of patients as well. Because information gained from information systems such as EHRs can potentially transform a worker's knowledge structures (Ingwersen, 1992), we posit that EHRs can help health care providers by easing their cognitive load and providing useful information about disease conditions and recommendations for tasks that are more complex than simpler tasks. Using detailed patient level data, we develop various measures of patient complexity to determine whether meaningful use of EHRs incentivized by the HITECH Act is more effective in improving resource efficiency for complex tasks. Figure 1.2 schematically shows the model that we test in Study 1.

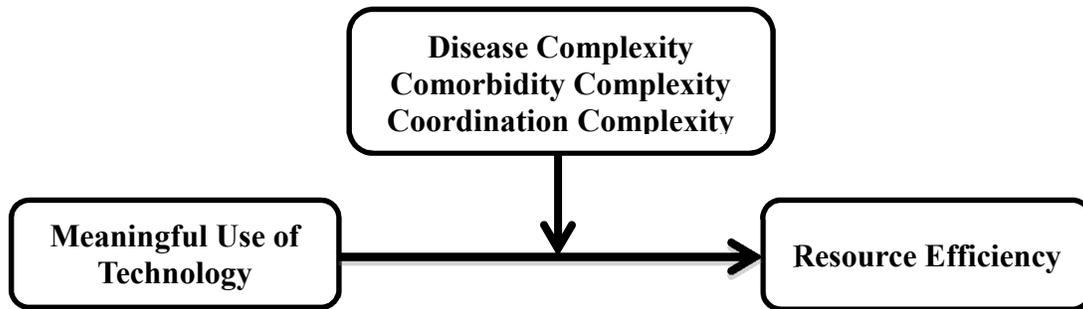


Figure 1.2: Schematic for Study 1

Study 2

Even though EHRs represent an important structural investment for hospitals, there are other important investments that hospitals have to consider given the changing reimbursement system within which they must function. The economics literature suggests that increased competition improves quality (Tirole, 1988; Gaynor and Town, 2011; Gravelle et al., 2014). In the second study, we seek to understand how a shift toward more competitive conditions for capturing patient demand affects process of care (PoC) at the hospital level. Further, given hospitals' financial constraints, we also seek to understand how hospital managers should make resource allocation decisions that improve hospital processes that ultimately improve patient outcomes. We posit that the impact of process improvement factors will be positive in both more and less competitive markets. However, considering that hospitals in more competitive markets make additional investments in technology and state of the art equipment, we posit that the marginal benefit will be stronger in less competitive markets. Accordingly, we use panel data collected over 7 years from 2007 to 2013 and various sources such as CMS' Hospital Compare website, California Office of Statewide Planning and Development's

(OSHPD) Annual Financial database, Dartmouth Atlas, Inpatient Prospective Payment System (IPPS), OSHPD's Healthcare Atlas and American Nurses Credentialing Center (ANCC). Using longitudinal data analysis, we study the role that three key process improvement factors - operational slack, nursing skill mix and a focused service strategy - play in affecting PoC within the altered competitive landscape created by the introduction of the ACA. Figure 1.3 captures the schematic for Study 2.

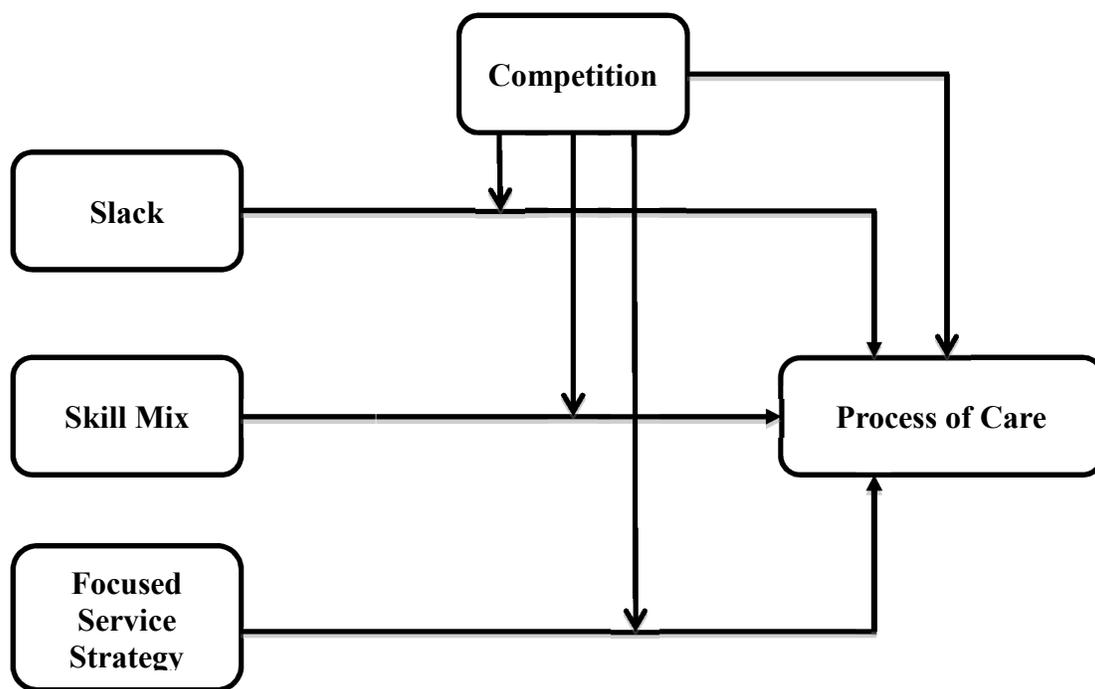


Figure 1.3: Schematic for Study 2

Study 3

While the above two studies focus on the supply side of the equation i.e. how internal and external factors impact outcomes at the hospital and patient level, the final study looks at the demand side of the equation. In recent years, there has been a proliferation in the

number of organizations that seek to signal a hospital's reputation via ranking systems. The government also posts information on the quality of care e.g. patient satisfaction, timeliness of care for certain conditions, readmissions, etc. at over 4,000 hospitals via its Hospital Compare website. As millions of newly insured people seek hospital services, there is a need to help people make informed choices and also improve the quality of care they provide. While reputation signaling is an external factor that may influence patient decisions, hospitals also make several structural and infrastructural investments in order to be more attractive to insurers, patients, and referring physicians. In this study, we seek to understand whether such internal resource investments, perceptual patient satisfaction or external hospital rankings are more influential in patient choice of hospitals. Further, we investigate whether patients with greater comorbidity complexity emphasize certain factors over others in their hospital choice decision. We focus on elective surgeries rather than emergent conditions as patients have more time to deliberate various options of hospitals in such cases, and hopefully make an informed choice. We posit that fundamental hospital characteristics such as technology, registered nurse staffing, focus, etc., along with third party reputation and patient satisfaction drive patient choice. We also posit that the effects are likely to be heterogeneous across patients with greater comorbidity complexity. Using a discrete choice model, this study seeks to provide insights into patient choice behavior, and has implications for how hospitals should allocate their limited financial resources. Figure 1.4 provides the schematic for study 3.

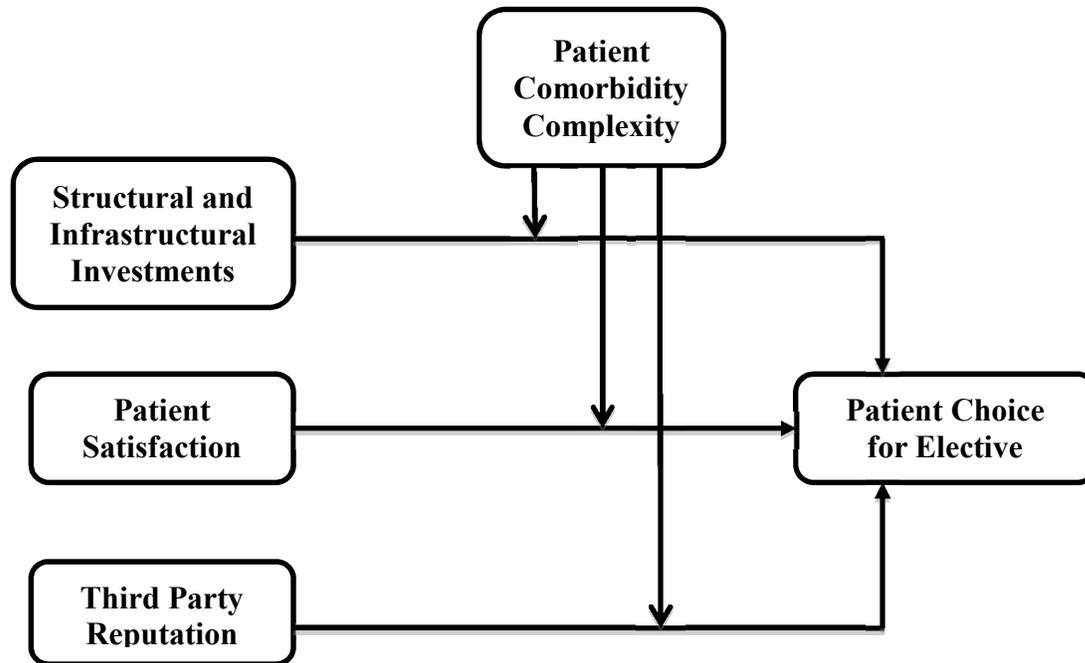


Figure 1.4: Schematic for Study 3

Table 1.1 provides details of the internal and external factors and outcome variables used in each of the three studies, and which together form this dissertation.

Table 1.1: List of variables used in different studies within the dissertation

	Internal Factors	External Factors	Outcomes
Study 1	Electronic Health Records (EHRs)	Health Information Technology for Economic and Clinical Health (HITECH) Act	Resource Efficiency - Patient Length of Stay
Study 2	Operational Slack, Nursing Skill Mix, Focused Service Strategy	Local Competition, ACA	Hospital level Process of Care Measures
Study 3	Technology, Registered Nurse Staffing, Hospital Focus, Patient Satisfaction	Reputation Signals generated by Third Parties	Patient Choice

CHAPTER 2

DOES THE MEANINGFUL USE OF ELECTRONIC HEALTH RECORDS IMPROVE PATIENT OUTCOMES?¹

Abstract

Electronic Health Records (EHRs) have the potential to transform healthcare delivery through the use of built-in evidence based medical guidelines, and efficient coordination of patient treatment and care. Meaningful use of EHRs can play an especially important role in easing a health care provider's cognitive load while working on complex tasks. In this study, we examine the impact of meaningful use of EHR after the mandated HITECH (Health Information Technology for Economic and Clinical Health) Act on patients' length of stay (LOS) in the context of treating patients with varying dimensions of complexity: (i) complexity arising from the treatment of a patient's disease, (ii) complexity arising from a patient's comorbidities and (iii) complexity arising from coordination required from various healthcare providers to treat the patient's disease. We conduct our analysis by using a large-scale dataset with detailed patient level data from acute care hospitals in California that is coupled with relevant data from several other sources. After accounting for self-selection bias, our analysis reveals that meaningful use of EHRs reduces the overall LOS by about 9%; and that the magnitude of this effect is greater for patients with higher disease and comorbidity complexity and for patients with

¹ Wani, D. and M. Malhotra. To be submitted to *Manufacturing and Service Operations Management*

higher coordination needs. Further, these changes in LOS do not come at the expense of increased readmissions. In fact, we find an overall decrease in readmissions and a greater reduction in readmissions for patients with a higher disease and coordination complexity profile. Apart from theoretical contributions, practical implications of these results are also discussed.

Keywords: Electronic Health Records, Healthcare, Meaningful Use of Technology, Task Complexity, Length of Stay

2.1 Motivation

The importance and benefits of information technology (IT) in improving the efficiency and quality of customer-facing operations has been highlighted in previous literature (Froehle and Roth 2004). Firms in industries such as telecommunications, retail, etc. have seen benefits as a result of widespread use of IT throughout their organizations (Bower, 2005). Healthcare, which comprises nearly 20% of the gross domestic product (Berwick and Hackbarth, 2012), has also adopted various information technologies but none have received the kind of scrutiny that electronic health records (EHRs) have received. Researchers generally agree that electronic health records (EHRs) have the potential to transform healthcare delivery through the use of evidence based medical guidelines and efficient coordination of patient treatment and care (Jha et al., 2009, Blumenthal and Tavenner, 2010). Despite EHRs' potential to improve the efficiency and effectiveness of care, its adoption has been notoriously slow among U.S. hospitals, with less than 10% of U.S. hospitals reporting a comprehensive EHR system across all clinical units in 2009 (Jha et al., 2009). Studies using large scale data in the healthcare and economics literature

that evaluate the impact of adoption of EHRs on various outcomes such as process quality, mortality and cost have yielded mixed results (See Appendix A). In order to overcome barriers and accelerate the adoption of EHRs, the Obama Administration introduced the HITECH Act in 2009 (HHS, 2009). Under this Act, the government committed \$27 billion to incentivize hospitals and clinicians to adopt and meaningfully use EHRs. The government set a high bar in this Act on healthcare providers to improve quality through the use of scientifically supported decision support systems and sharing of data to reduce costs. While the government mandate may encourage hospitals to adopt and use EHRs, can these systems really improve patient outcomes given that past large scale studies have not found overwhelming support from the adoption of EHRs on outcomes?

The main goal of our paper is to investigate whether a hospital wide meaningful use of EHRs, arising from the passage of the HITECH Act, has improved the effectiveness with which hospitals treat patients. This is important to investigate because in a knowledge-intensive industry like healthcare, diagnosing a patient's condition and treating it effectively is a complex task due to the fact that there are currently about 13,600 diagnoses with 6000 drugs and 4000 procedures to treat these diagnoses (The New Yorker 2011). In addition, comorbidities such as hypertension, diabetes, obesity, etc. are increasing in the United States, and clinicians have to take these factors into consideration while designing effective treatment plans. Given the heterogeneity and complexity that healthcare providers face, does the meaningful use of EHRs (henceforth called MU_EHR) add any value so that patients are treated more efficiently? Does the value of MU_EHR increase with increasing patient complexity? We conduct a thorough

examination of the arguments that associate meaningful use of EHRs with improved operating efficiency.

One of the key challenges in measuring the effect of MU_EHR on patient outcomes is the presence of self-selection bias that requires us to model a hospital's decision to go for meaningful use sooner rather than later. It is possible that hospital factors associated with earlier adoption of such EHRs may play a role in earlier attestation of meaningful use of EHRs. Financial incentives also get progressively lower if hospitals delay attestation for MU_EHR. Without controlling for this endogenous selection process, the impact of MU_EHR on outcomes may be biased. In our analysis, we propose a two-stage framework that explicitly deals with the endogeneity inherent in self-selecting to attest for meaningful use sooner. Our econometric model of patient length of stay and readmission is based on detailed patient data from acute care hospitals in California in 2012, a new dataset made available from the Medicare EHR Incentive Program, and data from various other sources. Our model and related analysis offers a new perspective on this issue, which has captured the attention of healthcare providers, policy makers, and academicians over the last few years.

After accounting for self-selection in the EHR incentive program, our results show that patients treated at hospitals that have undertaken MU_EHR attestation have about a 9% lower length of stay as compared to patients that are treated at hospitals that have not undertaken MU_EHR attestation. Thus MU_EHR helps in treating patients with greater efficiency as measured by patient length of stay (LOS). Second, we find that MU_EHR further helps in reducing LOS for patients with higher complexities. Third, we show that a reduction in LOS is not at the expense of increased readmissions. We attribute these

results to the fact that meaningfully using EHRs helps in providing the right treatment at the right time and in the right amount as healthcare providers can gain relevant information about disease conditions by accessing the embedded knowledge base, which results in improved medical decision making (Bulkley and Van Alstyne 2004).

The remainder of our paper is organized as follows: In section 2.2, we discuss the problem background on the meaningful use of EHRs followed by a review of the relevant literature in section 2.3. Our hypotheses are described in section 2.4. Data description and econometric model used in this paper are in sections 2.5 and 2.6 respectively. We present our results and post-hoc tests in section 2.7. We finally conclude with a discussion of implications for research and practice in section 2.8.

2.2 Meaningful Use of Electronic Health Records

The implementation of EHRs has been very slow, with less than 10% of hospitals reporting a comprehensive EHR system by the end of 2009 (Jha et al. 2009). The HITECH Act was passed in October 2010 to encourage hospitals to not just adopt EHRs but also meaningfully use them. Full details of the MU_EHR program can be found here (<https://www.healthit.gov/providers-professionals/how-attain-meaningful-use>), but we provide a brief summary next.

The MU_EHR initiative is rolled out in three stages. In the first stage, which is the focus of this paper, hospitals have to “successfully attest to demonstrating meaningful use of certified EHRs to qualify for an incentive payment scheme through the Medicare EHR program administered by the Centers for Medicare and Medicaid Services (CMS)” (Healthit.gov). Hospitals have to demonstrate use of EHRs at the hospital-wide level to

receive financial incentives. This use includes capturing patient information electronically in a standardized format, using patient information to track key clinical conditions, communicating the information to all providers for the purposes of care coordination, initiating reporting of key clinical quality measures, and finally using the information to engage families and patients in their care. For the successful attestation of first stage of MU_EHR, hospitals are also required to maintain a current list of diagnosis, maintain active medication and allergy lists, implement drug-drug and drug-allergy checks for at least 80% of their patients, record vital statistics and demographics, enter medication orders electronically, and provide electronic copy of health records and discharge instructions for at least 50% of the patients. Based on the certification requirements, MU_EHR depends not only on demonstrating the successful adoption of EHRs from certified vendors, but also on demonstrating the actual use of the system through a series of measures developed by the government. Finally, incentives get progressively lower if hospitals delay attestation of MU_EHR. For example, hospitals that attested meaningful use in 2011 received 100% of the incentive payments that can be anywhere between \$2 million to \$10 million depending on the size of the hospital (Jha, 2010). Incentive payments get progressively lower to 75%, 50% and 25% in the later years. Hospitals also lose 1% of their Medicare reimbursements, which can grow each year up to a maximum of 5%, if they fail to achieve stage 1 certification for each year beyond 2015. Thus it is in the hospitals' best interest to successfully attest for MU_EHR as soon as possible, while also being cognizant of the impact of information technology and EHRs on patient outcomes. This MU_EHR program gives us a way to clearly identify hospitals that are using EHRs meaningfully through well-defined criteria.

2.3 Literature Review

In this section, we preview existing work in the area of information technology and EHRs in particular. Although several studies in the operations management literature have looked at the effect of either IT investments or technologies on various patient outcomes, to the best of our knowledge, none have looked at the impact of meaningful use of EHRs on patient outcomes arising from a mandate. Examining the literature more holistically enables us to identify the gaps and also highlight the importance and need for this study.

2.3.1 Impact of Information Technology on Patient Outcomes

At the hospital level, studies in the OM and IT literature have looked at the impact of IT on outcomes. Angst et al. (2011) and Angst et al. (2012) find a positive outcome between IT adoption and dependent metrics of costs and quality. Devaraj et al. (2013) look at the impact of investments in strategic, clinical and administrative IT on revenue and mortality rate. Sharma et al. (2016) look at the effect of clinical and augmented clinical health information technology on patient satisfaction and cost measures. Queenan et al. (2011, 2016) examine the impact of computerized physician order entry systems and IT investments on patient satisfaction and other patient safety dimensions, while Aron et al. (2011) focus on the impact of systems automation on medical errors. These studies are summarized in Table A of the Appendix.

Most of these studies look at a wide variety of technologies, so it is difficult to understand the specific benefits that accrue from adopting a specific technology. Also, most of these studies focus on hospital level outcomes reported by CMS that are restricted to the Medicare population, but do not apply to general population level

outcomes. Finally, all these studies examine outcomes under a scenario where adoption is self-reported and voluntary. We overcome the drawbacks of previous studies by narrowing our focus to a specific bundle of technologies as defined by MU_EHR (which we explain in more detail in section 4.1), and discussing the specific mechanisms through which information technology impacts patient outcomes and examining its impact on heterogeneous patient types. This is important because hospitals would like the benefits of expensive IT systems to accrue to all patients rather than to specific segments of the patient population. Finally, we focus on patient outcomes when hospitals are mandated to use technology through an Act rather than voluntarily using it. Although Devaraj and Kohli (2003) study the effect of actual use of a basic technology on hospital level mortality and revenue, we believe that our study is different in several ways. First, we consider the meaningful use of technology under a major policy change that affects all hospitals in the US. This is significant because the motivation, challenges and barriers to usage are very different now than when only a small group of hospitals participated voluntarily in their study. Second, our paper is more nuanced and in-depth as it not only evaluates how technology impacts a patient's length of stay, but also studies the contingent impact of task complexity on the relationship between MU_EHR and length of stay.

2.3.2 Impact of Electronic Health Records on Patient Outcomes

There are numerous studies in the economics and healthcare literature documenting the effect of electronic health record (EHRs) and electronic medical record (EMRs) adoption on outcomes. We focus on only large-scale empirical studies, and ignore single site or

case studies because they are too numerous to summarize in a single paper (See Table A). There has been little consensus on the measurement of health information technologies in the past literature. EHR adoption has been measured in several ways such as a generic electronic medical record (EMR) adoption (Miller and Tucker 2011; Furukawa 2011), EMR (Electronic medical record), and CDS (clinical decision support) adoption (Agha 2014), eMAR (electronic medical administration record) and CPOE (computerized physician order entry) adoption (Appari et al. 2012), EHR and CPOE adoption (McCullough et al. 2010; McCullough et al. 2013), or all functionalities including CDR, CDS, eMAR and CPOE adoption (Dranove et al. 2012; Appari et al. 2013; Jones et al. 2014). There are also differences in the way patient outcomes are measured; however process quality, mortality and cost have received the most attention. Results have been mixed - EHRs improve some process quality measures (McCullough et al. 2010; Appari et al. 2013) and patient safety indicators (Hydari et al. 2014), but do not improve mortality, readmissions (McCullough et al. 2013; Agha 2014), costs (Agha 2014; Dranove et al. 2012), or efficiency (Lee et al. 2013). These studies are again summarized in Table A of the Appendix.

Given that the reference technologies and outcome are different in different studies, it is difficult to interpret and reconcile differences in outcomes between these studies that have been conducted using data prior to 2010. These studies also predate the government mandate on meaningful use of EHRs, and as such leave open the question of whether patient outcomes resulting from MU_EHR has changed materially since the mandate was signed in October 2010. Other major issues with these prior studies are as follows: (i) they capture adoption and not actual use of IT, (ii) it is unclear whether the adoption has

occurred only in one clinical unit, or whether an adoption has occurred hospital wide, and (iii) they use self-reported measures of use that are highly susceptible to self-reporting bias.

What sets our study apart is its focus on meaningful use of EHRs, not just adoption, in a hospital-wide implementation under a government mandate. We consider a setting where some hospitals have been using EHRs meaningfully, as measured by their successful attestation of MU_EHR, while others have not. Our study also overcomes the issue of self-reporting bias as the criteria to demonstrate MU_EHR is the same for all hospitals. We also consider MU_EHRs impact on a much broader set of patients and conditions rather than confine our findings to specific patient segments e.g. Medicare patients or patients suffering from pneumonia, heart attack, stroke, etc. Finally, we also conceptualize the task of treating patients along three different complexity dimensions: disease complexity, comorbidity complexity and coordination complexity, and study the value of MU_EHRs in treating patients with lesser or greater complexity profiles. This brings forth a better understanding of how EHR technology, when used meaningfully, can assist healthcare providers in dealing with more complex tasks where it is critical to quickly review relevant information gathered at various points in time, navigate through the built-in knowledge base, synthesize various information pieces at once, and arrive at the correct medical diagnosis and path of action in a time effective fashion.

2.4 Hypothesis Development

We develop our two main hypotheses in this section by first discussing our choice of the dependent variable. We then explore how meaningful use of EHRs can affect patient care. Subsequently, this linkage is contextually examined to develop an understanding of

how different dimensions of task complexity impact the relationship between MU_EHR and patient care.

While LOS has received less attention in terms of the outcome variable than mortality, process quality, etc. we choose it as our outcome variable for several reasons. First, LOS has been used in the operations management literature as a measure of resource efficiency (Andritsos and Tang, 2014; Kc and Terwiesch, 2012). While mortality and readmissions are extreme outcomes that do not affect a large segment of the population and take time for improvement, the impact of EHRs on resource efficiency measures such as LOS can be quickly measured. Studying the impact on LOS is also important because hospitals are under pressure to reduce this measure under the current fixed pay reimbursement. But reduced LOS may lead to a reduction in necessary care, and possibly also increase readmissions (Bartel et al. 2014). This consequently increases penalties to hospitals under the Hospital Readmission Reduction Program. Thus both LOS and readmission metrics are important, and must be considered in conjunction with one another.

There have been proponents and critics of EHRs, and their impact on LOS. Proponents argue that EHRs help healthcare providers work with higher productivity, make fewer errors in diagnoses and treatment resulting in reduced adverse events (Chaudhry et al., 2006). Reduction in errors and right diagnoses and treatment are likely to reduce a patient's LOS. On the other hand, critics argue that EHRs slow down the decision making process due to increased time spent in documenting a patient's medical history, waiting for results from additional diagnostic tests due to ease of ordering through these systems, or an increase in medical errors due to incorrect medication

guidelines (Koppel et al., 2005; Vartak et al., 2009). Either an increase in the number of tests or an increase in errors resulting in rework on the patient will increase a patient's LOS. In either case, MU_EHR is likely to have an impact on patient's LOS. As LOS is a direct reflection of the quality and cost of care, we use this as our focal metric to study the impact of MU_EHR. Even though it is not a part of the main hypotheses, our study also looks at whether reducing LOS compromises readmissions for patients because any efforts made by hospitals to improve LOS should also ensure that they do not lead to increased readmissions. This link has not been previously studied in the context of meaningful use of EHRs.

2.4.1 Meaningful use of IT and mechanisms through which it improves process of care

In order to achieve MU_EHR objectives, hospitals have to adopt several information technology application systems such as CDR, CDS and CPOE. The CDR application helps in storing real time information about a patient's demographics, hospitalization history, problem list, medication and allergy list, past radiology and pathology reports and past lab test results (Dranove et al., 2012). By converting the patient's entire history from paper to a standardized electronic format, care providers can quickly assess the patient's condition. The CDS application generates recommendations for patient care based on evidence-based guidelines. It also performs critical drug-drug and drug-allergy checks and raises any red flags due to potential interactions between drugs prescribed for the treatment and any other drugs that the patient may be currently taking, or interactions with any allergies that the patient may have. CDS also provides antibiotic dosing reminders, thereby ensuring timely administration of medications (Garg et al., 2005).

CPOE enables providers to electronically access and change medication and lab tests. By allowing providers to access notes from other providers, CPOE helps improve the coordination of care, and reduces the chances for miscommunication and delays in care (Classen et al., 2007; Poon et al., 2004).

Research has shown that when agents are expected to make efforts that they are not compensated for or where the outcomes are unclear, it results in suboptimal effort on the part of agents (Holmstrom and Milgrom 1991). Unclear returns on investment and physician resistance have been cited as factors associated with the slow adoption and use of EHRs in the past (Jha et al. 2009; Ford et al. 2009). Literature has theorized that “in a computer usage context, the direct compliance-based effect of subjective norm on intention over and above perceived usefulness and perceived ease of use will occur in mandatory, but not voluntary, system usage settings” (Venkatesh and Davis, 2000, pg. 188). Thus the meaningful use of EHRs, under the mandate, will result in healthcare providers accessing various features such as drug-drug and drug-allergy checks, alerts and reminders, generation of right treatment choices through the knowledge of evidence based guidelines. Thus MU_EHR strives to improve the overall quality of the treatment process by reducing the occurrence of infections and other complications such as reoperations (Bozic et al., 2010; McCabe et al., 2009) and adverse events (Chaudhry et al., 2006). We expect MU_EHR to lead to a decrease in LOS, and formally state our hypotheses as follows.

H1: Meaningful use of EHRs is associated with a shorter length of stay

2.4.2 Impact of MU_EHR when Task of Treating Patients is More Complex

Task complexity has been identified as an important factor affecting performance in various settings such as organizational studies, information seeking studies, psychological studies, etc. (Payne 1976, Van de Ven and Ferry 1980, Locke et al. 1981, Culnan 1983, Campbell and Gingrich 1986, Wood 1986, Campbell 1991, Argote et al. 1995). Task complexity determines the information processing behavior, cognitive load and decision making process of a person or a team (Campbell, 1988), and is often divided into objective and subjective task complexities. Liu and Li (2012) provide a review on task complexity.

In our paper, we focus on objective task complexities that are related to task characteristics, and independent of the characteristics of the person who performs the task. Task complexity can arise due to several factors: the number of distinct acts and information cues that have to be processed, the amount of coordination required, and the relationship between task inputs that have to be taken into account in order to complete the task (Wood, 1986; Campbell, 1988). As the complexity of the task increases via the amount of information that needs to be processed, it puts a larger information load on a person's memory and attention. It forces humans to put greater cognitive resources to use in such situations, which in turn may force people to either make tradeoffs between the time required to make a decision and the decision accuracy, or to make suboptimal decisions (Johnson and Payne, 1985; Milkman et al., 2009).

In our study, we consider treating the patient as the main task. Given that patient diagnosis and treatment are complex tasks, several mental processes have to be synchronized in order to provide the best outcomes. In healthcare, complexity can arise in

various forms. For example, performing a coronary artery bypass grafting procedure is more complex than treating a fractured bone. The former involves more critical steps such as ensuring that the correct drugs are administered before and after surgery, the necessary checklists are followed, correct tests are performed before and after surgery, etc. Thus more complex procedures require care providers to access and keep track of a greater amount of information. As the amount of patient information that needs to be processed increases, the knowledge and memory requirements to perform the task also increases because the care provider must process all this information at once and arrive at the best course of action (Chandler and Sweller, 1991). Presence of comorbidities such as hypertension, diabetes and obesity are known to increase post-operative complications and discharge decisions in patients undergoing shoulder, hip or knee surgery (Jain et al. 2005). When care providers encounter such patients, their treatment decision will depend on several factors such as selection of the right treatment drugs, deciding the correct amount of drug dosage, the method of drug administration, potential drug interactions, and the duration of the treatment. Thus cognitive requirements would increase as comorbidities that a person arrives with increases. Finally, some tasks require greater coordination in the timing and sequencing of activities than others (Wood 1986, Braarud and Kirwan 2011). As the steps involved in performing a task become more interconnected, people who perform the later steps in the execution of a given task will have to learn based on the information provided by the previous steps. The right information on treatment plans, dosing schedules, and other protocols have to be communicated to all parties involved to avoid errors such as performing surgery on the wrong part of the body, overdosing, etc. (Seiden and Barach, 2006). Further, treatment

notes and instructions written by various clinical specialists have to be made available to all care providers, especially during handoffs (Solet et al., 2005). Thus greater coordination implies that greater amount of information has to be formally exchanged among the involved agencies.

Typically, doctors and nurses are trained to diagnose problems and identify patterns of symptoms, and this ability gets better with experience (Elstein and Schwarz, 2002). However, when a clinician encounters complex cases, it is possible that his or her ability to make good decisions becomes compromised under high cognitive load. This can lead to poorer decision-making, improper medications, failure to treat all accompanying conditions, etc. (Burgess, 2009; Parchman et al., 2007; Redelmeier et al., 1998). This issue is further complicated in hospitals where providers encounter patient heterogeneity, and may have to accommodate interruptions and unscheduled requests that may increase the time required to complete the job as providers have to revisit task details (Froehle and White 2013).

Previous literature has shown that (1) The correct fit between task and technology is critical in predicting the success of information technology and that (2) Fit is determined by the interaction between the characteristics of task and technology (Cooper and Zmud, 1980, DeSantis and Poole, 1994, Goodhue 1995, Goodhue and Thompson 1995, Zigurs and Buckland 1998, Dennis et al. 2001, Banker et al. 2002). It has also been suggested that group decision support systems technology may work better for complex tasks as compared to simple tasks (Dennis and Gallupe, 1993). In the case of complex tasks, technology that provides rich information, clarifies task assignment, supports communication, and enables feedback results in better performance (Andres and Zmud,

2002; Gebauer et al., 2005; Ren et al. 2008). A pioneering study conducted by Autor et al. (2003) on the effect of computerization across multiple industries suggests that information technology can “complement workers in executing non-routine tasks demanding flexibility, creativity, generalized problem-solving capability and complex communications”. Mapping these results to the healthcare settings, it is plausible that key features of EHRs such as checking for drug-drug or drug-allergy interactions, referring to treatment guidelines, ordering additional tests, communicating with other physicians, etc., that are mandated to be used in a meaningful way, may possibly add more value when tasks are non-routine and more complex as argued by Autor et al. (2003). We can view MU_EHR as a group decision support system comprising of a set of technologies such as CDR, CDSS and CPOE. As information on disease conditions, treatment protocols, and checks for drug-drug and drug-allergy interactions are embedded into these group support systems, providers can quickly and easily navigate this knowledge database for more complex tasks and accrue larger benefits for higher complexity patients. Thus we hypothesize:

H2: While meaningful use of EHRs will reduce length of stay for all patients, the magnitude of effect will be larger for high complexity patients than for low complexity patients

2.5 Data Description

Our study looks at the impact of MU_EHR on patient LOS, and further argues that magnitude of effect will be greater for higher complexity patients. Our first source of data

comes from California's Office of Statewide Health Planning and Development (OSHPD) for the year 2012. This dataset contains detailed patient level discharge records and includes information on patient demographics (e.g. age, gender, race and insurance), dates of admission, procedures and discharge, diagnosis related group (DRG) codes and type of procedures conducted. To identify hospitals that are meaningfully using EHRs, we use a brand new dataset from the Medicare EHR Incentive program which provides the year in which hospitals successfully attested for stage 1 of meaningful use across all years (https://www.cms.gov/Regulations-and-Guidance/Legislation/EHR_Incentive_Programs/DataAndReports.html). It should be noted that hospitals have to attest each year to meaningful use to receive incentive payments. So when hospitals attest successfully in 2011, the first year of attestation, they also have to attest in the later years thus ensuring continued meaningful use. Our measure for hospitals that achieved meaningful use of EHRs in 2011 is a binary 0/1 measure. While this measure may seem trivial at the surface, it should be noted that in order to successfully attest to meaningful use and receive incentives under the program, hospitals must achieve 14 core meaningful use objectives and 5 out of 10 menu meaningful use objectives. Each objective is accompanied with a very specific measure (Blumenthal and Tavenner 2010), and a hospital can successfully attest to meaningful use only if it meets all requirements. Thus, under the binary 0/1 measure for MU_EHR, there is an underlying continuous score on which hospitals are measured. The commonly used Healthcare Information and Management Systems (HIMSS) dataset in previous studies provides a measure of whether EHR systems such as CDS, CDR, CPOE, etc. have been adopted or not, not the actual use of these systems. In contrast, using this new dataset gives us confidence that

we are capturing not just adoption but also meaningful use of EHRs. Out of the 300+ nonfederal short-term acute care hospitals in California, 60 had attained meaningful use in 2011. We join these two datasets using the unique CMS ID number. We would like to highlight two points here. First, we ensure that hospitals that had undergone meaningful use attestation in 2011 also did so in 2012. Second, we choose to study the performance of 2011 meaningful use attested hospitals using 2012 data as it would ensure that we are measuring the longer-term stable efficiency effects after the phase of learning and recovery has taken place (Bhargava and Mishra 2014).

Our dependent variable is patient length of stay (LOS) from admission until discharge. This measure is provided in the OHSPD dataset. The LOS in our dataset is an integer value, and ranges from 1 day to 35 days for 99% of the observations, but the distribution is right skewed. To adjust for this skew and ensure normality, we take the natural log transformation.

We conceptualize three types of task complexity. *Disease complexity* arises from how complex it is to treat the disease itself. Complex diseases consume greater resources and require a greater number of steps to be performed in order to achieve the task (Campbell, 1988; Wood, 1986). CMS assigns a relative weight to each DRG code that reflects the resource consumption by each DRG. More complex procedures consume more resources and are assigned higher weights. For example, coronary bypass with cardiac catheterization is a more complex procedure with a weight of 5.4, while treatment of a femur fracture is a relatively simple procedure and is assigned a weight of 1.19. DRG weights range from 0 to 24 in the CMS dataset, and are available from CMS ([https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/ AcuteInpatientPPS](https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS)

/FY-2012-IPPS-Final-Rule-Home-Page-Items/ CMS1250507.html). We join the dataset containing patient level data and MU_EHR certification data with the DRG weights dataset using a unique CMS Medicare identifier number.

Comorbidity complexity refers to the number of pieces of information about the patient that need to be processed in order to complete the task of treating the patient (Wood, 1986). We calculate this as an Elixhauser severity score based on literature (Berry Jaeger and Tucker 2016). This score is calculated using two pieces of information about a patient: (i) information on the Elixhauser Index which is a vector of 29 different variables where each variable is binary in nature and represents the presence of a specific comorbidity with a value of 1 and 0 otherwise and (ii) information on the severity score on each comorbidity, ranging from -7 to 12 with larger weights representing more severe comorbidities (Elixhauser et al. 1998). Thus the Elixhauser severity score is the dot product of the Elixhauser Index and the severity score. Information on comorbidities is provided in the OSHPD database. We convert the comorbidity description as a 0/1 binary variable, and use the severity score published in literature (Elixhauser et al. 1998) to arrive at the severity score for each patient. The scores in our sample range from -18 to 60.

Finally, we define and capture a new complexity variable associated with coordination requirements, and name it *Coordination Complexity*. This represents the total number of procedures done on a patient for diagnostic or exploratory purposes or necessary to take care of a complication rather than one performed for definitive treatment. Thus greater amount of information has to be formally exchanged among the involved agencies which may have implications for developing treatment plans and

medication types, treating the right part of the body, etc. (Seiden and Barach, 2006). The OSHPD database provides information on up to 21 procedures performed on a patient besides the main procedure that was performed for definitive treatment. We sum up the procedures done on each patient to arrive at our measure of coordination complexity.

We also control for various characteristics such as patient age (years), gender (female = 1, male = 0), race (three categories), insurance type (Medicare, Medicaid, Private, Self-pay), admission type (unscheduled = 1, scheduled = 0), day of admission (weekend = 1, weekday = 0), month of admission, major diagnostic codes, and hospital fixed effects. We drop observations with missing data on any of the control variables. We delete observations with incorrect dates e.g. discharge date before the admission date, procedure dates before the admission date as these were listed with negative LOS in the OSHPD dataset. We also consider only 99% of the observations, as the remaining 1% of the observations have very high LOS (several values ranged from 100 to 1000 days, possibly due to data entry errors) and which can potentially result in a highly skewed distribution. Joining the various datasets described above results in 2.20 million patient records. A summary of the variables described above is given in Tables 2.1 and 2.2

Table 2.1: Descriptive Statistics of Variables used in main analysis

Variables	Mean	Std. Deviation	Minimum	Maximum
LOS	4.314	4.566	1	35
Readmission	0.104	0.305	0	1
Disease Complexity	1.465	1.549	0	24
Comorbidity Complexity	3.241	5.937	-18	60
Coordination Complexity	2.534	2.145	1	21
Patient Age	45.866	4.556	1	102

Categorical Variables	Sub Category	Percentages
Gender	Male	39.18%
	Female	60.82%
Race	White	64.53%
	Black	7.82%
	Other	27.65%
Insurance	Medicare	30.99%
	Medi-Cal	25.85%
	Private	34.19%
	Other	8.97%
Admission Type	Unscheduled	25.57%
	Scheduled	74.43%
Admission Day	Weekday	74.95%
	Weekend	25.05%

Table 2.2: Hospital Level Characteristics used in selection model

Variables	Mean	Std. Deviation	Min	Max
Teaching Status (0 = Non-Teaching, 1 = Teaching)	0.091	0.288	0	1
Profit Goals (0 = For Profit, 1 = Not For Profit)	0.582	0.494	0	1
Location (1 = Rural, 2 = Semi-Urban, 3 = Urban)	1.752	0.500	1	3
Hospital Size	248.193	170.874	10	1500
Case Mix Index	1.519	0.260	0.782	2.604
IT Technologies	38.484	12.193	7	62
System Membership (0 = Yes; 1 = No)	0.445	0.497	0	1
Competition	34.859	28.842	8	81

It is in the best interest of hospitals to attest for meaningful use as soon as possible, as incentives get progressively lower if they delay the attestation. However, the decision to go for MU_EHR sooner or later may depend on several observable and unobservable characteristics leading to self-selection. We address this issue in the econometric model section, but would like to briefly discuss additional data collected for this purpose. The decision to adopt EHRs and go for MU_EHR certification is dependent on hospital characteristics (Jha et al. 2010; Diana et al. 2014). We collect hospital characteristics from three different sources: OSHPD Annual financial database (AFD),

CMS Inpatient Prospective Payment System (IPPS) file and HIMSS database. All data sources are joined together with the CMS unique Medicare Identifier number. Since we have missing hospital identifier data in various datasets, after joining, we end up with 282 hospitals in the combined dataset. As information from the self-selection model is incorporated into our main analysis, our final patient level data has 2.18 million patient records. In this dataset, we have 47 hospitals that underwent MU_EHR in 2011 and treated 0.48 million patients using these systems. The remaining 235 hospitals did not undergo MU_EHR at the end of 2011 and treated 1.70 million patients. We provide a comparison of MU_EHR certified and Non MU_EHR certified hospitals in Table 2.3 below.

Table 2.3: Comparative Statistics for MU_EHR certified and Non MU_EHR certified hospitals

Variables	MU_EHR Certified (Means)	Non MU_EHR Certified (Means)
LOS	4.098	4.375
Readmission	0.097	0.108
Disease Complexity	1.519	1.451
Comorbidity Complexity	3.377	3.202
Coordination Complexity	2.478	2.549
Patient Age	46.173	45.780
Teaching Status (0 = Non-Teaching, 1 = Teaching)	0.155	0.079
Profit Goals (0 = For Profit, 1 = Not For Profit)	0.80	0.541
Location (1 = Rural, 2 = Semi-Urban, 3 = Urban)	1.777	1.747
Hospital Size	274.556	243.250
Case Mix Index	1.556	1.513
IT Technologies	47.844	36.729
System Membership (0 = Yes; 1 = No)	0.667	0.404
Competition	30.311	35.713

Categorical	Sub Category	MU_EHR Certified	Non MU_EHR Certified
Gender	Male	40.19	38.90

	Female	59.81	61.10
Race	White	53.74	67.56
	Black	8.93	7.51
	Other	37.33	24.92
Insurance	Medicare	31.96	30.72
	Medicaid	11.35	29.93
	Private	51.19	29.41
	Other	5.50	9.94
Admission Type	Unscheduled	27.27	25.09
	Scheduled	72.73	74.91
Admission Day	Weekday	74.71	75.02
	Weekend	25.29	24.98

2.6 Econometric Model

A major concern in evaluating the impact of MU_EHR on patient LOS is a hospital's potential endogenous decision-making process on whether to go sooner or later for the attestation. While certain observable hospital characteristics such as hospital size, profit goals of the hospital, system membership, etc. have been identified in previous literature as factors that likely affect early attestation decision (Jha et al. 2010; Diana et al. 2014), other unobservable factors such as a cost benefit analysis could also play a key role in impacting this decision. Ignoring the impact of these characteristics may render a biased estimate of the effect of meaningful use of EHRs on patient length of stay (LOS). We use a two-stage treatment effects model to account for endogeneity in the binary variable measuring MU_EHR certification (Maddala 1983; Guajardo et al. 2012). This approach allows us to estimate the effect of a binary treatment, MU_EHR in this case, on patient LOS. The two-stage treatment effects model is represented by the following set of equations:

$$Y_{ih} = \beta X_{ih} + \alpha Z_h + \varepsilon_{ih} \quad (1)$$

$$Y_{ih} = \beta X_{ih} + \alpha Z_h + \gamma Z_h \cdot \text{Complexity} + \varepsilon_{ih} \quad (2)$$

$$Z_h = 1 \text{ if } (\lambda W_h + v_h > 0) \quad (3)$$

The main coefficient of interest is α in equation 1 and γ in equation 2. Y_{ih} , which denotes the log transformed patient i 's LOS at hospital h , is explained by exogenous covariates X_{ih} , described in the previous section, and the endogenous binary variable Z_h , which is coded as 1 for hospitals that achieved meaningful use in 2011 and 0 for hospitals that did not. It should be noted that although a hospital received MU_EHR certification at the organizational level, this certification is achieved only if at least 80% of its patients are treated via these systems. Thus MU_EHR affects individual patients and is not just a change that happens at the hospital level, which in turn justifies our approach of studying the impact of MU_EHR using patient level data.

The standard procedure is to model the binary variable for MU_EHR attestation decision as an indicator function that depends on a set of exogenous covariates W_h , which drive the decision to attest for meaningful use sooner than later. The unobservables are captured through their mean effect in the treatment decision on the treatment outcome (Tucker 2011); ε_{ih} denotes the error term in the performance model, and v_h denotes the error term in the choice model. This treatment effects model allows us to correlate the error terms from both equations. The choice model is determined using a Probit model and a selectivity term is calculated from the results of the choice model. This is substituted as a regressor in the performance equation to consistently estimate the impact of MU_EHR on patient length of stay while also accounting for the endogeneity in the choice process. The selectivity terms is given by equation 4, where ϕ and Φ represent the standard normal pdf and cdf respectively.

$$Selectivity Term_h = \frac{\phi(\lambda W_h)}{\varphi(\lambda W_h)} \text{ if } Z_h = 1; \frac{-\phi(\lambda W_h)}{(1 - \varphi(\lambda W_h))} \text{ if } Z_h = 0 \quad (4)$$

We select the following covariates in the choice model that may influence the decision to self-select for early MU_EHR attestation. Literature indicates that hospitals with larger bed size, not for-profit status, teaching and urban hospitals are more likely to meet meaningful use criteria and receive incentives (Jha et al. 2010; Diana et al. 2014). It has been suggested that hospitals with a more severe case mix may see more benefits from such systems, so we include it as a covariate (McCullough et al. 2013). All variables mentioned above are collected from CMS IPPS files. Hospitals may make other clinical, administrative, and strategic IT investments such as diagnostic information systems, scheduling systems, business intelligence, etc. and when hospitals integrate these technologies with EHR systems, it is likely to improve hospitals' quality improvement efforts (Devaraj et al. 2013). Also, it is reasonable to assume that when hospitals choose to invest in various other quality enhancing technologies, they would do so in EHRs as well. The HIMSS database provides information on presence of each of these technologies, and we create a count value to capture technology related investments made by hospitals. Environmental conditions such as local competition in the service area in which a hospital is located and system membership i.e. whether a hospital belongs to a system may influence a hospital's decision to achieve MU_EHR sooner or later (Diana et al. 2014). System membership is collected from OSHPD AFD as a binary variable, and competition is calculated as the number of hospitals in each hospital service area as determined by the Dartmouth Atlas (<http://www.dartmouthatlas.org/>).

2.7 Results

Results of the performance model are presented in Table 2.4, and the choice model results are presented in Table 2.5. Table 2.4 provides results for the overall LOS. We discuss the effects of MU_EHR on the overall LOS (column 1) and LOS by complexity type (columns 2-4). Column 1 shows the effect of MU_EHR on patient LOS and indicates that, on an average and all else being equal, MU_EHR significantly reduces LOS ($p < 0.001$). This provides support for hypothesis H1. Columns 2-4 indicate the impact of MU_EHR, on average and all else being equal, shows that MU_EHR has a greater impact on reducing LOS for patients with higher disease, comorbidity and coordination complexity. These results provide support for hypothesis H2. As discussed previously, our model controls for the endogenous nature of early self-selection in the MU_EHR attestation process. The selection correction term is highly significant at the 0.001 significance level. This evidence confirms the important role of accounting for the selection process in order to estimate the effect of MU_EHR on patient LOS. After exponentiating the coefficients, our analysis shows that MU_EHR can reduce this length of stay by approximately 9%. In order to properly estimate the impact of MU_EHR on reducing the length of stay for all patients, we use data from Bartel et al. (2014), which shows that marginal cost of an additional day spent in the hospital is approximately \$600. Given that the average length of stay for such patients is approximately 4 days (as given by our descriptive statistics in Table 2.3); this is equivalent to a reduction of 0.36 days. If a hospital treats about 10,000 patients in a year, this alone translates to an annual savings of \$2.16 million for each hospital. Our analysis also shows that while each of the complexity types considered in our model increases the LOS, hospitals with meaningful

use of EHRs actually see a slight reduction in their LOS for such patients. While the effects may not seem very high, it is still preferable to the alternative where such patients would have stayed longer in the hospital and potentially increased the risk of hospital-acquired readmissions.

With respect to the choice equation, the results indicate that larger hospitals, non-profit hospitals, hospitals that do not belong to a system and hospitals with greater investments in other clinical, administrative and strategic technologies are more likely to go for meaningful use sooner.

Table 2.4: Main Results

	(1)	(2)	(3)	(4)
LOS	Base Model	Disease Complexity	Comorbidity Complexity	Coordination Complexity
MU_EHR	-0.088*** (0.004)	-0.069*** (0.002)	-0.081*** (0.003)	-0.109*** (0.003)
Disease Complexity	0.090*** (0.002)	0.142*** (0.003)	0.090*** (0.002)	0.092*** (0.002)
Comorbidity Complexity	0.053*** (0.0008)	0.053*** (0.001)	0.55*** (0.0009)	0.053*** (0.0008)
Coordination Complexity	0.051*** (0.002)	0.049*** (0.002)	0.050*** (0.002)	0.071*** (0.004)
MU_EHR X Complexity		-0.004*** (0.0002)	-0.006*** (0.001)	-0.002*** (0.0003)
Selectivity Term	-0.026*** (0.004)	-0.038*** (0.004)	-0.090*** (0.006)	-0.017*** (0.004)
Patient Demographics	Yes	Yes	Yes	Yes
Time Controls	Yes	Yes	Yes	Yes
Hospital Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.380	0.384	0.382	0.382
Observations	2.18 million	2.18 million	2.18 million	2.18 million

Note: Robust standard errors are in parentheses and are clustered at the hospital level.
*, **, *** Indicate significance at the 5%, 1%, and 0.1% confidence levels, respectively

Table 2.5: Choice Model Results

	MU_EHR Certification
Bed Size	0.0033***(0.0009)
Profit Goals	0.985†(0.463)
Teaching Hospitals	0.378(0.382)
Location	0.341(0.273)
Case Mix Index	0.183(0.612)
IT Investment	0.074***(0.014)
System Membership	0.612**(0.255)
Competition	-0.001(0.004)
R-squared	0.254

†, *, **, *** Indicate significance at the 10%, 5%, 1%, and 0.1% confidence levels, respectively

2.7.1 Post Hoc Analysis of EHRs' Impact on Readmissions

Previous literature has shown mixed results on the impact of reduced LOS. While reduced LOS may lead to increased readmissions because a patient is discharged quickly without recovering completely, a lower LOS may lead to a lower probability of hospital acquired infections and therefore reduced readmissions (Chen et al., 2010; Kc and Terwiesch, 2012). So we also evaluate the impact of change in LOS resulting from MU_EHR on readmissions. We expect the probability of readmissions to be lower as MU_EHR enables care providers to 'do it right the first time,' and provides discharge instructions so that patients can take care of themselves post-discharge. The equations to test readmissions are the same as those for LOS (and the notations are as used in equations 1-4, except that we include the LOS variable in the readmissions equation as it has been known to impact patient readmissions (Kc and Terwiesch, 2012).

As per CMS guidelines, we consider patient readmissions within 30 days. The OSHPD data provides a unique patient identifier, which we use to code our readmission as a binary variable, where 1 indicates that a person was readmitted within 30 days; and 0 indicates otherwise. Our dataset has missing information on several patients' unique identifier number. We deleted these records, as they are unusable in calculating the readmission measure. Our resulting sample size is 1.74 million records, with 0.47 million hospitals that have meaningfully used EHRs and 1.33 million for hospitals that have not. We run a Probit regression here, and results from this analysis are shown in Table 2.6. As shown in column 1, MU_EHR is associated with lower readmission rates for all patients. This is a very encouraging sign that while hospitals reduce LOS via MU_EHR, they also reduce readmissions for their patient population. In addition, as shown in columns 2 and 4 of Table 2.6, MU_EHR also reduces readmissions for patients with greater disease and coordination complexity. The impact of MU_EHR on readmissions is not significantly different between patients with higher and lower comorbidity complexity.. Managing comorbidities is challenging as it may require adherence to a self-management program, prioritizing care and initiating lifestyle changes (Kerr et al., 2007). Easy access to self-management tools is not required in the first stage of MU_EHR, but is built into stage 3 requirements (which have not yet been finalized). We conjecture that this might be the reason why we do not see an effect on readmissions for patients with higher comorbidity complexity as this study looks at only the first stage of MU_EHRs.

Table 2.6: Post-Hoc Results for Readmissions

	(1)	(2)	(3)	(4)
Readmission	Base Model	Disease Complexity	Comorbidity Complexity	Coordination Complexity
MU_EHR	-0.514***	-0.542***	-0.517***	-0.520***

	(0.015)	(0.016)	(0.033)	(0.017)
Length of Stay	0.033*** (0.001)	0.033*** (0.001)	0.034*** (0.002)	0.038*** (0.001)
Disease Complexity	0.031*** (0.003)	0.121*** (0.011)	0.030*** (0.003)	0.051*** (0.004)
Comorbidity Complexity	0.049*** (0.001)	0.047*** (0.001)	0.049*** (0.002)	0.051*** (0.002)
Coordination Complexity	0.924*** (0.028)	0.992*** (0.026)	0.925*** (0.027)	0.894*** (0.028)
MU_EHR X Complexity		-0.006*** (0.001)	-0.002 (0.002)	-0.003*** (0.0004)
Selectivity Term	0.738*** (0.021)	0.721*** (0.021)	0.742*** (0.023)	0.702*** (0.021)
Patient Demographics	Yes	Yes	Yes	Yes
Time Controls	Yes	Yes	Yes	Yes
Hospital Fixed Effects	Yes	Yes	Yes	Yes
Pseudo R-squared	0.153	0.155	0.154	0.154
Observations	1.74 million	1.74 million	1.74 million	1.74 million

Note: Robust standard errors are in parentheses and are clustered at the hospital level
*, **, *** Indicate significance at the 5%, 1%, and 0.1% confidence levels, respectively

2.8 Conclusions and Discussion

As with any empirical work, there are limitations to our analysis. First we study data on patient outcomes from one state only, namely California. Other important studies in OM healthcare have used single state studies as well (Diwas and Terweisch 2011; Berry Jaekar and Tucker 2016). Although generalizability to the rest of the country may be debated, our sample size is sufficiently large to ease such concerns. On the other hand from a methodological perspective, this sample choice could also be seen as a strength of the study since it helps with controlling for the effects of regulations that may vary from one state to another. Next we only look at hospitals that achieved meaningful use in the first year i.e. 2011 and compared it to hospitals that did not achieve it in that year. While

this analysis helps us to understand the impact of MU_EHR, it does not tell us whether the benefits were sustainable over subsequent years. Future research can use our study as a building block and look into this issue. We also do not compare the performance of hospitals that underwent MU_EHR certification in 2011 versus 2012 and so on.. Future research can address this issue as well. Nevertheless, our study makes several important theoretical and practical contributions to literature that can serve as a building block for future work in this area. We highlight these contributions next.

2.8.1 Contributions to Theory

Our research is one of the first studies to examine the effect of the meaningful use of EHRs, under a government mandate, on hospitals' operating efficiency measured as patients' length of stay. Although the past literature has seen support for impact of IT investments on hospital level patient outcomes (Angst et al. 2012), such support is not clear when specific EHR technologies are investigated. (Agha 2011, Appari et al (2012), Dranove et al. (2012), Freedman et al. 2014, Jones et al. (2010), McCullough (2010), McCullough (2013)). Our study extends this line of research by looking at not just the adoption, but rather the meaningful use of EHR technologies mandated under the HITECH Act. Mandates can be an effective tool in improving outcomes (Horton et al. 2013; Halpin et al. 2013; Ioannou and Serafeim, 2014), and our research adds to this stream of literature. Given that the effects of EHR adoption have been mixed in the past literature, a mandate for meaningfully using EHRs may be a step in the right direction. Past studies have used self-reported adoption by hospitals to evaluate the impact of EHRs. Such adoption measures are susceptible to self-reporting bias, and which and

make it difficult to evaluate which clinical units in a hospital are actually using these EHRs. The hospital-wide standardized criteria developed for MU_EHR attestation highlights a need to use well-defined measures to clearly evaluate the impact of EHRs on patient outcomes.

In this study, we have been able to delve into the specific mechanisms through which EHR technologies impact hospital resource efficiency for a diverse group of the patient population. To our knowledge, this is one of the first studies to consider the effects of the meaningful use mandate HITECH Act on a hospital's resource efficiency using detailed patient level data. We look at MU_EHR as a group systems support technology that helps in alleviating the cognitive load on healthcare providers, thus extending the discussion on the benefits of such systems in the healthcare operations area. We also conceptualize the task of treating a patient into three types of complexity profiles based on the degree of difficulty in accomplishing the task of treating a patient i.e. a patient's disease complexity, the degree of patient severity i.e. comorbidity complexity, and degree of coordination required among healthcare providers to accomplish the task of treating the patient i.e. coordination complexity. While these dimensions of task complexity have been conceptualized previously (Campbell, 1988; Wood, 1986), they have been focused mostly in the behavioral sciences and typically studied in controlled laboratory experiments or through case studies (Liu and Li 2012). *We are one of the first to do this in the context of healthcare operations management using objective large-scale secondary data.* Past healthcare literature has only controlled for patient demographics, and has ignored these task complexities (which are not demographic specific) while evaluating the impact of EHRs. Our study highlights the importance of including these

task complexities as they significantly increase the LOS in patients. We are thus able to uncover the additional value that EHR technologies, when used meaningfully, add while treating patients with greater complexities. Specifically, our analysis shows that while MU_EHRs reduce LOS for all patients, these systems improve to a greater degree the efficiency with which patients with a higher degree of disease complexity, comorbidity complexity, and greater coordination needs, are treated. By integrating the literature on task complexity and task-technology fit into the healthcare context, our study underscores the importance of implementing and meaningfully using a hospital wide EHR system, especially when hospitals treat patients with complex disease and comorbidity profiles who require treatment from multiple healthcare providers. In doing so, our paper also answers the call of various researchers on the use of more granular data for understanding and advancing research on the performance impacts of information technology (Agarwal et al. 2010, Athey and Stern 2002, and Himmelstein et al. 2010).

We also highlight that the decision to attest for MU_EHR is endogenous, and driven by factors such as hospital size, complementary IT investments, profit goals, and system membership. This underscores the importance of accounting for such self-selection in future studies that seek to understand the impact of Stage 2 and Stage 3 of meaningful use criteria (which focus on health information exchanges, electronic transmission of patient care across multiple settings, patient access to self-management tools, improving population health, etc.) on various outcomes. Finally, using our detailed patient level data, we are able to show that a reduction in LOS does not come at the expense of increased readmissions. While hospitals cannot control the sickness and comorbidities that their patients come in with, they can certainly ensure that these

patients spend less time in the hospital, which may reduce hospital acquired infections, and therefore readmissions. Providing the right treatment at the right time also ensures that patients are less likely to be readmitted to hospitals.

2.8.2 Implications for Practice

This study is motivated by the government's push to hospitals to adopt and use EHR technologies in a meaningful way, and so is highly relevant to hospital management and executives in the current healthcare environment characterized by cost containment pressures and reduced reimbursement for services. Collectively, our results show that MU_EHR, based on the first stage requirements that mandate hospitals to capture patient information systematically in an electronic format and use built-in treatment protocols for treating these patients, really helps in reducing overall length of stay and also readmission rates. These gains are even more beneficial for certain patient populations. A study by (Hillestad et al. 2005) noted that greater efficiency from EHRs could lead to potential savings of more than \$77 billion per year. Their study also noted that one of the most important sources of these savings come from reduced hospital length of stay, a result that our research confirms as well, though with a greater degree of granularity and contingencies in empirically confirming that the MU_EHR mandate can help achieve these projected savings by reducing the length of stay.

The results that we have presented previously in the results section are not just hypothetical. Hospitals have actually reported cost savings from use of EHRs. For example, Sentara Healthcare realized a return on investment of \$53.7 million at the end of 2011 of which 29% or \$15.5 million savings came from reduced length of stay and

avoiding adverse drug events, and another 18% or \$9.4 million of savings came from increased unit efficiency (<http://health.usnews.com/health-news/hospital-of-tomorrow/articles/2013/11/05/taking-a-close-look-at-electronic-health-records>). In view of increased workloads that hospitals are now facing due to a greater number of insured patients seeking hospital services under the Affordable Care Act, MU_EHR can facilitate more effective bed management and efficient operations by freeing up capacity through faster patient turnaround times. This approach will be preferable to making additional investments in beds or human resources.

Finally, as our post hoc tests reveal, the use of MU_EHR reduces readmissions for complex patients, which is an added benefit to hospitals that might otherwise face additional penalties under the CMS' Hospital Readmission Reduction Program. Thus MU_EHR is an important component in achieving the triple aim of care, health, and cost in patient population. Change in LOS is not at the expense of an increase in readmissions. Even greater benefits are likely to accrue when hospitals get certified for later stages of meaningful use that may focus on information exchanges among hospitals, patient self-management tools, and greater decision support for high-priority conditions. Past research suggests that returns to IT investments persist over time (Tambe and Hitt 2012) and we hope that this will hold true in the case of healthcare as well. Generating enthusiasm and participation for the use of EHR technologies among providers will be an important task for hospital administrators going forward. Our study provides them the empirical basis for doing so beyond just following the mandates of the HITECH Act.

CHAPTER 3

LONGITUDINAL IMPACT OF PROCESS IMPROVEMENT ON PATIENT CARE UNDER COMPETITION AND ACA²

Abstract

Our study examines the impact of competition on process of care (PoC), and the role process improvement factors play on affecting PoC within the altered competitive landscape that has been created in the healthcare industry by the introduction of the Affordable Care Act (ACA) of 2010. ACA acts as a catalyst in increasing competition among all hospitals to attract more patients and improve PoC. A longitudinal analysis of data combined from several different sources shows the contingent value of process improvement factors. Their impact on PoC is positive in both more as well as less competitive markets; however the marginal benefit is stronger in less competitive markets. These results are robust to alternate specifications of competition. We find similar results when considering the catalytic role played by ACA in enhancing competition. We discuss the prescriptive implications of our findings for designing better operational systems in the context of ACA and the increased financial burden that hospitals are facing due to reimbursements shifting from a fee-for-service based system to one based on the value of care provided.

Keywords: Slack, Skill Mix, Focused service strategy, Competition, ACA

² Wani, D., M. Malhotra and S. Venkataraman. To be submitted to *Journal of Operations Management*

3.1. Introduction

The US healthcare system over time has evolved from a fee-for-service system which traditionally focused on paying providers based on the volume and complexity of services, to a prospective payment system which encouraged a reduction in excessive and unnecessary care by providing a fixed payment for services rendered (James, 2012). However, researchers conjecture that this led to a reduction in treatment intensity and resulted in greater medical errors, readmissions and mortality (Cutler, 1995; Encinosa and Bernard, 2005). The Affordable Care Act (ACA) was introduced in 2010 to rein in such inefficiencies and to promote greater coordination across providers of services by creating financial incentives that encourage organizations to deliver efficient and high quality medical care (<http://obamacarefacts.com/affordablecareact-summary/>).

Transition from a cost-based reimbursement to a prospective payment system to the current pay for performance (P4P) system has forced hospitals to become price-takers instead of price-setters, and has reduced reimbursements for a majority of hospitals (Werner 2010; Shen, 2003). It has also put greater constraints on hospitals' financial resources due to slower revenue growth and decline in profits (Bazzoli et al., 2008). One of the key mechanisms that hospitals have used in the past to cope with such changes has been to consolidate through mergers and acquisitions in an attempt to gain market share and reduce their local competition (Cutler and Morton, 2013). However, it has been argued that such consolidations, if left unchecked, can stifle innovation-stimulating competition, have adverse effects on the access and quality of care, and add to the rising healthcare costs (Xu et al., 2015). In recent times, the Federal Trade Commission – the regulatory body overseeing business practices and consumer protection - has been

challenging and winning a number of recent attempts at consolidation in the healthcare industry by arguing that such consolidations operate without the checks and balances of a competitive marketplace (Brill, 2015; New York Times, 2014). So apart from consolidations, hospitals are also forced to seek ways to attract insurers, referring physicians, and patients to improve their revenues, and to improve profitability by emphasizing efficiency in various areas of their operations (Devers et al. 2003; Cutler et al., 2004; Tay, 2003). This competitive landscape is further enhanced by the ACA. It has increased insurance coverage for millions of people causing hospitals to compete for these patients, especially since demand for services is often localized (Tay 2003). In addition, the ACA has also created the hospital value based purchasing (VBP) program that provides financial bonuses to hospitals that improve the value delivered to patients and penalizes others that do not.

How does such a shift toward more competitive conditions for capturing patient demand affect process of care (PoC)? Further how should hospital managers make resource allocation decisions based on their constrained finances to improve hospital processes that ultimately improve patient outcomes? In particular, what is the value of investing in process improvement factors when localized competition for attracting patients is high? This is still an open issue. So in this study, we examine the effect of competition on quality of patient care. Then we unbundle the benefits arising from process improvement factors by validating a finer-grained contingency model that is longitudinally tested with over seven years of panel data.

In section 3.2, we review the relevant literature and develop associated hypotheses that flesh out our research model. In section 3.3, we describe our data sources,

along with the definition and operationalization of key variables, and our econometric model. Results of our analysis and robustness tests are presented in section 3.4. We discuss the impact of ACA on the quality of care in section 3.5. We finally conclude in section 3.6 with a discussion on major theoretical and practical contributions of this study, along with future research directions.

3.2. Literature Review and Hypothesis Development

In this section, we first discuss our choice of dependent variable, followed by a review of the impact of localized competition in the hospital industry on our dependent variable. Then we present theoretical arguments and hypotheses for how competition influences the relationship between our choice of process improvement factors and process of care (PoC).

3.2.1. Choice of Dependent Variable

We choose to study PoC as our dependent variable for the following reasons. First, PoC assesses the degree to which healthcare providers adhere to processes that are scientifically proven or “evidence based” (Jha 2006). Second, although PoC requires a good definition of eligible patient population, it does not require extensive risk adjustment modeling that are necessary for other outcome variables such as mortality and readmissions. Risk adjustment models require extensive psychological, anatomical and health status data that may not be captured or be readily available in a patient’s medical record (Rubin et al., 2001). Third, PoC is under greater control of healthcare providers and requires a shorter time frame for assessment, relative to other outcome measures that

may require longer time horizons to measure (Palmer 1997; Werner et al. 2008). Finally, good PoC has been linked to better patient outcomes such as lower resource usage (Andritsos and Tang 2014), lower readmissions and mortality (Newby et al. 2006; Ashton et al. 1995), and lower rates of infections and complications (McCabe et al. 2009; Bozic et al. 2010). Additionally, PoC leads to higher quality of care for patients because it is also a marker for other unmeasured quality processes that improve patient safety, coordination of care, emergency responsiveness, etc. (Werner et al. 2008). Thus we believe that PoC is an appropriate and comprehensive dependent variable to model in our study.

3.2.2. Choice of Independent Variables

We choose operational slack, nursing skill mix and focused service strategy as our key independent variables, and which together constitute our process improvement factors. We treat these structural and infrastructural choices not only as deliberate strategies that hospitals pursue, but also as emergent choices that evolve over time. Given the constraints that managers face with respect to resources, we believe that our choice of these three variables is most important in improving PoC. Spear (2005) points out that operational excellence in providing safe, efficient, reliable, timely and effective patient care is possible through work redesign, collaborative experimentation among various healthcare providers, and dissemination of knowledge through coaching, mentoring and training activities. However, investing time in rethinking and improving PoC cannot happen in an environment when people are constantly busy (De Marco 2001). Thus slack is necessary for improved PoC. Registered nurses provide important resource flexibility

in an environment that faces demand fluctuations and patient heterogeneity. Further, registered nurses are at the frontline of patient care and have the necessary technical expertise and knowledge to understand the root causes of various problems, identify and prioritize areas of PoC that need most attention, and conceptualize effective solutions through appropriate training (Fields and Sinha 2005; Mukherjee et al. 1998). Finally, a focused service strategy results in stable and standardized work processes through repeated encounters with a homogeneous set of patients (Skinner 1974), which in turn improve organizational learning capabilities as well as PoC (KC and Terweisch 2011). The three process improvement factors of slack, skill mix, and focused service strategy together represent the thrust of process improvement efforts that hospitals can leverage to positively affect PoC.

3.2.3. Impact of Competition

The economics literature argues that when prices are above the marginal cost, greater competition leads to higher quality (Tirole, 1988). In healthcare, roughly 50% of the healthcare spending is financed through Medicare where prices are regulated, while the remaining 50% is financed through commercial or private insurance (Gaynor, 2014). Gaynor (2014) also shows that when prices are regulated, the equilibrium quality has a positive association with the number of firms in the market. Even when prices are determined in hospital markets, as in the case of private insurers, models show that competition leads hospitals to offer higher quality (Gaynor and Town, 2011; Gravelle et al., 2014). These theoretical results have been supported by econometric studies which show that when markets are not concentrated i.e. when there are several competing

hospitals and prices are regulated, outcomes such as mortality and readmissions are better (Kessler and Geppert, 2005; Kessler and McClellan, 1999; Shen, 2003). Both Gaynor (2006) and Gaynor and Town (2011) provide a comprehensive review of studies that look at the relationship between competition and quality.

High PoC and quality is imperative in competitive hospital markets as it is likely to attract insurers, specialists, and referring physicians, which in turn results in higher patient demand (Cutler et al., 2004; Devers et al. 2003; Tay, 2003). Hospitals located in competitive markets choose to signal high quality through investments in innovative technologies, and state of the art diagnostic and medical equipment (Dranove et al. 1992, Tay 2003). Innovative technologies such as electronic medical records enable information exchange about patient health among various providers, provide clinical reminders, improve adherence to treatment guidelines and provide discharge instructions. Diagnostic equipment such as imaging for cardiovascular conditions improve the efficiency of diagnoses, which then results in less time needed to diagnose a patient's condition and provide correct treatment. Thus these investments play a significant role in improving PoC (Appari et al. 2013; Douglas et al. 2009) In addition, hospitals in competitive environments are also more likely to create organizational and structural changes by creating a board level commission on quality, hiring senior personnel to oversee quality improvement efforts, hiring hospitalists to improve care coordination, and adopting exploration type of quality management practices (Bloom et al., 2015; Silow-Carroll et al., 2007). Such actions lead to adoption of practices such as establishing standardized care protocols and performance monitoring systems, setting targets for improvements, and providing incentives to managers and employees to improve patient

outcomes. Such actions have been shown to improve process of care in cardiac patients (McConnell et al. 2013). Thus constant innovation spurred by competition results in continuous quality improvement (Teisberg et al., 1993) and better PoC. As a result, we would expect PoC to be higher in more competitive markets.

H1: Greater competition in hospital markets is associated, on average, with better PoC

3.2.4. Moderating Role of Competition on the Relationship between Process Improvement Factors and Process of Care

It is well known that resource allocation decisions are largely influenced by the resources' ability to outperform competitors when firms are faced with dynamic and changing environments (Sirmon et al., 2007). When hospitals in competitive markets take such actions, they also face greater costs. Furthermore, despite investments in expensive technology and increase in the number of referrals, an increase in hospital revenues is likely to be modest under the fixed reimbursement system. As a result, hospitals in competitive markets have lower profit margins (Dranove et al. 1993). Under greater cost pressures and competitive threats, hospitals may focus on conserving their resources by emphasizing efficiency in other areas of their operations (Staw et al., 1981). Because hospitals encounter heterogeneity in patients and associated medical conditions as well as demand fluctuations, process improvement factors are important to hospitals in their resource allocation decisions. However, the role and value of these process improvement factors discussed earlier under competition is yet unexplored, and which is what we focus on next.

3.2.5. Slack

Operational slack, a key process improvement factor, refers to the flexibility available to a firm to effectively manage variations in a dynamic environment (Anand and Ward, 2004). When utilization is high or slack is reduced, a greater number of patients have to be treated at any given time. Such high utilization has been associated with reduced time spent on each patient, a greater propensity for errors, reduced worker productivity, lower medical treatment quality, lower length of stay, and increased mortality (Berry Jaeker and Tucker, 2013; Kc and Terwiesch, 2009 and 2012). Patients may be placed in less appropriate units for recovery, because the primary unit that they need is unavailable (Green and Nguyen, 2001). Due to greater mental strain on healthcare workers when there is less slack, probability of adverse events unrelated to a patient's underlying medical condition is higher (Rudolph and Repenning, 2002; Weissman et al., 2007). Lower slack may also inhibit the efforts of healthcare workers to find the root causes of process failures (Tucker and Edmondson, 2003). Thus higher slack will improve PoC due to better adherence to necessary protocols of care driven by evidence-based medicine.

Faced with cost pressures and declining profit margins, hospitals see lower slack as a way to be efficient by spreading the fixed costs over a greater volume of patients (Gaynor and Anderson, 1995; Kc and Terweisch, 2009). Hospitals in competitive markets face significantly greater pressures to operate with high utilization rates as they try to balance efficiency goals with costly investments in equipment, technology and management. While these structural and infrastructural investments by hospitals in competitive markets are important in improving quality, enhanced slack is expensive, but likely to complement their quality improvement efforts.

Slack in less competitive markets can serve two purposes. First, it can serve as a deterrent for other hospitals to increase capacity or to prevent new hospitals from opening up i.e. slack creates entry barriers (Salop, 1979). Second, as hospitals in less competitive markets may not face pressures to continually invest heavily in the latest equipment and technologies, they may be able to tolerate more slack in their operations and use this slack to engage in relatively less expensive quality improvement efforts such as imparting training to existing workers on understanding correct protocols for reducing errors and preventing infections, creating cross-functional teams, and using appropriate problem identification and solving tools (Silow-Carroll et al., 2007). While the benefits of slack in improving quality are unequivocal, slack is more readily available in less competitive markets and so will provide relatively greater benefits.

H2A: Competition moderates the relationship between slack and PoC, such that the positive relationship between slack and PoC, on average, is stronger in less competitive markets

3.2.6. Nursing Skill Mix

Nurses have been recognized to be “at the front-line of patient care and in the best position to detect problems, monitor conditions, and rescue when necessary” (Joint Commission on Accreditation of Healthcare Organizations, 2002). A high nursing skill mix i.e. higher proportion of registered nurses promotes greater resource flexibility that is important in handling uncertainties in demand and managing system bottlenecks (Egger, 2000; Hopp et al., 2007; Jack and Powers, 2004). Higher knowledge and training associated with a higher skill mix ensures that quality control practices and standards of

care are followed correctly, which in turn help in detecting and treating complications, preventing adverse events such as surgical infections, pneumonia, wounds, etc. (Needleman et al., 2006; Lang et al., 2004; Cho et al. 2003). Finally, registered nurses are more productive than other nurses as they can perform the entire range of nurse related tasks without supervision (Barkell et al., 2002).

But this high nursing skill mix can be expensive. Registered nurses have significantly higher wages than licensed vocational nurses or nurse aids (Bureau of Labor Statistics, 2014a, 2014b). As hospitals face cost pressures due to changing government policies, nurse layoffs become more common (The Economist, 2014; The New York Times, 1996) and hospitals resort to a lower skill mix i.e. registered nurses get replaced with unlicensed assistive personnel in an attempt to reduce costs and improve profitability (Rivers et al. 2004; Thungjaroenkul et al., 2007). Further, registered nurses also have greater inter-employer mobility i.e. multiple hospital and non-hospital employment options (Hirsch and Schumacher, 1995) in more competitive markets. While increasing wages can be seen as a way to recruit more registered nurses in competitive markets (May et al., 2006), this is less likely as it puts a greater strain on hospitals' financial resources. Pressures to reduce costs are even more acute for hospitals in competitive markets as they have to constantly make investments in purchasing, maintaining and updating medical equipment and technology to improve the quality and safety of care by reducing human errors (Bates et al., 2001; Silow-Carroll et al., 2007). Greater investments in areas of information technology are also likely to reduce the extent of routine manual tasks, while assisting registered nurses with non-routine

cognitive tasks (Autor et al., 2003). Thus technology investments in competitive markets will likely complement a higher skill mix in improving PoC.

In less competitive markets, we have the opposite scenario where there are few employers of RNs. Thus hospital employers have more market power and registered nurse wages are lower (Bruggink et al. 1985; Robinson 1998). Hospitals in less competitive markets are also likely to put more emphasis on training, development and empowerment of their nurses than on providing high technology related services (Li and Benton 2006). Given the importance of skilled registered nurses in improving PoC and a less acute need to continually invest in new technology and equipment, we would expect such hospitals to improve their PoC to a greater extent through investments in higher skill mix. Thus greater benefits from high skill mix will be possible in less competitive markets.

H2B: Competition moderates the relationship between skill mix and PoC, such that the positive relationship between skill mix and PoC, on average, is stronger in less competitive markets

3.2.7. Focused Service Strategy

The operations management literature has highlighted the benefits of focus on outcomes such as reduced mortality, increased efficiency, and lower cost arising from reduced variations in patient heterogeneity, greater organizational learning due to higher volumes, and better alignment of people and processes (Ding, 2014; Huckman and Pisano, 2006; Kc and Terwiesch, 2011; McDermott and Stock, 2011). A strategic emphasis on a focused service strategy results in adoption of more standardized components and

processes, as well as better integration of processes which subsequently help in reducing variations in the delivery of care as well as improving efficiency of care. Thus a focused service strategy is likely to improve PoC.

Hospitals in more competitive markets may follow a focused service strategy to achieve economies of scale. On the other hand, they may choose to add an extensive range of complementary services and become a 'one stop shop' to achieve economies of scope. This approach also enables hospitals to attract insurers by providing an array of services thereby reducing contracting costs (Devers et al, 2003). While both scenarios are plausible, findings from studies suggest that hospitals in competitive markets adopt the latter approach (Baker and Phibbs, 2000; Friedman et al., 2002). We have argued earlier that hospitals in more competitive markets are forced to constantly innovate in order to improve their quality. While it is possible to use a focused strategy i.e. perform a narrow set of procedures on a larger volume of patients and achieve higher quality through organizational learning and exploitation of internal capabilities (Kc and Terweisch, 2009), focus on development of core capabilities in just a single area may lead to a decayed competitive stance (Miller et al, 2007). Therefore hospitals in a more competitive environment are likely to be less focused, and thus not be able to improve PoC to the same extent as hospitals in less competitive environments.

The success of a focused service strategy depends partly on patient volume (Hyer et al. 2009). Hospitals in less competitive markets may not have a sufficient pool of patients to justify offering the entire range of possible services. Offering targeted services i.e. a focused service strategy may be a better option for these markets where investments can be made in specific clinical areas and specialized infrastructure, and a higher patient

throughput to ensure high quality of care. Also, hospitals in less competitive markets may not be forced to constantly innovate, but they still need to improve their PoC. Focusing on a narrow set of procedures may also result in simplified routines through which knowledge can be acquired and exploited to treat patients. We would thus expect the marginal benefit from a focused service strategy to be greater in less competitive markets.

H2C: Competition moderates the relationship between a focused service strategy and PoC, such that the positive relationship between a focused service strategy and PoC, on average, is stronger in less competitive markets

Our models for analysis based on these hypotheses are provided in Figure 3.1.

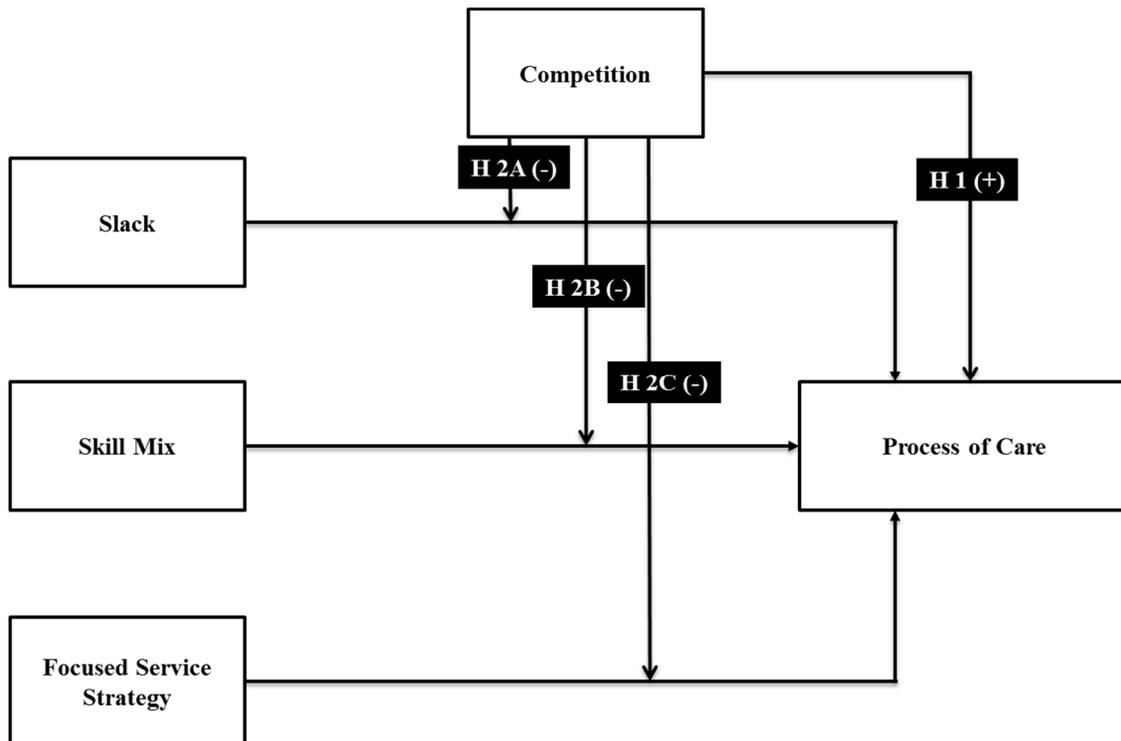


Figure 3.1: Theoretical Model

3.3. Data Sources, Variables and Econometric Model

Our data sample for this analysis is a comprehensive dataset that comes from three different databases. Although measuring all important processes of care is virtually impossible, we use the process of care measures reported on Center for Medicare and Medicaid Services' (CMS) Hospital Compare website as a proxy for our PoC. It should be noted that although CMS reports only a subset of PoC, they are an important marker for other measures of care that are equally important, but are not measured (Werner et al 2008). Data for the internal and external hospital factors are collected from California Office of Statewide Planning and Development's (OSHPD) Annual Financial database (AFD). Various hospital characteristics are compiled from CMS' Inpatient Prospective Payment System (IPPS). Our unit of analysis is acute care hospitals in the state of California. Our data is longitudinal in nature, covering years 2007 – 2013. We describe below the key measures for the variables used in the study.

3.3.1. Dependent Variable

PoC measures collected from CMS refer to the technical quality of patient care for common and serious health conditions including acute myocardial infarction (AMI or heart attack), heart failure (HF), pneumonia (PN), and surgical care improvement/surgical infection prevention (SCIP). Outcome measures related to these conditions are important as they assess critical steps in the overall patient care process that are evidence based and are correlated with lower mortality rates (Jha et al., 2007). We evaluate this outcome measure by using process of care measures reported on the CMS Hospital Compare website. We construct a composite measure of PoC based on the process quality

measures of AMI, HF, PN and SCIP used in the prior literature, and which are common across all years (Senot et al., 2015). Each measure represents the percentage of each hospital's patients as a ratio of the number of people who actually received the treatment to the number of patients that are eligible for the treatment. Following CMS guidelines, only measures based on a sample of at least 25 patients are included in the study. The PoC components used in this study are listed in Appendix B.

We compute a weighted composite measure across all selected measures. In order to satisfy normality and homoskedasticity assumptions of regression analysis, we transform this weighted measure into their Logit form similar to prior literature (Chandrasekaran et al., 2012). Thus our PoC measure for hospital i at time t with the weighted average percentage across process of care measures P_{it} is given by:

$$PoC_{it} = \ln\left(\frac{P_{it}}{1 - P_{it}}\right)$$

3.3.2. Key Variables

Our data for operational slack, skill mix and focused service strategy come from California Office of Statewide Planning and Development's (OSHPD) Annual Financial database (AFD).

Slack

The AFD provides the annual licensed bed occupancy rate as the ratio of patient days to the total available bed days for each hospital for each year. We calculate our slack measure with the following equation, where higher values represent greater operational slack.

$$Slack_{it} = 100 - Bed\ Occupancy\ Rate_{it}$$

Nursing Skill Mix

The AFD provides the annual number of productive hours spent in patient care by registered nurses, licensed vocational nurses (LVN) and nurse aides and orderlies. Based on prior literature (Cho et al., 2003), we calculate the skill mix as shown below, where higher values indicate a greater proportion of hours spent by registered nurses as compared to other nurses.

Skill Mix_{it}

$$= \frac{\text{Productive Hours of Registered Nurses}_{it}}{\text{Productive Hours of (Registered Nurses + LVNs + Aides and Orderlies)}_{it}}$$

Focused Service Strategy

Focused service strategy is measured based on the number of licensed beds in major clinical areas (e.g. general medical and surgery, coronary care, intensive care, nursery, etc.) Similar to prior literature (Ding, 2014), we measure focus as a Herfindahl-Hirschman Index by summing the squared share of licensed beds in each major clinical area, where higher values of the focus variable indicate a more focused or a less diversified hospital strategy.

$$Focus_{ht} = \sum_i \left(\frac{\text{Licensed Beds in area } i \text{ at hospital } h \text{ at time } t}{\text{Total number of licensed beds at hospital } h \text{ at time } t} \right)^2$$

Competition

We measure competition as the number of competing acute care hospitals within a given hospital service area (Shen 2003; Propper et al., 2003). We believe this measure to be appropriate as demand for patients is localized i.e. restricted to a given service area (Tay 2003). Our measure of the hospital service area comes from the Dartmouth Atlas

(<http://www.dartmouthatlas.org/>). In our robustness test, we consider another measure of competition - as measured by the Herfindahl -Hirschmann Index that is based on the market share of providers in a given health service area.

3.3.3. Control variables

Previous studies have identified several hospital characteristics as potential sources of heterogeneity, which may affect performance outcomes in hospitals. Accordingly, we control for bed size (log value) and location (urban/rural) (Jha et al. 2009), case mix index (Schwartz et al. 2011), multi-hospital membership (Ding 2014), teaching intensity (Sloan et al. 2001), corporate goals (for profit/ non-profit) and ownership (public/private) (Weiner et al. 2006), and magnet status of hospitals (Senot et al. 2015). We also control for ACA. We capture this as a binary variable, where 0 represents the period prior to 2011; and 1 represents the period after and including 2011. Finally, we also control for hospital and year fixed effects in our model. Our data for the control variables comes from various data sources such as OSHPD's AFD, CMS Inpatient Prospective Payment System (IPPS), OSHPD's Healthcare Atlas and American Nurses Credentialing Center (ANCC) (www.nursecredentialing.org). We merge all datasets using the CMS Medicare ID number, OSHPD hospital ID number, and the hospital zip code. After conjoining our different datasets, we have 211 hospitals per year giving us a total of 1477 hospital-year records for our analysis. Descriptive statistics and correlations for key variables are provided in Tables 3.1 and 3.2 respectively.

Table 3.1: Descriptive Statistics

Variable	Mean	Std. dev.	Minimum	Maximum
Process of Care	3.27	0.98	0.44	7.73
Slack	0.39	0.13	0.01	0.78
Skill Mix	0.75	0.10	0.18	1.00
Focus	0.48	0.14	0.22	0.89
Competition	26.02	20.41	4	63
Multi-Hospital System	0.49	0.50	0.00	1.00
Ownership (0 = Private, 1 = Public)	0.18	0.38	0.00	1.00
Profit Status (0 = For-Profit, 1 = Non Profit)	0.61	0.49	0.00	1.00
Teaching Status	0.11	0.31	0.00	1.00
Case Mix Index	1.56	0.22	0.99	2.55
Location	1.77	0.46	1.00	3.00
Bed Size	285.05	149.64	47.00	958.00
Magnet Status (0 = No, 1 = Yes)	0.07	0.26	0.00	1.00

Table 3.2: Correlations

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	PoC	1													
2	Focus	0.11	1												
3	Skill Mix	0.2	0.12	1											
4	Slack	0.22	0.24	0.14	1										
5	Competition	-0.11	-0.21	-0.14	-0.07	1									
6	ACA	0.49	0.03'	0.04'	0.17	0.03'	1								
7	MHS	0.25	0.09	0.29	0.18	-0.21	-0.002'	1							
8	Ownership	-0.11	-0.1	-0.15	-0.12	-0.11	-0.002'	-0.25	1						
9	Profit Status	0.12	-0.01'	0.15	0.03'	-0.03'	0.01'	0.17	-0.59	1					
10	Teach	-0.11	-0.21	-0.02'	-0.25	0.04'	0.04'	-0.1	0.21	-0.02'	1				
11	Case Mix Index	0.22	-0.06	0.23	-0.14	-0.001'	0.23	0.02'	-0.05†	0.09	0.25	1			
12	Location	0.08	-0.13	0.05'	-0.04'	0.35	-0.004'	-0.08	-0.02'	-0.09	0.12	0.04'	1		
13	Bed Size	0.03'	-0.34	0.05†	-0.31	0.17	0.04'	-0.16	0.08	0.12	0.5	0.42	0.19	1	
14	Magnet Status	0.04'	0.01'	0.09	-0.16	-0.03'	0.07	-0.14	0.06	0.06	0.2	0.31	0.14	0.38	1

Note: ' indicates that the correlation is not significant. † indicates significance at the 0.1 level. All other correlations are significant at the 0.01 level.

3.3.4. Econometric Research Models

Primary considerations in choosing an appropriate model for conducting our analysis included an unbalanced panel data, as well as autocorrelation among consecutive years. A fixed effect model can address autocorrelation and heteroscedasticity issues through robust clustered standard errors (Hoechle 2007). To ensure that a fixed effect model is appropriate over a random effects model, we conducted a Hausman test (Hausman, 1978). The p-value for the test is significant ($p < 0.001$), suggesting that the fixed effects model is more appropriate for this study (Wooldridge, 2010). We also checked for heteroscedasticity in the residuals of the fixed effects model through a modified Wald test (Baum et al., 2001). The Wald test indicates presence of heteroskedasticity in our model ($p < 0.001$). In order to address both autocorrelation and heteroskedasticity, we estimate our models with clustered robust standard errors. We also checked for variance inflation factors (VIFs) to ensure that there are no multicollinearity issues. As our VIFs were below 2, we rejected the presence of multicollinearity in our analysis. While our main model considers the key independent variables and competition as exogenous, we address endogeneity issues with our modeling approach in the robustness test section. We use the following equation to test hypotheses 1-3.

$$\begin{aligned} PoC_{it} = & \beta_0 + \beta_1 * PIF_{it} + \beta_2 * Competition_{it} + \beta_3 * PIF_{it} * Competition_{it} + \beta_4 * \\ & ACA + \beta_5 * MHS_{it} + \beta_6 * Ownership_i + \beta_7 * Profit Status_i + \beta_8 * \\ & Teaching Status_{it} + \beta_9 * CaseMix_{it} + \beta_{10} * Location_i + \beta_{11} * Bed Size_{it} + \beta_{12} * \\ & Magnet_{it} + \gamma_i + \delta_t + u_{it} \end{aligned} \quad (1)$$

Where PIF = Process Improvement Factor i.e. Slack, Skill Mix or Focused Service Strategy, ACA = Affordable Care Act; MHS = Multi-Hospital System; i = Hospital; t =

Time; γ = hospital fixed effect; δ = year fixed effects; u = error term. Based on our hypotheses, our main coefficient of interest is β_3 .

3.4. Results

Our regression results are shown in Table 3.3. Consistent with Carte and Russell (2003), we first provide the baseline model with only the direct effects of the three process improvement factors with control variables in column 1 of Table 3.3. We find support for H1 i.e. competition is positively associated with PoC ($p < .01$). Although, we do not postulate hypotheses for the direct effects of the process improvement factors, these results are important in assigning strength and validity to our model. As expected, slack, skill mix and focus have a positive effect on PoC.

We then add the three interaction terms serially in columns 2-4 and include all interactions in column 5 of Table 3.3. We find support for all our moderating hypotheses. The impact of slack, skill mix and a focused service strategy is stronger in less competitive markets ($p < 0.05$ for all three interaction terms). Our results should be interpreted with caution. Our direct effects indicate that slack, skill mix and a focused service strategy are positive indicating that these process improvement factors are important in improving PoC after controlling for the competition level that a hospital operates in. However, the marginal benefit that hospitals derive from these factors will depend on the level of competition. We illustrate this point further in Figure 3.2. Consider competition levels at the 25th and 75th percentiles. If we study the influence of slack at the 25th percentile of competition, we see that the average change in PoC with respect to slack i.e. the slope is 1.373. At the 75th percentile of competition, the average

change in PoC with respect to slack is 0.133. In both cases, the impact of slack on PoC is positive. However, the average effect of slack is much higher in less competitive markets. Similar effects for skill mix and focused service strategy are illustrated in Figure 3.2. To get a better sense of our findings, we see that a 10% increase in slack improves PoC by 1.64% and 0.2% in low and high competitive markets respectively, on average. A 10% increase in skill mix improves PoC by 3.13% and 0.1% in low and high competitive markets respectively, on average. Finally, a 10% increase in a focused service strategy improves PoC by 4.52% and 1.58% in low and high competitive markets respectively, on average. Although, the impact of our process improvement factors may seem small in competitive markets, we need to understand that there are ceiling effects on how much PoC can improve (it is capped at 100%). So, it is more difficult to improve PoC from say 96% to 99% on any given measure than it is to improve the same quality measure from, say 75% to 90%. Given this, factors such as slack, skill mix and focus still play an important role in improving quality in these markets and should not be neglected.

In addition, we find that among our control variables, ACA has a positive impact on improving PoC. This is expected as financial incentives are tied to improvements in PoC. We also find that hospitals that treat patients with a higher average case mix index have higher PoC possibly reflecting investments in resources and research. It is also possible that more difficult to treat patients may choose to go to higher quality hospitals.

Table 3.3: Regression Results for Process of Care Dependent Variable

Variable	Column 1	Column 2	Column 3	Column 4	Column 5
Competition	0.158*** (0.017)	0.172*** (0.015)	0.190*** (0.023)	0.181*** (0.015)	0.228*** (0.021)
Slack	0.971** (0.400)	1.714*** (0.489)	0.988*** (0.390)	1.008*** (0.393)	1.730*** (0.435)
Skill Mix	0.749** (0.378)	0.729** (0.375)	1.694*** (0.574)	0.758** (0.375)	1.752*** (0.439)
Focus	1.892*** (0.618)	2.097*** (0.582)	2.323*** (0.468)	3.626*** (0.783)	3.295*** (0.799)
Slack*Competition		-0.031*** (0.010)			-0.023** (0.009)
Skill Mix*Competition			-0.033** (0.016)		-.045*** (0.014)
Focus*Competition				-0.050** (0.023)	-0.038** (0.018)
ACA	0.159*** (0.049)	0.162*** (0.050)	0.144*** (0.047)	0.161*** (0.049)	0.151** (0.065)
Teaching Hospital	0.391** (0.188)	0.336* (0.188)	0.415** (0.180)	0.369** (0.181)	0.342* (0.176)
Case Mix Index	0.853*** (0.264)	0.844*** (0.259)	0.856*** (0.257)	0.829*** (0.257)	0.842*** (0.229)
Bed Size	-0.009 (0.225)	0.104 (0.221)	0.022 (0.221)	0.055 (0.227)	0.031 (0.207)
Magnet Status	-0.27* (0.151)	-0.221 (0.144)	-0.277* (0.149)	-0.260* (0.147)	-0.233 (0.151)
Number of Observations	1445	1445	1445	1445	1445
R-Square	0.623	0.626	0.629	0.625	0.63
Probability > F	0	0	0	0	0

Note: Robust clustered standard errors in parentheses.

*, ** and *** represent significant results at the 0.1, 0.05 and 0.01 levels respectively

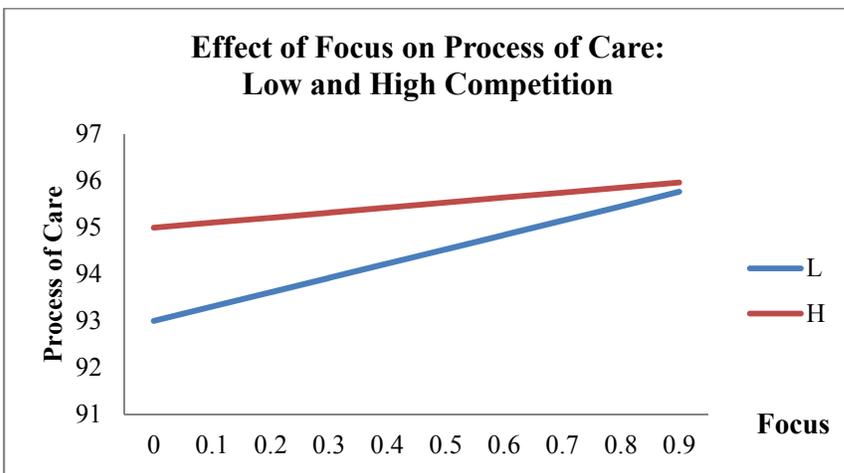
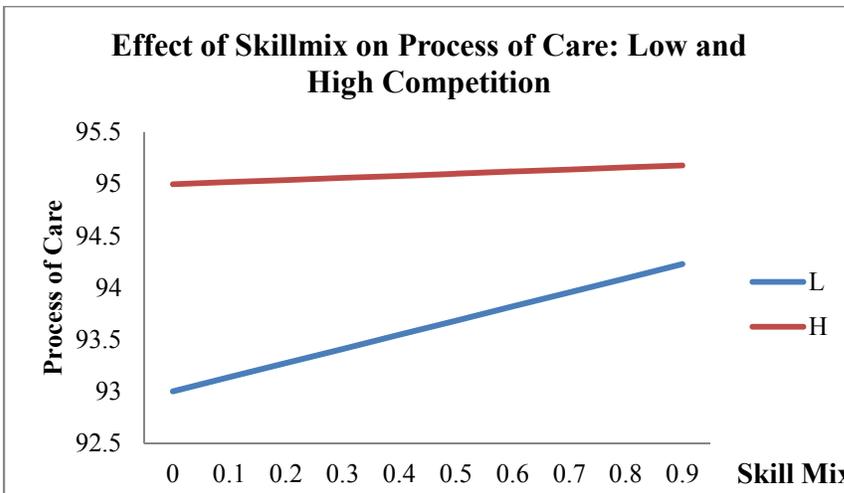
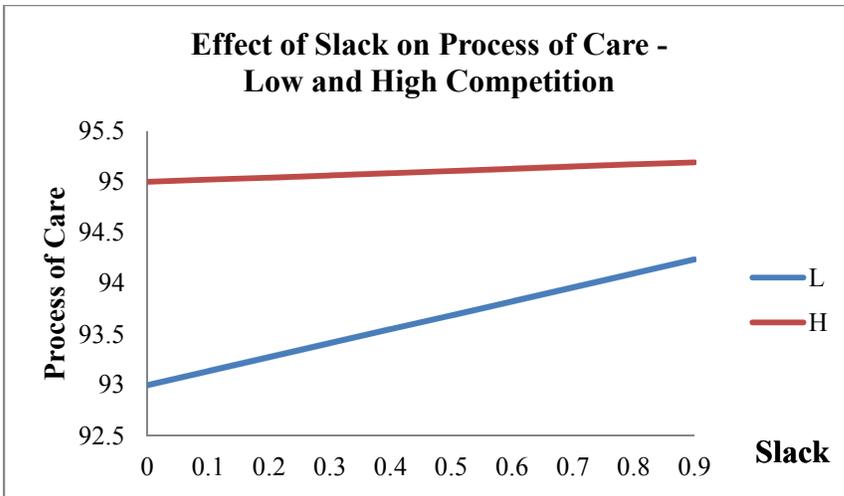


Figure 3.2: Impact of Process Design Factors on Process of Care in Low and High Competitive Markets

3.4.1. Robustness Test - Alternate measure of competition

In our analyses, we have used the number of competitors as our competition measure. However, it could be argued that that hospitals compete for market shares and thus a competition measure reflecting this should be considered. Accordingly, we quantify the underlying market structure based on the market share of providers in a given health service area. Our measure of the hospital service area comes from the Dartmouth Atlas, and the market share is based on the number of patients discharged from hospitals in each service area. Information on patient discharges is provided by the AFD, and the equation below is used to calculate our competition measure.

$$Competition_{jt} = -\ln \sum_{k=1}^N \left(\frac{n_{kt}}{N_{jt}} \right)^2$$

where n_{kt} is the number of patient discharges from hospital k within hospital service area j in year t and N_{jt} is the total number of patient discharges carried out within hospital service area j in year t . Our negative log transformation of the competition measure is easy to interpret where zero corresponds to a monopoly and infinity corresponds to perfect competition (Cooper et al. 2011). Our results using this competition measure are given in columns 1-3 of Table 3.4. Our hypotheses are mostly supported with this alternate measure of competition.

3.4.2 Robustness Test - Endogeneity of Process Improvement Factors

In the analysis reported in section 5, we treat slack, skill mix and focused service strategy as exogenous. However, it is possible that the choice of these levels is endogenous to hospitals. This is quite likely as we have hypothesized that cost pressures due to continual investments in technology and equipment and lower profit margins cause hospitals to be

efficient in other areas of their operations. A Hausman specification test also shows that our chosen process improvement factors are endogenous. A possible way to address this endogeneity is to convert these continuous variables into indicator variables, and use the Heckman two-stage procedure. Since our primary objective here is to estimate the interaction effects of competition, our approach is a little different. If any or all of the three process improvement variables is endogenous, their interaction terms with competition are endogenous as well (Maddala 1983). The Heckman procedure is not suitable in such situations, but we use an approach similar to that outlined in Gao et al. (2010).

First, we use standardized scores for the process improvement factors and competition. This approach has been shown to reduce the magnitude of bias (Harrison 2008). We use four instruments for the process choice factors -- percentage of Medicare and Medicaid patients, hospital wage index, unemployment rate, and per capita income in the county in which a hospital is located. Hospitals that treat a higher percentage of Medicare and Medicaid patients typically experience greater strain on their financial resources due to restricted reimbursements by these payers (Konetzka et al. 2008). Thus they are more likely to exercise greater efficiencies in their operations. Wage index measures differences in hospital wage rates among labor markets. Since labor accounts for a significant portion of hospital costs, this variable captures the financial strain on hospital costs (Bazzoli et al 2007). Per capita income and unemployment rate reflect a hospital's ability to not only collect revenue but also to make a profit (Everhart et al. 2013). Inadequate profits may hamper a hospital's ability to offer new services, invest in

newer technology and equipment, or hire qualified nurses (McCue et al 2003). As a result we use these as instruments in our robustness test.

The annual percentages of Medicare and Medicaid patients were calculated from California's AFD database. Annual hospital wage index values were collected from CMS' IPPS files. Annual county level unemployment rate and per capita income were downloaded from the State of California's Employment Development Department (<http://www.edd.ca.gov/>). All instrument variables are lagged to reduce correlation with the current variables. Following Wooldridge (2002), we devise another set of instruments by multiplying the instruments for the process improvement factors with competition. Together these instruments are used to identify the direct effects of the process improvement factors and the interaction effect of competition on PoC. Other variables are the same as in equation (1). The Sargan-Hansen test does not reject the null hypothesis ($p > .1$) in our models indicating that the selected instruments are valid instruments, i.e., uncorrelated with the error term. The Kleibergen-Paap rk Test of under identification shows that the selected instruments are valid ($p < .1$).

As seen in columns 4-6 of Table 3.4, the IV estimations of (Slack*Competition), (Skill mix*Competition) and (Focus*Competition) on PoC are negative and significant, consistent with our original hypothesis. We thus conclude that our results are robust even after considering the endogeneity of process improvement decisions made by hospitals.

Table 3.4: Robustness Test for Process of Care Dependent Variable

Variable	Market Share Measure of Competition			Instrument Variable Approach		
	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6
Competition	5.024*** (0.627)	5.407*** (0.294)	5.753*** (0.670)	4.409*** (1.335)	7.222*** (2.516)	3.163*** (1.156)
Slack	4.115*** (1.392)	0.887** (0.148)	0.924** (0.402)	3.171* (1.935)	0.943 (2.304)	2.052* (1.107)
Skill Mix	0.958** (0.642)	4.217* (1.316)	0.925** (0.395)	1.152** (0.341)	1.694*** (0.574)	1.135*** (0.299)
Focus	1.958*** (0.051)	1.932 (0.726)	9.725*** (2.417)	1.600 (2.523)	6.304* (3.399)	2.291 (2.061)
Slack* Competition	-1.138** (0.486)			-0.461* (0.279)		
Skill Mix* Competition		-1.285* (0.389)			-2.071* (1.242)	
Focus* Competition			-2.737*** (0.902)			-1.781** (0.902)
ACA	0.046 (0.050)	0.041*** (0.033)	0.047 (0.050)	0.162*** (0.050)	0.144*** (0.047)	0.161*** (0.049)
Teaching Hospital	0.372** (0.183)	0.459 (0.206)	0.414** (0.171)	0.463 (0.697)	1.334* (0.799)	0.583 (0.560)
Case Mix Index	0.895*** (0.273)	0.947* (0.242)	0.887*** (0.271)	0.937 (0.685)	1.181 (0.804)	1.005* (0.575)
Bed Size	-0.034 (0.227)	-0.058 (0.230)	0.023 (0.228)	-5.713 (4.044)	0.022 (0.221)	-1.774 (0.227)
Magnet Status	-0.231 (0.145)	-0.263** (0.033)	-0.250* (0.143)	-0.221 (0.144)	-0.746 (0.496)	-0.260* (0.147)
Number of Observations	1445	1445	1445	1413	1413	1413
Probability > F	0	0	0	0	0	0

Note: Robust clustered standard errors in parentheses.

*, ** and *** represent significant results at the 0.1, 0.05 and 0.01 levels respectively

3.5. Impact of ACA on Process of Care and the Role of Process Improvement Factors

The ACA introduced in 2010 emphasizes access to quality and affordable health insurance to all Americans. However, critics argue that there are design flaws related to patient enrollment and screening by insurers (Washington Post, 2013), that penalties are too low to induce hospitals to make major changes (Zhang et al., 2015) and that low performing hospitals may not have sufficient resources needed to improve quality (Joynt and Rosenthal, 2012). By requiring insurance carriers to provide healthcare coverage to everyone regardless of their medical condition, the ACA ensures greater insurance choice for consumers. It lowers premiums through greater competition (Collins et al., 2014; Wayne, 2014), which results in a greater number of people seeking services, and hospitals can in turn compete for this increased pool of patients.

In order to achieve its goals of making patient care safer and improving access, ACA has created the Pay for Performance (P4P) system. Under P4P, hospitals and other healthcare providers are provided financial incentives to achieve optimal outcomes for their patients. The P4P specifically establishes a Hospital Value Based Purchasing Program (VBP), under which a portion of Medicare payments is withheld from hospitals at the beginning of the year. A set of performance criteria comprising of clinical process quality measures, patient experience measures and outcome measures are defined, and hospitals are evaluated at the end of the year against these criteria. Hospitals are given financial bonuses based on how well they do on these quality measures as well as how much they improve over time. This program also penalizes hospitals that do not achieve

the specified goals, and encourages each hospital to improve its own quality over time, as well as its quality compared to other hospitals (CMS, 2014).

Thus we see that the ACA has built in provisions that force hospitals to compete for a larger patient pool, as well as a larger share of the bonuses that are tied to improvements in hospital quality. The ACA thus acts as a catalyst in increasing competition among all hospitals to attract more patients and improve their quality. As a result, ACA in conjunction with competition is likely to moderate the way in which internal factors in the hospital impact PoC. We test this theoretical argument by considering the joint moderating effect of ACA and competition on the relationship between internal factors and PoC. As ACA acts towards enhancing competition, we would expect that our process improvement factors become more important in improving quality under this new environment. Thus we would expect the direction of our joint simultaneous moderating factors with ACA, competition and process improvement factors to be similar to those with competition only as the moderator. These results summarized in Table 3.5, lend support to our argument that ACA indeed acts toward enhancing competition among hospitals.

Table 3.5: Joint Simultaneous Impact of Competition and ACA on Process of Care

	Column 1	Column 2	Column 3
Competition	0.194*** (0.016)	0.222*** (0.021)	0.219*** (0.017)
Slack	1.371*** (0.407)	1.744*** (0.317)	1.759*** (0.317)
Skill Mix	0.514 (0.322)	0.847 (0.545)	0.575* (0.320)
Focus	2.012*** (0.554)	2.072*** (0.544)	3.622*** (0.856)

Slack*Competition*ACA	-0.008*** (0.003)		
Skill Mix*Competition*ACA		-0.004*** (0.002)	
Focus*Competition*ACA			-0.005* (0.003)
ACA	1.015*** (0.125)	0.646** (0.275)	0.662*** (0.128)
Teaching Hospital	0.354* (0.191)	0.357* (0.188)	0.349* (0.188)
Case Mix Index	1.487*** (0.241)	1.495*** (0.241)	1.464*** (0.240)
Bed Size	-0.083 (0.232)	-0.025 (0.222)	0.029 (0.222)
Magnet Status	-0.115 (0.163)	-0.070 (0.161)	-0.072 (0.161)
Number of Observations	1445	1445	1445
R-Squared	0.566	0.572	0.573

Note: Robust clustered standard errors in parentheses.

*, ** and *** represent significant results at the 0.1, 0.05 and 0.01 levels respectively

3.6. Conclusions and Limitations

The healthcare operations literature has traditionally focused on various process improvement factors such as clinical focus, workload (or lower operational slack), process management and nurse empowerment that improve quality outcomes (Tucker 2007; Kc and Terweisch 2009, Chandrasekaran et al. 2012; Senot et al. 2015; Berry Jaeker and Tucker). The health economics literature, on the other hand, has only considered the impact of competition on hospital clinical quality such as mortality and does not emphasize the role that internal process improvement factors play in improving quality (Gaynor 2006; Gaynor and Town 2011). In uniting both the healthcare and

economics perspectives, our research suggests that the benefits of internal process improvement factors depend on the nature of competition.

By studying the impact of a focused service strategy, nursing skill mix and slack on process of care from 2007 – 2013, we make several research and practical contributions in better understanding whether the impact of these internal hospital factors on quality outcomes changes in the presence of competition and ACA. These contributions are particularly important due to the renewed focus on improving the quality of care with the introduction of the ACA.

3.6.1 Contributions to Theory

Tying our results back to the existing healthcare operations and economics literature, our H1 finding that hospitals in highly competitive environment are associated with better process of care corroborates the past findings on mortality and readmissions outcome measures (Kessler and Geppert, 2005; Kessler and McClellan, 1999; Shen, 2003). However, since competition is largely localized, exogenous and out of control of the hospitals, we examine three higher-level constructs that are the emergent characteristics of hospitals: focused service strategy, slack, and nursing skill mix in the context of competition and their impact on the process of care. We believe that focused service strategy, slack, and nursing skill mix are a combination of endogenous and exogenous factors. For instance, hospitals may choose to emphasize a few types of treatments based on the demand profile of the region, and slack in terms of vacant bed capacity that may vary over years based on the growth of a region. Similarly, although nursing skill mix is largely endogenous and within hospital control, it may be more difficult for hospitals to hire registered nurses in rural areas if there is a shortage in the availability of registered

nurses in such areas. By examining the contingency effects of competition on the main effects of focused service strategy, slack, and nursing skill mix on the process of care (the main effects have already been studied in the past healthcare operations literature), our paper provides richer understanding of these three emergent characteristics. We also add to other papers in the broader realm of service operations that study contingency effects (see for e.g. Gao et al. 2010).

A broad conclusion that emerges from our findings is that the marginal returns from investing in key process improvement factors such as slack, nursing skill mix and focused service strategy on process of care are heterogeneous, and based on the nature of competition within which a hospital operates; nevertheless the effects are still positive. Given that hospitals in more competitive markets have a higher base quality to begin with, as the result from our hypothesis H1 also confirms, the fact that we find that process improvement factors enhance process of care in competitive markets is an important finding.

Our paper is also one of the first to incorporate the impact of ACA on the relationship between internal process improvement factors and process of care metrics. By providing incentives and penalties, the ACA acts as a catalyst in increasing competition among hospitals by making them compete for patients and financial incentives. This further reinforces our theoretical arguments, and confirms our predictions related to the value of these process improvement factors in improving process of care metrics. Besides the use of technology, higher process of care is also the result of better teamwork, management's commitment to quality improvement through organizational restructuring, and design of more efficient processes. As previously

discussed, improved processes of care also improve other downstream outcome measures such as readmissions and mortality that are tied to bonuses and penalties under the VBP program.

3.6.2 Contributions to Practice

There are several significant takeaways for hospital administrators and executives based on our study, many of which are nuanced and not necessarily obvious at first blush. In the face of increasing competition, choices made for the process improvement factors not only affect both long-term and short-term cost structures, but also impact the hospital's responsiveness and ability to provide a high standard of care to its patients. For instance, by having a focused service strategy, hospitals will have less heterogeneity in the patients that they treat, and hence their tasks will be more standardized. This would allow more latitude for designing standard work flows and deliver better care with a higher level of efficiency. With respect to slack resources, clinical and non-clinical staff in hospitals that have more slack will be less busy, and hence will have more time to get trained in following established procedures and protocols for clinical treatment of different kind of patients. This better training will enable better adherence to the standard operating procedures, and hence will improve process of care score. Finally, hospitals that employ a higher proportion of registered nurses in their nursing skill mix will have better flexibility in using these nurses as and when required. Hospitals in the U.S. have a perennial nurse shortage (Goodin 2003), and hospitals usually spend much more to hire agency nurses when they experience nurse shortages (Kline 2003). Even though higher skill mix is more expensive, hospitals that create more flexibility by investing in a higher proportion of

registered nurses would be less likely to incur extra expenditures in their operating cost structure. Given the high cost associated with agency nurses, it may even lead to savings in the long run. These hospitals will have the added advantage of a higher proportion of better-trained registered nurses operating at the top of their license, which in turn will lead to higher process of care scores.

Due to declining reimbursements and financial constraints, hospital executives may be tempted to resort to lower slack and skill mix, erroneously thinking that quality can be improved by emphasizing efficiency in these areas. However, improvements in patient quality and care cannot happen when slack is low, because such hospitals will lack the ability to rethink current processes, or to devote the time needed to making them better and safer for patients (Demarco 2001), or to devote time for better training that will lead to better adherence and higher process of care scores. Recent research has highlighted the importance of better bed management, and has suggested optimizing hospital wing formation (i.e. partitioning of beds and care types) as a potential way to pool demand and bed capacity (Best et al., 2015). Slack is needed for developing appropriate measures to determine bed needs and delays in getting patients to these beds, doing adequate capacity planning by clinical unit after taking seasonality factors into account, and developing appropriate scheduling of elective surgeries to smooth out peaks and valleys in occupancy rates (Green and Nguyen, 2001; Litvak and Bisognano, 2011). Only then can hospitals avoid treatment delays and optimize utilization without compromising process of care. Better bed management decisions will enhance timely service, improve patient satisfaction, and decrease the costs per patient (Donabedian, 1988).

Hospitals also face cost pressures in maintaining a higher cost labor related to a high skill mix. However, a higher skill mix is more productive and efficient and more likely to detect and treat abnormal conditions on time, thereby reducing the number of patient complications and preventing adverse events (Cho et al. 2003). Thus even though a high skill mix may increase hospital payroll expenditures, it actually reduces the cost of patient care and ultimately contributes to hospital profitability (McCue et al., 2003). At the same time, caution is urged. A McKinsey study recently estimated that more than a third of routine patient related activities such as transporting patients, obtaining medications from pharmacy, scheduling diagnostic tests, etc. can be safely performed by non-RN healthcare providers (McKinsey, 2014). Hospitals thus need to carefully map work processes of both registered and other nurses to arrive at the optimal skill mix that fits their needs. Following this approach would ensure that the hospitals have higher flexibility, which would also allow the higher skilled RNs to spending more of their time on improving quality of processes and applying their enhanced skill sets.

It must be noted in this context that slack and skill mix go hand in hand. Low slack has been associated with nurse burnout and job dissatisfaction, threats to patient safety, and high nurse turnover (Vahey et al. 2004). In an environment where nurse shortages are reported and registered nurses are critical to providing patient care; creating a better work environment is critical in retaining this highly skilled labor to ensure continuity of quality improvement efforts, especially for hospitals in more competitive markets where nurses have greater inter-employer mobility. Dissatisfaction with the work environment is often cited for nurse turnover, which costs hospitals between \$10,000 to \$60,000 per nurse (Hayes et al., 2006).

Finally, even though our study has recommended a focused service strategy to improving process of care scores under higher competitive conditions, many hospitals may find it difficult to become a highly focused factory like Shouldice hospital (Heskett 2003). However, it may be possible for most hospitals to develop certain specialty areas as ‘centers of excellence’ to create differentiation, especially in markets that may have several high-quality competitors. This strategy has several benefits – it helps develop standardized and evidence-based protocols that enable hospitals to follow standard work procedures due to less patient heterogeneity, provides greater engagement on the part of physicians and nurses in the delivery of care, helps attract highly skilled physicians, and sets industry standards and a reputation for innovation by establishing best practices (Rodak, 2013). This strategy can be reputation enhancing, as it can help hospitals claim higher level of patient care outcomes as well as market leadership in specific specialty areas, while maintaining a full-service line (Devers et al., 2003).

3.6.3 Limitations and Future Research

We believe that our study can spur further work in this area. Our measures of slack, skill mix and a focused service strategy are all at the hospital level. Future research can examine more refined process of care measures at the department or unit level to understand specific elements that can improve patient quality. Future studies can also break down the various components of patient satisfaction quality to understand which of our process factors have the most impact. A similar approach can be used to examine the impact of these process improvement factors on other clinical outcomes such as readmissions and mortality. Since our data sample is limited to California acute-care

hospitals only, future studies can expand this analysis to other states in USA. Such studies may find interesting state-specific effects, and possibly use patient level data to examine the impact of various strategies on patient outcomes.

CHAPTER 4

IMPACT OF HOSPITAL CHARACTERISTICS ON PATIENT CHOICE BEHAVIOR FOR ELECTIVE SURGERIES³

Abstract

Studies in the healthcare operations management literature have typically focused on the supply side of the equation. Much less attention has however been paid to how hospital structural and infrastructural (SI) investments, reputational factors, and perceptual patient satisfaction influence choice of a hospital when patients have to undergo elective surgeries. Using detailed patient level data from California hospitals on elective hip and knee surgeries, our results indicate that SI investments, third-party reputation signals, and patient satisfaction influence patient choice, but to varying degrees. Our results reveal that hip and knee patients are willing to travel an additional 7.5 miles for a 10% increase in SI investments, an additional 2.2 miles for a more reputed hospital and an additional 1.5 miles for a 10% improvement in patient satisfaction scores. As the complexity of comorbidities in patients increases, they are more likely to choose a hospital based on its SI investments and reputation, and less likely to choose a hospital based on higher patient satisfaction scores. Higher comorbidity patients are also willing to travel further for better

³ Wani, D. and M. Malhotra. To be submitted to *Production and Operations Management*

hospital attributes. Such findings are of managerial importance. Our expanded analysis on elective heart surgery patients mostly support our results, but also indicates that the complexity of disease and its treatment may play a role in the way various hospital attributes are emphasized. Theoretical and practical implications of our results are discussed.

Keywords: Elective Surgeries, Hospital Characteristics, Patient Choice, and Comorbidity Complexity

4.1. Introduction

Changes in the government reimbursement system over time has put greater pressures on hospitals' financial resources due to slower revenue growth and decline in profits (Shen 2003; Bazzoli et al., 2008; Werner 2010). Thus hospitals have to seek ways to improve their bottom line and have sufficient financial resources that can then be invested in better quality of care for all patients. Some of the approaches adopted by hospitals to improve their bottom line in the past has been via cost-cutting efforts e.g. reducing bed capacity, replacing high cost of registered nurses with that of less qualified personnel, or through quality improvement efforts (Green and Nguyen 2001; Cummings and Estabrooks 2003; Lindenauer et al. 2007). Another potential way is to increase revenue by attracting more patients to their hospitals. The Affordable Care Act (ACA) signed in 2010 has resulted in a greater number of newly insured people seeking hospital services and provides an avenue for hospitals to bring in more patients. A recent report suggests that hospitals in several states have reported a significant decrease in unreimbursed costs of care and have actually made a profit (<http://www.reuters.com/article/us-usa-hospital-medicaid-insight-idUSKCN0PX0CY20150723>) as a result of increased volume of insured patients due to

ACA. Thus how and why patients choose a hospital can have a direct impact on its revenues, and hospitals have to compete to attract this increased pool of patients.

In the manufacturing literature, there is little dispute about the importance of quality in gaining competitive advantage. Studies have shown that markets react to both tangible aspects of a product's quality as well as to quality reputation of a firm that is more perceptual in nature (Garvin 1988; Hendricks and Singhal 1995). The services marketing literature considers factors such as responsiveness, competence, communication, and employee effort to understand customer needs as some of the key determinants of service quality (Parasuraman et al. 1985). Researchers have argued that in healthcare, consumers lack good information about the quality of their healthcare providers, and so are unable to make rational choices (Cutler 2010; Skinner 2011; Chandra et al. 2015). Patients seeking hospital services can potentially be at a disadvantage, as they may not have the necessary expertise to evaluate the clinical quality of services (Berry and Bendapudi 2007). A question that naturally emerges is what specific hospital attributes attract patients to hospitals?

In terms of increasing their profile, hospitals can make various structural and infrastructural (SI) investments in state-of-the-art diagnostic equipment, and also hire leading-edge healthcare providers to differentiate themselves from their competitors to attract insurers, physicians and patients (Dranove et al. 1992; Cutler et al., 2004; Devers et al. 2003; Tay, 2003). They may also choose to improve their patient experience by focusing on the experiential aspects of health care delivery such as patient-provider communication, and other non-care aspects (Manary et al. 2013). Reputation signaling, in the form of third party agencies generating ratings to inform consumers about various

products and services, have been prevalent for several decades in areas such as car and electronic gadgets buying, restaurant and hotel experience, etc. They have now been extended to healthcare as well. In recent times, there has been a surge in the number of private companies and non-profit organizations such as the US News and World Report (USNWR), Centers for Medicare and Medicaid Services' Hospital Compare website, the Joint Commission, Leapfrog Group, etc. that signal a hospital's reputation via rankings, scores, and awards posted on their websites. This is being done in an attempt to help patients make informed choices while selecting a hospital. It can also be confusing for patients and hospitals, as there are many quality signals that can potentially influence a patient's decision of a hospital.

How should hospital allocate their scarce resources to get the biggest bang for the buck in attracting patients? Should they make more SI investments that improve their clinical quality of care? Should they put greater emphasis on the patient experience and invest in resources that improve the communication, responsiveness and appearance of their facilities? Should they invest more in marketing by highlighting their ratings and awards in order to attract patients to their hospitals? Are some of these investments more effective than others? This study offers a more holistic approach to understanding and answering these questions by systematically evaluating the drivers behind patient choice. In particular, we focus on three important attributes that can drive patient choice (i) hospital's SI investments, (ii) hospital's perceptual quality as measured by patient satisfaction and (iii) hospital reputation signaling by third parties to understand what is important to patients as revealed by the patients' choice of hospital.

When looking at dominant trends in profiles of patients in US seeking hospital services, they are living longer and with a larger plethora of diseases that co-exist with one another. Comorbidities such as hypertension, obesity, diabetes, etc. are on the rise in the US. It is estimated that in 2010, over half of the US population had at least one comorbidity and almost a third of the population had multiple comorbidities (Gerteis et al. 2014). The same study also estimated that 86% of healthcare cost spending is for patients with one or more such conditions. Policy makers who monitor the prevalence of such conditions in the population are likely to develop new policies to slow down the growth of such conditions. Hospitals will also have to participate in this process and help develop more effective treatment protocols, design better care coordination and care transitions, and hire appropriate mix of nurses and physicians to address this growing problem (Bodonheimer et al. 2009; Hewner 2014). Knowing how patients with multiple conditions choose hospitals will provide some insight to hospital managers on how to put their financial resources to best use and provide high quality care to such patients in the future. Thus the second research question that we address in the study is whether patients with greater comorbidity complexity tend to emphasize certain hospital attributes over others?

To answer our research questions, we choose to study choice in the context of elective surgeries. These patients have sufficient time to talk to their primary healthcare provider, seek opinions from friends and family and gather information from online sources to deliberate various options, and hopefully make an informed choice. A study of patient choice as conducted here in this paper is unique because the operations management healthcare literature has traditionally focused at the supply side factors such

as investments in information technology, focus, nurses, etc. and their impact on various quality outcomes (Tucker 2007; KC and Terweisch 2011; McDermott and Stock 2011; Angst et al. 2012; Devaraj et al. 2013; Sharma et al., 2016; Gardner et al. 2015). Studies have also looked at the impact of improving clinical and patient satisfaction quality on outcomes such as cost and readmissions (Senot et al. 2015). The impact of third party reputation signaling via awards and certifications on a firm's financial performance has been studied (Hendricks and Singhal 1996; Corbett et al., 2005), but not in the healthcare context. To the best of our knowledge, the OM healthcare literature has not simultaneously studied the impact of (SI) investments, patient satisfaction, and third party reputation signaling on the demand side of the equation i.e. whether such factors enhance demand for services. We also do not know what role patient characteristics, such as comorbidity complexity, plays in shaping up patients' choices.

In our study, we use revealed preference empirical data from California patient discharge records. Our analysis focuses on elective hip and knee surgeries to test our hypotheses, but subsequently we also validate and extend our results to elective heart surgeries. Our study is one of the few that uses secondary data rather than surveys to construct a choice model using patients' revealed preferences to understand how patients emphasize certain attributes of hospitals over others. More importantly, we emphasize understanding patient choice from the perspective of a different patient segment i.e. patients with complex comorbidities rather than focusing on differences based on age, gender and race. This is especially important as the percentage of this segment in the overall patient population is exhibiting an increasing trend.

To preview our findings, we find that patients undergoing elective hip and knee surgeries emphasize SI investments, reputation, and patient satisfaction to varying degrees, thus providing a more holistic treatment of revealed patient preferences. Our analysis also reveals that as the complexity of comorbidities in patients increases, patients are more likely to choose hospitals based on their SI investments and hospital reputation, and less likely to select hospitals based on patient satisfaction scores. Extended analysis of elective heart surgeries mostly confirms our findings for hip and knee surgeries, but also shows some differences, which we surmise may be due to differences in the complexity of disease and its treatment between these two different types of elective surgeries.

The rest of the paper is structured as follows: In sections 4.2 and 4.3, we discuss the literature on patient choice and develop our hypotheses. In section 4, we describe our data and econometric modelling approach. Section 4.5 deals with the empirical specification of the patient choice model. Results and robustness tests are discussed in section 4.6. Conclusions and theoretical and managerial contributions are discussed in section 4.7.

4.2. Literature Review

Although extensive research efforts have been devoted to understanding drivers of patient choice in both primary care and hospital settings, most of these studies have been in the health economics literature. These studies adopt a survey based or a stated choice approach focusing on issues such as accessibility, qualification and communication style of providers, type and size of institution, cost of service, waiting time and patient

demographics (see Victoor et al. (2012) for a recent review). Despite some studies in the health economics literature, the analysis of revealed patient preference (RPP) data using choice models (CM) is still rare in the healthcare operations management literature. Table 4.1 summarizes the RPP/CM studies in the health economics literature, datasets and data period considered in the study, type of surgery (i.e. emergent or elective), variables and controls (first and second lines in the column), main results and patient segments used in the choice model. We are currently aware of only one study in the OM healthcare literature by Wang et al. (2015) in this domain.

Table 4.1: Summary of Prior Revealed Patient Preference and Choice Model Studies

Study	Datasets and Data Period	Type of Surgery	Variables and Controls	Patient Segments	Results
Luft et al. (1990)	Patient discharge records from 3 geographic areas in California Year: 1983	Mix of elective and emergent surgical and medical procedures	Mortality rate for each procedure. Distance, Teaching hospital, Hospital ownership, Hospital charges	None	1. Mixed results - Mortality rates may increase or decrease likelihood of choice depending upon the surgery/medical procedure
Tay (2003)	Patient discharge records from California, Oregon and Washington Year: 1994	Medicare Heart Attack patients	Staff per bed, Specialty diagnostic equipment, Complication, Mortality rates. Distance, Teaching hospital, Hospital size	Patient age, Gender, Race	1. Patients prefer hospitals with specialty equipment, more staff per bed and lower mortality rates 2. Older and female patients are less likely to travel further

Pope (2009)	National Inpatient Sample Years: 1998-2004	Volume of Elective Heart Surgeries for Medicare Patients	Ordinal Rank (by specialty) in US News and World Report. Year, Specialty	None	1. Improvement in rank by one spot increases non-emergency volume by 1% 2. Consumers more sensitive to rank changes that happen at the top rather than at the bottom of the list
Goldman & Romley (2010)	Los Angeles Patient Discharge Data; Survey Data from National Research Corporation Year: 2002	Heart Attack and Pneumonia Medicare Patients	Mortality Rate, Amenities (good food, pleasant surroundings, attentive staff, etc.). Distance, Teaching hospital	Patient age, Gender, Race, Income, Poor health index	1. Pneumonia patients value amenities more highly than mortality rate, and vice versa for heart attack patients 2. Interactions of amenities and mortality rate with patient segments are mostly insignificant
Varkevisser et al. (2012)	Patient insurance claims records in Netherlands Year: 2006	Elective Angioplasty Surgery	Readmission Rate, Pressure Ulcer rates, Overall reputation (ratings agency), Cardiology reputation. Distance, Medical Center, Size	None	1. Overall hospital reputation score and readmission rates influence patient choice
Wang et al. (2015)	Patient discharge records from New York Year: 2009-2012	Mitral Heart Valve Surgery	Mitral valve repair rate Distance, Teaching hospital, US News ranking, Advertising budget, Hospital surgery volume	Patient age, Gender, Race, Insurance, Existence of certain comorbidities	1. Less than a majority of patients go to hospitals with better repair rates 2. Lack of information, payer restrictions and travel cost prevent patients from choosing better hospitals

					3. Younger, male and white patients more likely to choose higher quality hospitals; results on comorbidities are mixed
Current Study	Patient discharge records from California Year: 2012	Elective hip and knee surgeries, elective heart surgeries	Structural and Infrastructural investments Patient satisfaction, Hospital reputation Distance, Teaching hospital, For-profit status, Location	Patient Comorbidity Complexity	1. All three attributes impact patient choice, but to varying degrees 2. Choice based on hospital attributes is heterogeneous in nature, and based on the complexity of comorbidities, disease and treatment

Several insights emerge from these studies shown in Table 4.1. First, we see that the RPP/CM studies have mostly, been on heart patients. Distance is often critical for patients experiencing heart attack who need immediate medical attention; however these studies have found that specialized cardiac equipment, lower mortality rates, good staff to bed ratios and hotel like amenities influence patient choice of hospitals (Tay 2003; Goldman and Romley 2010). The role of hospital reputation in influencing patient choice has also received some attention, but the evidence is mixed. While Varkevisser et al. (2012) find that patients undergoing elective heart surgeries (e.g. angioplasty, coronary artery bypass graft, etc.) are influenced by reputation scores, Pope (2009) found that patients undergoing elective surgeries do not respond to the actual reputation scores, but

only to the year-over-year changes in ordinal rating. Further, the authors of the first study (Varkevisser et al. 2012) note that hospitals that are rated high on one quality dimension are ranked low on other quality dimensions, thereby bringing into question the use of multiple reputation scores to understand patient choice. As reported in a study by Luft et al. (1990), better outcome measures also do not reliably predict patient choice. The authors found that higher mortality rates may either increase or decrease the likelihood of selection for different categories of elective surgeries. Finally, Wang et al.'s (2015) study focuses on developing a methodology for determining the quality outcome for a specific type of heart surgery known as the mitral valve surgery. Their study finds that lack of information; travel costs and payer restrictions prevent patients from seeking better hospitals. So patients do not overwhelmingly choose hospitals with better outcomes. To summarize the studies listed in Table 4.1, patients may prefer hospitals that perform better on quality outcome measures and reputation signals only under certain conditions. But the evidence is not clear, especially for elective surgeries.

Our study extends the current literature on RPP/ CM along several important dimensions. A central premise of the reported research in services marketing is that examining only a limited subset of the direct effects of quality, or only considering one variable at-a-time, may confound our understanding of consumers' decision-making (Cronin et al. 2000). This in turn can lead to strategies that either overemphasize or underappreciate the importance of one or more of these variables. The RPP/CM studies focus on either hospital characteristics or reputation measures, but do not study them together. This approach is likely to overemphasize the impact of the key independent variable under study. Moreover the role that "soft" factors such as patient-provider

communication, provider responsiveness, etc. play in determining revealed patient choice has not been studied before. Second, a lot of emphasis has been placed on patients requiring heart procedures, but relatively little is known about how patients choose hospitals for other common elective surgeries e.g. hip and knee replacements. It is important to understand the differences for different types of surgeries, because although hospital and surgeon report cards and government based reports on mortality rates are available for both elective and emergency heart surgery patients, such measures are not readily available for other elective surgeries. In such situations, where publicly available information is scarce, patients may spend a significant amount of time gathering information from various sources such as physicians, family members and media before selecting a hospital. We focus on three specific groups (or clusters) of hospital attributes: (i) hospital SI investments, (ii) patient satisfaction and (iii) reputation signaling by third parties. By focusing on one of the most common types of surgeries performed in the US i.e. hip-knee surgeries, we are able to uncover the degree to which various hospital attributes are emphasized. In addition, we also conduct our analysis on heart surgeries to understand if any differences occur among different types, but commonly performed, elective surgeries.

Heterogeneity in the way patients choose hospitals has received attention in some studies, but the focus has mostly been on demographic differences based on age, gender and race. When issues such as poor patient health or the presence of comorbidities are considered, the results are either insignificant or mixed (Goldman and Romley 2010; Wang et al. 2015). However, given the increased prevalence of comorbidities in the patient population that we have previously highlighted, it is critical to understand whether

any heterogeneity in patient choice exists based on the comorbidity complexity of patients. Patients with higher comorbidity complexity may emphasize certain attributes more over others, and our study seeks to uncover such preferences.

4.3 Hypothesis Development

In our study, we assume that the decision to choose a hospital for an elective surgery could be made by the patient himself or herself or in consultation with the primary physician, family and friends. A similar assumption has also been made in previous literature (Tay 2003). Revealed preferences of patients undergoing an elective surgery based on three specific attributes: hospital SI investments, perceptual patient satisfaction, and reputation of the hospital is more relevant to our study rather than who makes the decision for the patient.

4.3.1 Role of Structural and Infrastructural Investments in Influencing Hospital Choice

For our first attribute, we choose to focus on three specific hospital SI investments: technology, registered nurse staffing, and hospital focus on specific elective surgeries. These attributes have been known to have a positive impact on patient quality in the past literature. Thus they serve as excellent proxies for hospital quality.

Technology here comprises of key clinical, administrative, and strategic technologies that a hospital invests in an attempt to signal their state-of-the-art technology preparedness and quality to potential insurers, physicians, and patients (Robinson 1988; Devers et al. 2003). Clinical technologies have a direct impact on

patient outcomes (Angst et al. 2012, Sharma et al. 2016). However, a robust supporting administrative and strategic IT infrastructure also signals that the hospital has good organizational learning capabilities and can integrate IT into its processes. These help in improving the efficiency and effectiveness with which patient flow occurs in the hospital, and in turn improves patient outcomes and satisfaction (Queenan et al., 2011; Devaraj et al. 2013; Gardner et al. 2015; Sharma et al. 2016). Thus we expect that patients are more likely to select hospitals with more sophisticated technology.

It has been recognized that “nurses are at the front-line of patient care and are in the best position to detect problems, monitor conditions, and rescue when necessary” (Joint Commission on Accreditation of Healthcare Organizations 2002). In a hospital setting, patients value competence, knowledge and technical skills associated with registered nurses (Bassett, 2002). Registered nurse (RN) staffing (as defined by the number of hours spent by registered nurses per patient day) is also associated with better patient monitoring, detecting and treating complications, preventing adverse events such as infections, and adhering to high standards of care as they have the necessary knowledge and skill levels (Schultz et al. 1998; Provonost et al. 1999; Cho et al. 2003). Given that the qualities associated with registered nurses (skilled personnel) are highly valued, we would expect greater staffing of registered nurses to play a significant factor in patient choice.

The operations management literature has previously highlighted the benefits of focus on outcomes such as reduced mortality, increased efficiency, and lower cost arising from reduced variations in patient heterogeneity, greater organizational learning due to higher volumes, and better alignment of people and processes (Ding, 2014; Huckman and

Pisano, 2006; KC and Terwiesch, 2011; McDermott and Stock, 2011). A focused service strategy is also the result of greater investment in upgraded operating rooms, medical equipment, hiring and retaining of well-known specialists and physicians, investing in specialized skills of nursing and hospital staff, and engaging with patients and providers to understand how new therapies that could keep them healthy (McKinsey, 2008). Hospitals may also hire additional staff and provide necessary training to improve patient outcomes. Such actions taken by hospitals improve patients' perceptions of technical competency and responsiveness (Greenwald et al. 2006). All these factors are likely to have a positive influence on patient choice. Thus we hypothesize:

H1: Revealed patient choice of hospital is positively associated with better structural and infrastructural investments in technology, RN staffing, and hospital focus

4.3.2 Role of Perceptual Patient Satisfaction in Influencing Hospital Choice

Patient satisfaction in a hospital setting captures aspects such as communication and responsiveness of caregivers. The services marketing literature argues that in the services industry where quality is difficult to evaluate, a contact personnel's knowledge to perform a service, communication skills to keep customers informed in a language that they can understand, and credibility to keep the customers' best interests in mind have emerged as top service quality determinants (Parasuraman et al. 1985, Bitner 1990, Grönroos 1990). When firms invest in resources that improve the perceptual satisfaction among customers, it generates positive word of mouth that influences other consumers' future purchases (Anderson 1996). This in turn improves the firm's market share and profits (Rust and Zahorik 1993; Kamakura et al. 2002). While hotel-like amenities are

associated with patient choice of hospitals (Romley and Goldman 2010), the role of perceptual patient satisfaction in influencing patient choice of hospitals has not been studied previously.

A recent survey conducted by PricewaterhouseCoopers Health research found that patients emphasize factors such as other patients' experience with medications, treatments and specific healthcare providers, and fast response time while making their decision to choose a specific hospital (PwC Consulting, 2012). Patients may not be able to judge technical quality of care, but they may be able to assess care through the dimensions that they can see, feel, understand and value (Kenagy et al. 1999). Consumers and patients are also known to have a high degree of interest in hospital quality; especially in the form of patient satisfaction scores (Sofaer et al., 2015). Their study found that potential patients considered items on the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) Survey to be so important that they would consider changing hospitals in response to information about them (Sofaer et al., 2005). We thus hypothesize that perceptual patient satisfaction is likely to have a positive impact on patient choice.

H2: Revealed patient choice of hospital is positively associated with better perceptual patient satisfaction

4.3.3 The Role of Third Party Reputation Signaling in Influencing Hospital Choice

The role of hospital rankings and report cards to convey important quality information, and thereby influence patient choice, has been discussed previously in the health economics literature (Dranove and Sfekas 2009; Pope 2009; Varkevisser et al. 2012).

However the results that have emerged from these studies are not consistent. For example, Dranove and Sfekas (2009) found that people respond to report cards only when such reports provide information that is contrary to prior beliefs. Pope (2009) found that ordinal changes in hospital ranking near the top of the list are more influential in patient choice than rank changes at the bottom of the list. The Centers of Medicare and Medicaid Services (CMS) publishes data on hospital performance for certain conditions on its Hospital Compare website. Such comparative performance data on hospitals is likely to help consumers reduce the knowledge gap and increase control over their health care experiences and outcomes. However, when an abundance of information is provided to consumers, as is the case with the CMS website, it may not always translate to informed choice partly because of the way the information is presented, the cognitive resources required to process all the information, and whether the information is applicable to the individual's unique situation, preferences and needs (Marshall et al., 2000; Hibbard and Peters 2003). For example, how should patients infer information between two hospitals when one hospital has high scores on effectiveness but low scores on patient safety, and the other hospital has high safety scores but average scores on effectiveness?

Recent research in behavioral economics shows that the simplicity with which information is presented to the consumer is an important factor in predicting consumer behavior (Bertrand et al. 2005). When people are faced with too much information, they tend to take shortcuts and let a single factor dominate their thinking while leaving other factors out of the decision-making process (Montgomery and Svenson 1989). The second aspect in the decision making process are the cues that patients or consumers might respond to. The marketing literature suggests that when product quality is not easily

observable, consumers face uncertainty. In such cases, they search within available product related cues that are both marketing controlled (e.g. advertising, branding) or non-marketing controlled (e.g. third party information) to make an informed choice (Erdem and Swait, 2004; Baek et al., 2010). Third party information reduces information symmetry when the true product quality is not observable. A survey suggests that a majority of the people trust third party reviews when making a choice (Miller 2008). Since giving incorrect information might hurt credibility, independent third party information is also viewed as more objective and less biased than marketing cues that are generated by the firms themselves (Darke et al., 1998; Hendricks and Singhal 1996). Thus given the simplicity with which third parties provide credible information about a hospital's quality reputation, we hypothesize the following.

H3: Revealed patient choice of hospital is positively associated with hospitals' reputation as signaled by third parties.

4.3.4 Moderating Role of Patient Comorbidity Complexity in Influencing Hospital Choice

In addition to studying hospital choice for mostly heart patients, health economics has also looked at how patient demographics affect choice. The research finds that women, people with less education, and older patients are less willing to travel unless their health condition is bad (Monstad et al., 2006; Varkevisser et al., 2010). However, missing from this discussion is an important patient segment i.e. patients with complex comorbidities such as obesity, diabetes, hypertension, etc. As the complexity of comorbidities increases, such patients undergoing surgery have longer length of stay, greater incidence of postoperative complications, and higher mortality risk (McAleese and Odling-Smee,

1994; Roques et al., 1999; Dindo et al., 2004). They may require more intensive care management as compared to patients with fewer or no comorbidities. Presence of comorbidity complexity may in turn affect their choice of hospital.

A priori, we expect patients with greater comorbidity complexity to prefer hospitals with better SI investments based on the arguments that we present next. There is a significant amount of literature on the role that technology can play in improving the quality of health care (Halvorson et al., 2003; Health Affairs 2005). These technologies enable healthcare providers to gain access to clinically relevant research, provide more coordinated care, facilitate communication with patients, and provide them information on various treatment options to create better patient engagement. Such features of technology can be especially important for patients with comorbidities to ensure their proper management through careful monitoring, timely information, cooperation and good communications with teams of health professionals (Mechanic 2008). Thus technology innovativeness is likely to play a bigger role in the choice of hospitals for patients with greater comorbidity complexity. The medical literature has noted a positive association between comorbidities and complications arising from a surgical procedure (Luft et al., 1987; Roche et al., 2005; Deyo et al., 2010). Preventing or reducing the incidence of perioperative complications relies heavily on the experience and expertise of the hospital and surgeons performing the procedure, greater familiarity of hospital staff with the correct protocols and procedures, and the skills, education and the amount of time registered nurses spend with patients (Katz et al., 2004; Needleman et al., 2006). Thus registered nurse staffing and hospital focus will also be more helpful when patient comorbidity complexity is high. Taken together, these hospital SI investments are likely

to play an important role in determining hospital choice for patients with greater comorbidities.

H4: The positive relationship between revealed patient choice and hospital SI investments is amplified for patients with greater comorbidity complexity

The role of perceptual patient satisfaction in impacting hospital choice for people with greater complexity of comorbidities is not clear *a priori*. It is possible that patients with greater comorbidity complexity may attach greater value to provider communication and responsiveness because their condition is more difficult to treat and has a greater potential for post-surgery complication. However, if a choice has to be made between the technical competency and patient satisfaction, it is more likely that such patients with higher comorbidity complexity will put a lower premium on satisfaction simply because higher satisfaction by itself does not guarantee that such patients will receive more effective treatment. Limited research in this area also seems to suggest that patients put a greater premium on the technical rather than interpersonal skills of the provider (Cheng et al., 2003; Fung et al. 2005). Thus we hypothesize the following.

H5: The positive relationship between revealed patient choice and patient satisfaction is weakened for patients with greater comorbidity complexity

Finally we consider the role of hospital reputation in impacting hospital choice for people with greater comorbidities. We have previously hypothesized that patients may find it easier to let one factor dominate their choice and trust the credibility of reputation signaling generated by a third party source. However, the decision making process may

be a little more complicated for patients with greater comorbidity complexity because there are greater risks associated with their surgery as previously discussed. They may thus prefer hospitals with a better reputation for quality. A study argued that rural patients with greater illness severity are likely to need treatment with advanced technology and highly skilled personnel, and may thus prefer larger hospitals (because larger hospitals may have more financial resources to invest in processes that improve quality), even though such hospitals may be in more distant locations (Adams et al., 1991). Studies also show that hospitals rated highly by third party sources have lower mortality risk and better process adherence across a range of different measures (Chen et al., 1999; Osborne et al., 2009). Thus third party generated hospital reputation is likely to play a stronger role in hospital choice of patients with greater comorbidity complexity.

H6: The positive relationship between revealed patient choice and hospital reputation (as signaled by third parties) is amplified for patients with greater comorbidity complexity.

4.4 Data Description and Econometric Model

Our first and main source of data comes from California's Office of Statewide Health Planning and Development (OSHPD) for the year 2012. This dataset contains detailed patient level discharge records, and includes information on patient demographics (e.g. age, gender, race and insurance), procedures and discharge, diagnosis related group (DRG) codes, dates of admission and discharge, patient and hospital zip codes, and whether the surgery was elective or not i.e. scheduled in advance or emergent.

We focus our study on patients undergoing elective hip and knee surgery and who are also Medicare patients for several reasons. First, hip and knee surgery is a high impact area. The American Academy of Orthopedic Surgeons (AAOS) reports that the percentage of total knee replacements increased by 120% from 2000 to 2009 while the percentage of total hip replacements increased by 73% from 2000 to 2009, and that Medicare pays for over 50% of these surgeries (<http://newsroom.aaos.org/media-resources/Press-releases/25-million-americans-living-with-an-artificial-hip-47-million-with-an-artificial-knee.htm>). In addition, Medicare patients have flexible coverage (i.e. they are free to choose any hospital) and the price that hospitals get reimbursed for Medicare procedures are fixed. This is in contrast to privately insured patients who may have network-provider constraints and prices may vary significantly from one patient to another. Also, in order to test the impact of hospital characteristics, perceptual patient satisfaction, and reputation on patient demand, price has to be exogenous. If price changes endogenously based on any of these three factors, then our estimates of hospital characteristics, satisfaction, or reputation will be biased. Restricting our attention to just Medicare patients avoids this problem. Other US based studies have also used a similar logic in studying Medicare patients only (Tay 2003; Goldman and Romley 2010). Finally, California is among the very few states with the highest number of both hip and knee replacement patients as reported by AAOS, thus making it an ideal study setting. We start with 48,869 Medicare patients undergoing elective hip-knee surgeries at 277 acute care hospitals. Based on past literature, we delete patient-hospital records where hospitals performed less than 10 hip-knee replacement surgeries in a year (Pope 2009). We also remove patients with missing unique patient identifier as missing values create

problems while building the choice set and running the analysis. Although the main focus of our study is on elective hip and knee surgeries, we also create a similar dataset for elective heart surgeries because it serves two purposes. First, it helps us evaluate whether results of our study are consistent across different elective surgery types or whether differences exist. Secondly, elective heart surgeries have been the major focus of RPP/CM studies in the current literature, and analyzing them allows us to extend our current knowledge of hospital attributes that drive choice of hospital by heart surgery patients.

We measure a hospital's innovativeness in the use of technology through the Saidin Index. This Index has been used in prior literature, and is calculated as a weighted sum of clinical, administrative and strategic technologies adopted by each hospital such that the weights are inversely proportional to the number of hospitals adopting that technology (Queenan et al. 2011; Sharma et al. 2016). Thus hospitals that are the frontrunners in adopting new and more complex technologies receive a higher Saidin Index score. We collect information on the various technologies available within a hospital using the HIMSS 2011 database. The Saidin Index S_i is then calculated as follows:

$$S_i = \sum_{k=1}^K a_k \tau_{i,k} \quad \text{where} \quad a_k = 1 - \left(\frac{1}{N}\right) \sum_{i=1}^N \tau_{i,k}$$

where k = technologies available in a given year and indexed by $k = 1, 2, \dots, K$; a_k = weight for a given technology across all hospitals; N = number of hospitals in 2011; $\tau_{i,k}$ = 1 if hospital i has technology k in 2011, 0 otherwise. This dataset is joined with the

OSHPD database using the Centers for Medicare and Medicaid Services (CMS) unique identifier.

We measure the staffing of registered nurses as the number of hours spent by registered nurses per patient day per hospital (Cho et al., 2003). This measure is computed from the 2011 California Annual Financial Database (AFD). A higher ratio indicates that registered nurses spend more time with patients. This database is joined with the OSHPD database using the CMS unique identifier. We measure hospital focus as a ratio of the number of elective hip and knee surgeries performed by a hospital to the total number of elective surgeries performed by that hospital. The operationalization of this measure is similar to prior literature on focus (Diwas and Terweisch, 2011). We use the OSHPD database again to compute this ratio. A higher ratio indicates that the hospital has a greater focus on hip-knee surgeries and is a good proxy for substantial SI investments made in this service line., We first convert each measure to z-score, and then calculate the average value to get an overall measure of a hospital's SI investments.

As discussed previously, factors such as provider communication, responsiveness, and hospital environment pay an important role in perceptual patient satisfaction, and this in turn may influence a patient's hospital stay. We accordingly use the HCAPHS survey items to create measures for communication and responsiveness based on prior literature (Senot et al. 2015). We first consider only data that had survey responses from at least 100 patients. The response categories for the measures are "Never/Sometimes", "Usually" or "Always" and we use the percentage of patients who answered "Always" as the measure for that survey item. We use COMP1-COMP4 measures to calculate the average communication score; and COMP5-COMP6 measures to calculate the average

responsiveness measure. Our measure of hospital environment is based on patient responses on measures of cleanliness (CLEAN) and quietness of rooms (QUIET) from the HCAPHS survey, and we use a similar approach to get the average value for this measure. To get the overall perceptual patient satisfaction, we first convert our scores of communication, responsiveness and environment to z-scores and then calculate the average.

Finally, we create a measure of reputation generated by third party as a binary 0/1 variable generated by US News and World Report (USNWR). Hospitals ranked as ‘best’ national or regional hospitals in their orthopedics specialty list (or in Cardiology and Heart Surgery for our elective heart surgery analysis) are defined as 1, and 0 otherwise. Our rationale for choosing this scheme is as follows. First, USNWR is the only rating agency that creates a list of best hospitals by specialty, and which is used as a marketing tool by hospitals to promote themselves as high quality providers on their websites. This is important, since potential patients may not care about overall hospital reputation, but they definitely consider hospital reputation in the specialty area for which they are getting treatment. Second, USNWR has great name recognition and has provided ratings for the past several decades. It has a wide circulation with over 20 million visitors and 120 million page views. The best hospitals list is available online and accessible to people for free. Third, other rating agencies such as the Leapfrog Group, Joint Commission, and Consumer Reports have also recently started generating hospital rankings. But their first available ratings are after our study period, and hence were unusable. We join the hospital reputation dataset with the OSHPD database using the OSHPD unique identifier.

We have argued that the complexity of patient comorbidities plays a moderating role in the impact of various hospital related factors on the revealed preference of patients. We calculate a patient's comorbidity as an Elixhauser severity score based on literature (Berry Jaeger and Tucker 2016). This score is calculated using two pieces of information about a patient: (i) information on the Elixhauser Index which is a vector of 29 different variables where each variable is binary in nature and represents a specific comorbidity; its value is 1 if the comorbidity is present and 0 otherwise and (ii) information on the severity score on each comorbidity ranging from -7 to 12 with larger weights representing more severe comorbidities (Elixhauser et al. 1998). Thus the Elixhauser severity score is the dot product of the Elixhauser Index and the severity score. Information on up to 20 comorbidities are provided in the OSHPD database. We convert the comorbidity description as a 0/1 binary variable and use the severity score published in literature to arrive at the severity score for each patient. The scores in our sample range from -14 to 35. As with the other variables, we convert this to a z-score as well.

In addition to comorbidity scores, we also compile information on hospital characteristics such as teaching hospitals, profit status, size and location as they have been used as controls in prior literature (Tay 2003; Varkevisser et al. 2012). We get this data from CMS' Inpatient Prospective Payment System Files (IPPS). Teaching hospital is reflected in the teaching intensity as measured by the residents to bed ratio in the IPPS database. Non-profit hospitals are assigned a value of 1, and 0 otherwise. Hospital size is measured by the number of beds. Finally, location is assigned as 1 if the hospital is located in an urban area and 0 otherwise. Finally, distance is an important factor in

choosing hospitals. The OSHPD data provides information on patient and hospital zip codes. Accordingly, we calculate the distance between the patient's home and hospital in miles as a straight line distance between the centroids of the patient and hospital's zip codes (Goldman and Romley 2010; Chandra et al., 2015; Wang et al., 2015). We also include the square of the distance in our specification under the assumption that the willingness to travel further is concave in nature (Tay 2003; Chandra et al., 2015). We have missing data in various datasets - missing zip code data in the OSHPD database, missing CMS identifiers in the HIMSS, AFD, and IPPS databases or missing data on technology, registered nurse hours or patient satisfaction. After accounting for missing hospital level data and joining various datasets, we have 37,049 Medicare patients who underwent elective hip-knee surgeries at 246 hospitals (and 21,172 patients who underwent elective heart surgeries at 167 hospitals) in California in 2012.

4.5 Empirical Specification of the Demand Model

To estimate patient choice of hospital, we use a patient-level utility function in which travel distance, hospital characteristics, and reputation reflecting quality differences are the main determinants of patient hospital choice. When patients select hospitals, they are assumed to weigh the cost of increased distance (in monetary costs and the opportunity cost of family members' time) against the benefits (better quality of hospital). The utility of patient i who chooses hospital j is given by:

$$U_{ij} = \alpha d_{ij} + \beta d_{ij}^2 + \sum_m \gamma_m \mathbf{H}_j + \sum_m \delta_m PC_i \cdot \mathbf{H}_j + \sum_o \zeta_o \mathbf{R}_j + \varepsilon_{ij} \quad (1)$$

U_{ij} is the utility that a patient derives by choosing a hospital, d_{ij} is the distance from the patient's home to a hospital, H_j is a vector of hospital j 's quality attributes of SI investments, perceptual patient satisfaction, and third party reputation signal. PC_i is patient comorbidity measured by the Elixhauser Index. This term is interacted with the hospital quality attributes of interest in this study. Other patient demographics such as age, race, gender, etc. do not enter into the equation as they are invariant across each patient's choice set. R_j represents hospital control variables such as teaching intensity, size, location, and profit status. ε_{ij} represents the idiosyncratic part of patient i 's evaluation of hospital j . We assume that ε_{ij} is a distributed Type I extreme value, which means that the problem can be readily estimated as a conditional logit model (McFadden 1974). This is commonly used in the healthcare choice literature (Dranove and Satterthwaite, 2000; Varkevisser et al. 2010; Tay 2003). Note that prices are not included in this function because we study patient choice for Medicare patients only for whom prices are fixed. We assert that patient i , given his or her needs and preferences, will visit hospital j when visiting any alternative hospital in the choice set will result in a lower utility.

For the actual empirical specification of equation (1), we define a dependent variable $Chosen_{ij}$ as a binary 0/1 variable. For each patient, we create a choice set based on hospitals that are within a 50 mile radius of the patient's zip code. $Chosen_{ij}$ is assigned a value of 1 if patient i chooses hospital j in the choice set, and 0 otherwise. We have 2.48 million patient-hospital pairs in this choice set. For this approach, we assume that for each patient, the relative probabilities of choosing any two hospitals are independent of any other available alternatives. This restriction, called the independence of irrelevant

alternatives (IIA) assumption, assumes that all systematic variation in patients' taste is captured sufficiently by the variables specified in the logit model. The remaining unobserved portion of utility ε_{ij} is just white noise, and is assumed to be independent across observations. There is a large variation in the locations of both patients and hospitals in our dataset, ensuring heterogeneity in our model. Thus restrictive substitution patterns imposed by the conditional logit model will apply only to patients of similar demographics (i.e. age, race, gender) and who live in the same zip code. Hence IIA is less of a concern here, whereby when a patient makes a comparison between Hospitals 1 and 2, his or her decision-making process is not affected by the attributes of Hospital 3. Similarly, choice between Hospitals 1 and 3 is not affected by the attributes of Hospital 2, and so on. This logit model also has the advantage of being tractable. Also, we have two ways of using different geographic definitions to construct the patient choice set, which then serve as an additional check for violation of IIA. As a final check of IIA, we run the Hausman-McFadden (1984) test. This is a chi-square test that rejects the restrictions imposed by the conditional logit model if deletion of one hospital from the choice set causes significant changes in the coefficient and covariance estimates. Results of this test indicate that IIA is not a concern here.

Patient i 's probability of visiting hospital j is represented by:

$$P(\text{Chosen}_{ij} = 1) = \frac{\exp(\alpha d_{ij} + \beta d_{ij}^2 + \sum_j \gamma_j \mathbf{H}_j + \sum_j \delta_j PC_{ij} \cdot \mathbf{H}_j + \sum_j \zeta_j \mathbf{R}_j)}{\sum_{j=1}^{N_i} \exp(\alpha d_{ij} + \beta d_{ij}^2 + \sum_j \gamma_j \mathbf{H}_j + \sum_j \delta_j PC_{ij} \cdot \mathbf{H}_j + \sum_j \zeta_j \mathbf{R}_j)}$$

In order to assess whether hospital characteristics, perceptual patient satisfaction, or third party reputation signaling play a role in determining hospital choice, and whether patient comorbidities play a moderating role in influencing the relationship for elective

hip-knee surgeries (or elective heart surgeries), we proceed as follows. We first convert our distance measure to a z-score similar to other hospital attributes of interest. We also convert teaching intensity and bed size to z-scores. The advantage of using z-scores for analysis is that it reduces the magnitude of bias of the estimates (Harrison 2008). While it is difficult to get measures for every conceivable hospital characteristic or quality measure, endogeneity of hospital attributes that attract patients to certain hospitals is a potential issue in such estimations. Since we are only partially measuring hospital quality via its characteristics, patient satisfaction, or reputation, the unobserved quality is included in the error term. If this unobserved quality is correlated with other quality measures that we have included in our model, the estimates of outcomes are likely to be biased. By considering Medicare patients only, we have avoided using any price related measures (e.g. insurance type) to be included in our model and also likely reduced the magnitude of the bias. Secondly, as hypothesized in H1-H3, better hospital attributes are likely to increase the probability of patient choice of the hospital.

With our endogeneity issue, the coefficients on hospital characteristics and perceptual patient satisfaction may be upward biased. However, by making a holistic examination of several quality attributes at once, this is less likely to be the case. Second, by excluding unobserved quality, we are under measuring the overall quality anyway and the upward biased estimates will offset this. Thus we do not expect our estimates to be overly biased. Additionally, there can be systematic differences among patient preferences for hospitals. In the conditional logit model, differences among hospital SI investments, patient satisfaction and reputation are used to identify the model. Since

patient specific variables are constant across hospital choices for a given patient, these are differenced out and do not affect our estimation process.

Our main patient specific variable of interest is patient comorbidity complexity, which we capture as an interaction term with our hospital attributes of interest. Our use of patient level data also ensures that endogeneity in the unmeasured quality is uncorrelated with specific patient-hospital error term because only aggregate components in the error terms lead to endogeneity issues. Thus bias (or endogeneity) in this error term is less likely to be a concern when we use finer grained measures of patient level data in this case as opposed to measuring choice via total number of patients choosing a given hospital. Finally, perceptions of quality based on technology, staffing of registered nurses, focus, satisfaction or reputation take time to adjust. So the endogeneity of unmeasured quality is not a concern, as we consider a static model which draws data from one year only. All these arguments help alleviate endogeneity related concerns in our model estimation process.

4.6 Results

Descriptive statistics for elective hip-knee surgeries are reported in Table 4.2. As seen here, the mean distance to the chosen hospital is about 9 miles. Hospital characteristics, as measured by technology innovativeness, registered nurse staffing, and focused operations in hip-knee surgery, vary widely among chosen hospitals. About 11% of the hospitals are teaching hospitals, and a majority of hospitals are non-profit hospitals. Bed size also varies considerably, with the mean value indicating preference for larger hospitals.

Table 4.2: Descriptive Statistics for Elective Hip-Knee Surgeries

Variable	Mean	Std. Dev	Min	Max
Distance	8.938	10.165	0	178
Technology Innovativeness	10.601	4.609	1.051	20.841
Registered Nurse Staffing (hours/patient)	13.590	4.907	2.488	54.247
Focus (%)	14.808	11.669	0.231	71.732
Reputation	0.213	0.409	0	1
Patient Satisfaction (%)	65.663	5.595	52	91
Teaching Intensity (Residents per bed)	0.052	0.147	0	0.946
Profit Goals (1=Non-Profit, 0 = For-Profit)	0.579	0.493	0	1
Bed Size	218.746	137.859	10	836
Location (1=Urban, 0 = Suburban/Rural)	0.727	0.445	0	1

We present the estimates of the full conditional logit model in Table 4.3 for elective hip knee surgeries. The distance coefficient is negative and highly significant, indicating as expected that patients are less likely to travel to further hospitals. The coefficient on the composite z-score representing hospital characteristics of technology, registered nurse staffing, and focus is positive and highly significant ($p < 0.001$), indicating that the revealed choice of patients for hospitals is associated with better SI investments. The coefficient on perceptual patient satisfaction is also positive and highly significant ($p < 0.001$). Finally, the coefficient on third party hospital reputation is positive and highly significant ($p < 0.001$), indicating that the revealed choice of patients is more likely to be associated with hospitals with higher reputation. Thus all three of our main hypotheses H1-H3 are supported.

While significant, not all factors have similar impact. A comparison among the coefficients for hip-knee surgeries (since all the variables are standardized) in the full

conditional logit model indicates that, after controlling for distance and other hospital characteristics, the revealed choice of patients is highly influenced by third party hospital reputation, followed by hospital SI investments, and finally by patient satisfaction. This is an important finding and we are able to uncover it due to our holistic examination of various different hospital characteristics.

The interaction term between hospital characteristics and patient comorbidity complexity for hip-knee surgeries is positive and highly significant ($p < 0.001$), indicating that as complexity increases, patients emphasize hospital SI investments. Likewise, the interaction term between hospital reputation and patient comorbidity complexity is also positive and highly significant ($p < 0.001$) indicating that hospital reputation is important for patients with greater comorbidity complexity. Finally, the interaction between perceptual patient satisfaction and patient comorbidity complexity is negative and significant ($p\text{-value} < 0.05$) indicating that higher complexity patients are less likely to choose hospitals based on patient satisfaction once other factors are taken into account. These results support hypotheses H4 - H6.

In economics, the marginal rate of substitution (MRS) is defined as the rate at which a consumer is ready to give up one good in exchange for another good while maintaining the same level of utility. To understand the tradeoffs that patients are willing to make among various hospital attributes and travelling further, we compute the MRS derived from the full conditional logit model as follows:

$$MRS = \frac{\frac{\partial U_{ij}}{\partial H_j}}{\frac{\partial U_{ij}}{\partial d_{ij}}}$$

Our results indicate that patients, on an average, will be willing to travel an additional 7.5 miles for a 10% increase in SI investments and willing to travel an additional 1.5 miles for a 10% improvement in the patient satisfaction scores. We cannot similarly compute the impact of a 10% increase in reputation on willingness to travel as our reputation measure is not a continuous measure but a binary 0/1 measure. However, analysis of the data indicates that for similar characteristics, patients are willing to travel an additional 2.2 miles on an average to get to a more reputed hospital. We calculate the MRS for interaction terms for the 25% and 75% comorbidity complexity scores to represent low and high comorbidity complexity patients. Our results indicate that low comorbidity patients will be willing to travel an additional 5.4 miles, while high comorbidity complexity patients will be willing to travel an additional 8.1 miles for a 10% increase in a hospital's SI investments. Patients with low comorbidity complexity will be willing to travel an additional 1.7 miles, while patients with high comorbidity complexity will be willing to travel an additional 1.3 miles for a 10% increase in patient satisfaction, thereby indicating that the latter are less likely to travel further to hospitals with better scores. Similarly, we cannot compute how much a 10% change in reputation would impact the willingness to travel for low and high comorbidity patients as we do not have a continuous reputation score. However, our data indicates that low comorbidity patients would be willing to travel an additional 1.45 miles, while high comorbidity patients would be willing to travel an additional 3.04 miles, on an average, to get treated at a hospital with better reputation.

Among the control variables, the coefficient on teaching hospitals is negative while the coefficient on hospital size is positive, indicating that once other hospital

characteristics have been controlled for, patients are less likely to choose teaching hospitals and more likely to choose larger hospitals. This is in line with previous findings (Tay 2003). Patients are more likely to choose hospitals located in urban areas than those located in suburban and rural areas. Finally, the individual components that make up our hospital SI investments i.e. technology innovativeness, RN staffing, and focus are also all positive and highly significant.

Since several prior studies have looked at preferences for heart surgeries, we perform similar analysis for elective heart surgery patients to further understand whether patients' preferences between the two types of elective surgeries are similar. These results are summarized in Table 4.3. We find that hospital SI investments and reputation are also important to heart surgery patients ($p < 0.001$ for both attributes), but patient satisfaction is not important ($p > 0.1$). Between the two significant attributes, however, hospital SI investments are more important to elective heart surgery patients as compared to reputation.

We provide a potential explanation for the differences in results between hip-knee and heart surgeries. First, these two types of surgeries are inherently different. While hip-knee replacements are primarily done to improve the quality of life (www.aaos.org), heart surgeries (such as coronary artery bypass grafting (CABG) or similar surgeries) are done to lower the risks of more serious problems such as a heart attack or death (<http://www.nhlbi.nih.gov/>). Second, treating patients for elective heart surgeries is more resource intensive as compared to elective hip-knee surgeries. The average diagnosis related group (DRG) weight (routinely used by Centers for Medicare and Medicaid Services to determine resource intensity of a surgery/ procedure) for elective heart

surgeries in our analysis is almost twice as high (4.603) as the average DRG weight for elective hip-knee surgeries (2.56). This may indicate why SI investments in technology, registered nurses and focus may be more highly valued than reputation for elective heart surgeries. Third, reputation rankings are so prevalent in heart related surgeries that patients react to them only when such rankings are contrary to their prior beliefs (Dranove and Sfekas 2009), while this is not the case with hip-knee surgeries where such ‘report cards’ are not easily available and hence hip-knee patients might emphasize reputation to a larger extent. Finally, given that heart surgeries have more debilitating consequences if not treated correctly, such patients likely emphasize technical competence over patient satisfaction (Cheng et al., 2003), and this argument can be extended to reputation as well. The results of our interaction terms are as before, indicating that elective heart surgery patients with greater comorbidity complexities are more likely to select hospitals based on its SI investments and reputation, and less likely to do so based on its patient satisfaction scores.

Table 4.3: Conditional Logit Estimates of Hospital Choice

Variable	Choice Set: 50 Mile Radius		
	Hip-Knee Surgery		Heart Surgery
Distance	-1.521***(0.011)	-1.776***(0.013)	-1.282***(0.013)
Distance Squared	0.354***(0.007)	0.565***(0.008)	0.411***(0.009)
Hospital Investments	0.490***(0.010)	0.489***(0.010)	0.976***(0.015)
Patient Satisfaction	0.081***(0.007)	0.098***(0.007)	0.018 (0.012)
Reputation	0.609***(0.013)	0.629***(0.013)	0.527***(0.021)
Hospital Investments * CC		0.067***(0.011)	0.177***(0.014)
Patient Satisfaction * CC		-0.015*(0.006)	-0.098***(0.011)
Reputation * CC		0.209***(0.011)	0.092***(0.018)
Teaching Intensity	-0.075***(0.005)	-0.078***(0.005)	-0.109***(0.007)
Profit Goals	0.113***(0.013)	0.093***(0.013)	0.434***(0.020)
Hospital Size	0.212***(0.006)	0.212***(0.006)	0.187***(0.009)
Location	0.087**(0.017)	0.051**(0.017)	0.117***(0.026)

Pseudo R-Squared	0.37	0.385	0.295
------------------	------	-------	-------

Note: CC = Comorbidity Complexity.

DRGs for hip and knee surgery: 462, 466-470, 480-482, 486-489.

DRGs for heart surgery: 216, 219-221, 227-229, 234-238, 243, 244, 246, 247, 249, 251-254, 264

Robust standard errors are reported in parentheses and are clustered at the patient level.

*, **, *** Represent significance at the 5%, 1% and 0.1% levels respectively.

4.7 Robustness Test

To ascertain the robustness of our results, we consider a second choice set that is more restrictive, and based on just 10 hospitals closest to the patient’s zip code. Building this choice set gives us a total of 0.37 million hospital-patient pairs for hip-knee elective surgery. Results with the alternate specification are consistent with the main analysis - patients are more likely to choose hospitals with better reputation, SI investments, and patient satisfaction in decreasing order of importance. Patients with increasing comorbidity complexity are more likely to select hospitals with better SI investments and reputation, and less likely to select hospitals based on perceptual satisfaction scores. Results on elective heart surgery (0.21 million hospital-patient pairs) and other control variables are also as before. These results are summarized in Table 4.4.

Table 4.4: Robustness Check

Variable	Choice Set: Nearest 10 Hospitals		
	Hip-Knee Surgery		Heart Surgery
Distance	-8.798***(0.051)	-8.789***(0.051)	-12.983***(0.206)
Distance Squared	3.914***(0.041)	3.892***(0.041)	9.149***(0.574)
Hospital Investments	0.560***(0.013)	0.549***(0.013)	0.824***(0.015)
Patient Satisfaction	0.042***(0.008)	0.044***(0.008)	0.017 (0.011)
Reputation	0.703***(0.012)	0.710***(0.012)	0.488***(0.020)
Hospital Investments * CC		0.125***(0.012)	0.148***(0.014)
Patient Satisfaction * CC		-0.074***(0.007)	-0.081***(0.011)
Reputation * CC		0.181***(0.012)	0.095***(0.019)

Teaching Intensity	-0.098***(0.006)	-0.097***(0.006)	-0.101***(0.007)
Profit Goals	0.178***(0.013)	0.026*(0.014)	0.292***(0.019)
Hospital Size	0.129***(0.007)	0.132***(0.007)	0.164***(0.009)
Location	0.245***(0.018)	0.241***(0.018)	0.171***(0.026)
Pseudo R-Squared	0.304	0.314	0.176

Note: CC = Comorbidity Complexity

DRGs for hip and knee surgery: 462, 466-470, 480-482, 486-489.

DRGs for heart surgery: 216, 219-221, 227-229, 234-238, 243, 244, 246, 247, 249, 251-254, 264

Robust standard errors are reported in parentheses and are clustered at the patient level.

*, **, *** Represent significance at the 5%, 1% and 0.1% levels respectively.

4.8 Study Contributions and Conclusion

This is the first study of its kind that shows that the revealed preference of patients for choosing a hospital is not homogenous, and that the complexity of patient comorbidities plays an important role in determining factors are important to such patients. To summarize our findings, hospital SI investments, patient satisfaction, and reputation are important determinants of hospital choice but differ in their degree of importance. Patients with greater comorbidity complexity emphasize hospital SI investments, as well as its reputation as signaled by third parties. They are less likely to select hospitals based on its perceptual satisfaction. Extending our analysis to elective heart surgery patients further emphasizes the role of SI investments and reputation, but finds that the impact of patient satisfaction on choice is insignificant. We find that such heart surgery patients emphasize SI investments over reputation. These insights can help hospitals with better SI investments and reputation to target such patients.

4.8.1 Theoretical and Practical Contributions

The impact that quality factors have on influencing patient demand has been an understudied area. Past studies that have looked at consumer or patient behavior have

mostly focused on behavioral intentions using surveys (Victoor et al. 2012). It has been suggested that models that utilize behavioral intentions only may exhibit low predictive validity when compared to models using actual choice behavior (Cote and Umesh, 1988). Ours is one of the few studies that investigates the revealed choice of patients to overcome this issue of predictive validity. Other studies that have investigated the revealed preferences of patients have mostly been on the influence of quality outcome measures and rankings as drivers of choice (Tay 2003; Pope 2009; Varkevisser et al. 2012; Wang et al., 2015). Outcome measures and rankings are not prevalent in most kinds of elective surgeries. Further, a significant majority of the studies have mostly considered choice issues related to elective and emergent heart surgeries where information availability on hospitals, surgeons and outcomes through report cards and public reporting are widely and easily accessible. In contrast, our study considers a scenario where information availability on quality outcomes such as complications arising from surgery, readmissions, mortality, etc. for elective surgeries is scarce. Under this information vacuum situation, our study highlights the importance of SI investments, perceptual patient satisfaction and third party hospital reputation, in enhancing patient demand. It thus provides inputs to managers on how their financial resources can be best utilized.

Extending our analysis of RPP/CM to elective heart surgery patients supports our results that SI investments and reputation play an important role in hospital choice. Our analysis also uncovers additional insights - complexity of the disease and its treatment may drive the degree to which each hospital attribute is considered important from a choice perspective for a given type of elective surgery. Such insights have been missing

in prior work on RPP/CM as studies have mostly considered a single type of surgery. Even when multiple types of surgery are considered, the role of disease complexity has not been explored.

Investments in technology or registered nurses are not cheap. Technology in particular leads hospital expenditures as reported by a recent survey (<https://www.premierinc.com/shift-to-population-health-requiring-larger-provider-investments-premier-inc-survey-finds/>). However, besides its role in improving the quality of patient care, it can also result in increased revenues for hospitals via increased patient choice. Similarly, hospitals have been cutting back on registered nurses in an attempt to reduce costs (Thungjaroenkul et al., 2007). But increased registered nurse staffing, besides giving better quality outcomes, is also viewed favorably as revealed by patient choice of hospitals. So the managers may have to take a second look at such layoff practices. Finally, big companies such as Walmart, Lowe's, Blue Cross Blue Shield, etc. are increasingly tying up with certain hospitals to ensure that their employees and insured patients get high quality care (http://corporate.walmart.com/_news_/news-archive/2013/10/08/walmart-lowes-pacific-business-group-on-health-announce-a-first-of-its-kind-national-employers-centers-of-excellence-network; <http://www.bcbs.com/why-bcbs/blue-distinction/?referrer=https://www.google.com/>). These hospitals, recognized as 'centers of excellence,' emphasize the role that hospital focus can play in attracting more patients.

The positive impact of patient satisfaction on revealed choice is also important to note. The effort by CMS to provide this information via its Hospital Compare website is a step in the right direction. A particular advantage of this measure is that it does not

require case-mix risk adjustment, and thus hospitals will not be tempted to engage in risk selection to improve the patient satisfaction rating. This is particularly relevant as a significant portion of the government incentives under its Value Based Purchasing Plan are tied to patient satisfaction scores.

Third party reputation provides a valuable service to patients by helping such patients identify top hospitals for care. Our study shows that a simple reputation signaling system by third parties which recognizes best hospitals is just as effective (if not more) than reporting multiple reputation scores or tracking year-on-year changes in the ordinal rankings of hospitals. Other agencies have also stepped up efforts to bring more information to patients. For example, CMS has been taking steps in this direction by initiating the Comprehensive Care for Joint Replacement (CJR) Model that holds hospitals accountable for the quality of care they deliver to Medicare patients undergoing hip and knee surgery (<http://www.hhs.gov/about/news/2015/11/16/cms-finalizes-bundled-payment-initiative-hip-and-knee-replacements.html>). However, the payment model, which begins in April 2016, is currently limited to hospitals in 67 geographic areas only. As such reporting matures; it will be interesting to see whether there is a shift in the revealed patient preference towards such reporting programs.

Finally, our study also has policy implications. The merits of regionalization of care, which refers to the creation of a regional health authority or board that assumes responsibility for organizing and delivering health care services to a defined patient population (Baker et al., 1998), have been debated (Rathore et al., 2005; Carr and Asplin 2010; Luke et al., 2011). The results of this study may point towards factors that should be considered in the decision making process if regionalization of care is determined as

the best way forward. Such a formation is likely to improve the quality of care, as well as help contain rising health care costs (Bunker et al., 1982; Gordon et al., 1995).

4.8.2 Limitations and Future Research

While interpreting our findings, it is possible that patient referrals to hospitals may have been driven by physician preferences. Unfortunately, our dataset does not have any identifiers related to the referring physician, and thus we cannot check for this situation. In addition, although we have captured the main SI investments, future studies should take a look at the impact of other characteristics such as magnet certification of hospitals on revealed patient preferences.

We have used the USNWR list to determine reputation, as it is the only one that we have found so far that publishes ratings by specialties. Other third party rating agencies such as the Leapfrog Group, Joint Commission, Consumer Reports, HealthGrades etc. have also started rating hospital level quality on a variety of outcome measures but more ratings may not necessarily be better. Given that such agencies focus on different measures and have different rating methodologies, they may end up confusing patients rather than informing them. This was highlighted in a recent study by Austin et al. (2015) which compared the ratings of 844 hospitals by four national rating systems, and found that no hospital was rated as a high performer by the top four national rating systems, and only 10% of the hospitals rated as a high performer by one rating system were rated as a high performer by any of the other rating systems. Thus it remains to be seen how much impact these ratings will have on the revealed choice of patients, and which is a fruitful area for future research.

CHAPTER 5

CONCLUSION

This dissertation is motivated by various changes in the healthcare landscape over the last several years. Policy initiatives such as the Meaningful of Technology under the HITECH Act provide incentives to hospitals to use health information technology in a meaningful way to improve patient outcomes. The Affordable Care Act has provided insurance coverage to millions of previously uninsured people, but has also increased competition among hospitals to attract these patients through various investments. Hospitals are now also held accountable for providing high quality care via the Value Based Purchasing initiative. In this dissertation, we have attempted to integrate the economics and the operations management perspectives by investigating the role of various structural and infrastructural factors in impacting hospital and patient level quality outcomes, and in impacting patient choice of hospitals.

Electronic Health Records (EHRs) have the potential to transform healthcare delivery through the use of built-in evidence based medical guidelines, and efficient coordination of patient treatment and care. Meaningful use of EHRs can play an especially important role in easing a health care provider's cognitive load while working on complex tasks. In the first study, we examine the impact of meaningful use of EHRs after the mandated HITECH (Health Information Technology for Economic and Clinical

Health) Act on patients' length of stay (LOS) in the context of treating patients with varying dimensions of complexities: (i) complexity arising from the treatment of a patient's disease, (ii) complexity arising from a patient's comorbidities and (iii) complexity arising from coordination required from various healthcare providers to treat the patient's disease. We conduct our analysis by using a large-scale dataset with detailed patient level data from acute care hospitals in California, which is also coupled with relevant data from several other sources. After accounting for self-selection bias, our analysis reveals that meaningful use of EHRs reduces the overall LOS by about 9%; and that the magnitude of this effect is greater for patients with higher disease and comorbidity complexity and for patients with higher coordination needs. Further, these changes in LOS do not come at the expense of increased readmissions. In fact, we find an overall decrease in readmissions and a greater reduction in readmissions for patients with a higher disease and coordination complexity profile. These are important findings. While hospitals cannot control the sickness and comorbidities that their patients come in with for treatment, they can certainly ensure that these patients spend less time in the hospital. Reduced length of stay may reduce hospital acquired infections, and therefore readmissions. Providing the right treatment at the right time also ensures that patients are less likely to be readmitted to hospitals.

Our second study examines the impact of competition on process of care (PoC), and the role process improvement factors play on affecting PoC within the altered competitive landscape that has been created in the healthcare industry by the introduction of the Affordable Care Act (ACA) of 2010. ACA acts as a catalyst in increasing competition among all hospitals to attract more patients and improve PoC. A longitudinal

analysis of California patient data combined from several different sources shows the contingent value of process improvement factors such as operational slack, nursing skill mix and focused strategy. Their impact on PoC is positive in both more as well as less competitive markets; however the marginal benefit is stronger in less competitive markets. These results are robust to alternate specifications of competition. Nevertheless, the fact that process improvement factors can impact processes of care in more competitive markets despite other investments in technology and equipment having already being made that led to a higher quality to begin with, is an important finding. We find similar results when considering the catalytic role played by ACA in enhancing competition. Declining reimbursements and financial constraints may force hospital executives to invest less in process improvement factors, erroneously thinking that quality can be improved by emphasizing efficiency in these areas. Our results show that these factors will continue to remain important under an increasingly competitive environment, as they have an impact on a hospital's responsiveness and ability to provide a high standard of care to its patients.

Studies in the healthcare operations management literature have typically focused on the supply side of the equation. Much less attention has however been paid to how hospital structural and infrastructural (SI) investments (as a cluster of technology, registered nurse staffing and focus), reputational factors, and perceptual patient satisfaction influence choice of a hospital when patients have to undergo elective surgeries. Our third study addresses this gap by focusing on the demand side of the equation. Once again, using detailed patient level data from California hospitals on elective hip and knee surgeries, we find that SI investments, third-party reputation

signals, and patient satisfaction influence patient choice, but to varying degrees. Our results reveal that hip and knee patients are willing to travel an additional 7.5 miles for a 10% increase in SI investments, an additional 2.2 miles for a more reputed hospital, and an additional 1.5 miles for a 10% improvement in patient satisfaction scores. As the complexity of comorbidities in patients increases, they are more likely to choose a hospital based on its SI investments and reputation, and less likely to choose a hospital based on higher patient satisfaction scores. Higher comorbidity patients are also willing to travel further for better hospital attributes. Such findings are of managerial importance. Our expanded analysis on elective heart surgery patients mostly support our results on hip-knee surgery patients, but also indicates that the complexity of disease and its treatment may play a role in the way various hospital attributes are emphasized. While hip-knee replacements are primarily done to improve the quality of life, surgeries (such as coronary artery bypass grafting (CABG) or similar surgeries) are done to lower the risks of more serious problems such as a heart attack or death which we surmise are reasons for differences in different types of surgeries. Our study provides inputs to managers on how their financial resources can be utilized to enhance patient demand, especially in the light of increasing comorbidities in the US patient population.

To conclude, this dissertation provides additional building blocks towards understanding how internal factors such as technology, operational slack, skilled registered nurses, focused strategy, patient satisfaction, and external factors such as competition and third party reputation signals play in enhancing both quality outcomes and patient choice. It has important implications for the government, hospitals and patients in light of the changes that are underway in healthcare.

REFERENCES

- Adams, E.K., Houchens, R., Wright, G.E. and Robbins, J., 1991. Predicting hospital choice for rural Medicare beneficiaries: the role of severity of illness. *Health Services Research*. **26**(5): 583.
- Agha, L., 2014. The Effects of Health Information Technology on the Costs and Quality of Medical Care. *Journal of Health Economics*. **34**(3): 19–30
- Anand, G. and Ward, P.T., 2004. Fit, flexibility and performance in manufacturing: coping with dynamic environments. *Production and Operations Management*. **13**(4): 369-385.
- Anderson, E.W., 1996. Customer satisfaction and price tolerance. *Marketing letters*. **7**(3): 265-274.
- Andritsos, D.A. and Tang, C.S., 2014. Linking process quality and resource usage: An empirical analysis. *Production and Operations Management*. **23**(12): 2163-2177.
- Angst, C.M., Devaraj, S. and D'Arcy, J., 2012. Dual Role of IT-Assisted Communication in Patient Care: A Validated Structure-Process-Outcome Framework. *Journal of Management Information Systems*. **29**(2): 257–92.
- Appari, A., Carian, E.K., Johnson, M.E. and Anthony, D.L., 2012. Medication administration quality and health information technology: a national study of US hospitals. *Journal of the American Medical Informatics Association* **19**(3): 360-367.
- Appari, A., Eric Johnson, M. and Anthony, D.L., 2013. Meaningful Use of Electronic Health Record Systems and Process Quality of Care: Evidence from a Panel Data Analysis of US Acute Care Hospitals. *Health services research*. **48**(2): 354-375.
- Argote, L., Insko, C.A., Yovetich, N. and Romero, A.A., 1995. Group Learning Curves: The Effects of Turnover and Task Complexity on Group Performance. *Journal of Applied Social Psychology*. **25**(6): 512–29.
- Ashton, C.M., Kuykendall, D.H., Johnson, M.L., Wray, N.P. and Wu, L., 1995. The association between the quality of inpatient care and early readmission. *Annals of internal medicine*, **122**(6): 415-421.
- Austin, J.M., Jha, A.K., Romano, P.S., Singer, S.J., Vogus, T.J., Wachter, R.M. and Pronovost, P.J., 2015. National hospital ratings systems share few common scores and may generate confusion instead of clarity. *Health Affairs*. **34**(3): 423-430.

- Autor, D.H., Levy, H., Murnane, R. J., 2003 The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics* **118**(4): 1279-1333.
- Baek, T.H., Kim, J. and Yu, J.H., 2010. The differential roles of brand credibility and brand prestige in consumer brand choice. *Psychology & Marketing*. **27**(7): 662-678.
- Baker, L.C. and Phibbs, C.S., 2000. Managed care, technology adoption, and health care: the adoption of neonatal intensive care. No. w7883. *National Bureau of Economic Research*.
- Barkell, N.P., Killinger, K.A., & Schultz, S.D., 2002. The relationship between nurse staffing models and patient outcomes: A descriptive study. *Outcomes Management*. **6**(1): 27-33.
- Bassett, C., 2002. Nurses' perceptions of care and caring. *International journal of nursing practice*. **8**(1): 8-15.
- Bates, D.W., Cohen, M., Leape, L.L., Overhage, J.M., Shabot, M.M. and Sheridan, T., 2001. Reducing the frequency of errors in medicine using information technology. *Journal of the American Medical Informatics Association*. **8**(4): 299-308.
- Baum, C.F., Cox, N.J. and Wiggins, V., 2001. Tests for heteroskedasticity in regression error distribution. *Stata Technical Bulletin*. **10**(55).
- Bazzoli, G.J., Chen, H.F., Zhao, M. and Lindrooth, R.C., 2008. Hospital financial condition and the quality of patient care. *Health economics*. **17**(8): 977-995.
- Bazzoli, G.J., Clement, J.P., Lindrooth, R.C., Chen, H.F., Aydede, S.K., Braun, B.I. and Loeb, J.M., 2007. Hospital financial condition and operational decisions related to the quality of hospital care. *Medical Care Research and Review*. **64**(2): 148-168.
- Berry Jaeker, J.A. and Tucker, A.L., 2016. Past the Point of Speeding Up: The Negative Effects of Workload Saturation on Efficiency and Patient Severity. *Management Science*.
- Berry, L.L. and Bendapudi, N., 2007. Health care a fertile field for service research. *Journal of Service Research*. **10**(2): 111-122.
- Bertrand, M., Karlin, D., Mullainathan, S., Shafir, E. and Zinman, J., 2005. What's psychology worth? A field experiment in the consumer credit market. No. w11892. *National Bureau of Economic Research*.
- Best, T.J., Sandıkçı, B., Eisenstein, D.D. and Meltzer, D.O., 2015. Managing hospital inpatient bed capacity through partitioning care into focused wings. *Manufacturing & Service Operations Management*. **17**(2): 157-176.
- Bitner, M.J., 1990. Evaluating service encounters: the effects of physical surroundings and employee responses. *The Journal of Marketing*. **54**(2): 69-82.

- Bloom, N., Propper, C., Seiler, S. and Van Reenen, J., 2015. The impact of competition on management quality: evidence from public hospitals. *The Review of Economic Studies*. **82**(2): 457-489.
- Bodenheimer, T., Chen, E. and Bennett, H.D., 2009. Confronting the growing burden of chronic disease: can the US health care workforce do the job?. *Health Affairs*. **28**(1): 64-74.
- Brill, J., 2015. Competition in Health Care Markets. *Health Affairs*. URL <http://healthaffairs.org/blog/2015/01/26/competition-in-health-care-markets/>
- Bruggink, T.H., Finan, K.C., Gendel, E.B. and Todd, J.S., 1985. Direct and indirect effects of unionization on the wage levels of nurses: A case study of New Jersey hospitals. *Journal of Labor Research*. **6**(4): 405-416.
- Bunker, J.P., Luft, H.S. and Enthoven, A., 1982. Should surgery be regionalized?. *The Surgical clinics of North America*. **62**(4): 657-668.
- Bureau of Labor Statistics, 2014a. Registered Nurses : Occupational Outlook Handbook : U.S. Bureau of Labor Statistics. <http://www.bls.gov/ooh/healthcare/registered-nurses.htm>
- Bureau of Labor Statistics, 2014b. Licensed Practical and Licensed Vocational Nurses : Occupational Outlook Handbook: U.S. Bureau of Labor Statistics . <http://www.bls.gov/ooh/healthcare/licensed-practical-and-licensed-vocational-nurses.htm>
- Califf, R.M. and Faxon, D.P., 2003. Need for centers to care for patients with acute coronary syndromes. *Circulation*. **107**(11): 1467-1470.
- Campbell, D.J. and Gingrich, K.F., 1986. The Interactive Effects of Task Complexity and Participation on Task Performance: A Field Experiment. *Organizational Behavior and Human Decision Processes* **38**(2): 162–180.
- Campbell, D.K. 1991. Goal Levels, Complex Tasks, and Strategy Development: A Review and Analysis. *Human Performance* **4**(1): 1–31.
- Carr, B.G. and Asplin, B.R., 2010. Regionalization and emergency care: the institute of medicine reports and a federal government update. *Academic Emergency Medicine*, **17**(12): 1351-1353.
- Carte, T. A., C. J. Russell. 2003. In pursuit of moderation: Nine common errors and their solution. *MIS Quarterly*. **25**(3): 478–502.
- Chandra, A., Finkelstein, A., Sacarny, A. and Syverson, C., 2015. Healthcare Exceptionalism? Performance and Allocation in the US Healthcare Sector. No. w21603. *National Bureau of Economic Research*.

- Chandrasekaran, A., Senot, C. and Boyer, K.K., 2012. Process management impact on clinical and experiential quality: managing tensions between safe and patient-centered healthcare. *Manufacturing & Service Operations Management*. **14**(4): 548-566.
- Chen, J., Radford, M.J., Wang, Y., Marciniak, T.A. and Krumholz, H.M., 1999. Do “America's Best Hospitals” perform better for acute myocardial infarction?. *New England Journal of Medicine*. **340**(4): 286-292.
- Cheng, S.H., Yang, M.C. and Chiang, T.L., 2003. Patient satisfaction with and recommendation of a hospital: effects of interpersonal and technical aspects of hospital care. *International Journal for Quality in Health Care*. **15**(4): 345-355.
- Cho, S.H., Ketefian, S., Barkauskas, V.H. and Smith, D.G., 2003. The effects of nurse staffing on adverse events, morbidity, mortality, & medical costs. *Nursing research*. **52**(2): 71-79.
- CMS.gov A. <https://www.cms.gov/research-statistics-data-and-systems/statistics-trends-and-reports/nationalhealthexpenddata/nationalhealthaccountshistorical.html>
- CMS.gov B <https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/hospital-value-based-purchasing/index.html?redirect=/hospital-value-based-purchasing/>
- Collins, S.R., Rasmussen, P.W., Doty, M.M., 2014. Gaining ground: Americans’ health insurance coverage and access to care after the Affordable Care Act’s first open enrollment period. Issue Brief Commonw. Fund 16, 1–23.
- Cooper, Z., Gibbons, S., Jones, S. and McGuire, A., 2011. Does hospital competition save lives? evidence from the English NHS patient choice reforms. *The Economic Journal*. **121**(554): 228-260.
- Corbett, C.J., Montes-Sancho, M.J. and Kirsch, D.A., 2005. The financial impact of ISO 9000 certification in the United States: An empirical analysis. *Management science*. **51**(7): 1046-1059.
- Cronin, J.J., Brady, M.K. and Hult, G.T.M., 2000. Assessing the effects of quality, value, and customer satisfaction on consumer behavioral intentions in service environments. *Journal of retailing*. **76**(2): 193-218.
- Culnan, M. J. 1983. Environmental Scanning: The Effects of Task Complexity and Source Accessibility on Information Gathering Behavior. *Decision Sciences* **14**(2): 194–206.
- Cummings, G. and Estabrooks, C.A., 2003. The effects of hospital restructuring that included layoffs on individual nurses who remained employed: A systematic review of impact. *International Journal of Sociology and Social Policy*. **23**(8/9): 8-53.
- Cutler, D. M. 2010. “Where Are the Health Care Entrepreneurs?” *Issues in Science & Technology*. **27**(1): 49–56.

- Cutler, D., 1995. The Incidence of Adverse Medical Outcomes under Prospective Payment. *Econometrica*. **63**: 29–50.
- Cutler, D.M., Huckman, R.S. and Landrum, M.B., 2004. *The role of information in medical markets: an analysis of publicly reported outcomes in cardiac surgery*. No. w10489. National Bureau of Economic Research.
- Cutler, D.M., Morton, F.S., 2013. Hospitals, market share, and consolidation. *JAMA* 310, 1964–1970.
- Darke, P.R., Chaiken, S., Bohner, G., Einwiller, S., Erb, H.P. and Hazlewood, J.D., 1998. Accuracy motivation, consensus information, and the law of large numbers: Effects on attitude judgment in the absence of argumentation. *Personality and Social Psychology Bulletin*. **24**(11): 1205-1215.
- DeMarco, T., 2002. *Slack: Getting past burnout, busywork, and the myth of total efficiency*. New York: Broadway Books.
- Devaraj, S., and Kohli, K., 2003. Performance Impacts of Information Technology: Is Actual Usage the Missing Link? *Management Science*. **49**(3): 273–89.
- Devers, K.J., Brewster, L.R. and Casalino, L.P., 2003. Changes in hospital competitive strategy: a new medical arms race?. *Health services research*. **38**(1-2): 447-469.
- Deyo, R.A., Mirza, S.K., Martin, B.I., Kreuter, W., Goodman, D.C. and Jarvik, J.G., 2010. Trends, major medical complications, and charges associated with surgery for lumbar spinal stenosis in older adults. *JAMA*. **303**(13): 1259-1265.
- Dindo, D., Demartines, N. and Clavien, P.A., 2004. Classification of surgical complications: a new proposal with evaluation in a cohort of 6336 patients and results of a survey. *Annals of surgery*. **240**(2): 205-213.
- Ding, D.X., 2014. The effect of experience, ownership and focus on productive efficiency: A longitudinal study of US hospitals. *Journal of Operations Management*. **32**(1): 1-14.
- Donabedian, A., 1988. The quality of care: How can it be assessed?. *Jama*. **260**(12): 1743-1748
- Douglas, P.S., Taylor, A., Bild, D., Bonow, R., Greenland, P., Lauer, M., Peacock, F. and Udelson, J., 2009. Outcomes research in cardiovascular imaging: report of a workshop sponsored by the National Heart, Lung, and Blood Institute. *JACC: Cardiovascular Imaging*, 2(7), pp.897-907.
- Dranove, D. and Satterthwaite, M.A., 2000. The industrial organization of health care markets. *Handbook of health economics*. 1093-1139
- Dranove, D. and Sfekas, A., 2008. Start spreading the news: a structural estimate of the effects of New York hospital report cards. *Journal of health economics*. **27**(5): 1201-1207.

- Dranove, D., Forman, C., Goldfarb, A. and Greenstein, S., 2012. The Trillion Dollar Conundrum: Complementarities and Health Information Technology. No w18281. *National Bureau of Economic Research*.
- Dranove, D., Shanley, M. and Simon, C., 1992. Is hospital competition wasteful?. *The Rand journal of economics*. **23**(2): 247-262.
- Dranove, D., Shanley, M. and White, W.D., 1993. Price and concentration in hospital markets: the switch from patient-driven to payer-driven competition. *Journal of Law and Economics*. **36**(1): 179-204.
- Egger, E., 2000. Hospitals are beginning to make creative use of excess capacity. *Health care strategic management*. **18**(4): 16.
- Elixhauser, A., Steiner, C., Harris, D.R. and Coffey, R.M., 1998. Comorbidity measures for use with administrative data. *Medical care*. **36**(1): 8-27.
- Encinosa, W.E. and Bernard, D.M., 2005. Hospital finances and patient safety outcomes. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*, **42**(1): 60-72.
- Erdem, T. and Swait, J., 2004. Brand credibility, brand consideration, and choice. *Journal of consumer research*. **31**(1): 191-198.
- Everhart, D., Neff, D., Al-Amin, M., Nogle, J. and Weech-Maldonado, R., 2013. The effects of nurse staffing on hospital financial performance: Competitive versus less competitive markets. *Health care management review*. **38**(2): 146-155.
- Field, J.M. and Sinha, K.K., 2005. Applying Process Knowledge for Yield Variation Reduction: A Longitudinal Field Study. *Decision Sciences*. **36**(1): 159-186.
- Friedman, B., Devers, K.J., Steiner, C.A. and Fox, S., 2002. The use of expensive health technologies in the era of managed care: the remarkable case of neonatal intensive care. *Journal of Health Politics, Policy and Law*. **27**(3): 441-464.
- Fung, C.H., Elliott, M.N., Hays, R.D., Kahn, K.L., Kanouse, D.E., McGlynn, E.A., Spranca, M.D. and Shekelle, P.G., 2005. Patients' preferences for technical versus interpersonal quality when selecting a primary care physician. *Health services research*. **40**(4): 957-977.
- Furukawa, M. F., 2011. Electronic medical records and the efficiency of hospital emergency departments. *Medical Care Research and Review*. **68**(1): 75-95.
- Gao, G., Gopal, A. and Agarwal, R., 2010. Contingent effects of quality signaling: Evidence from the Indian offshore IT services industry. *Management Science*. **56**(6): 1012-1029.
- Gardner, J.W., Boyer, K.K. and Gray, J.V., 2015. Operational and strategic information processing: Complementing healthcare IT infrastructure. *Journal of Operations Management*. **33**(1): 123-139.

- Garvin, D.A., 1988. *Managing quality: The strategic and competitive edge*. Simon and Schuster.
- Gaynor, M. and Anderson, G.F., 1995. Uncertain demand, the structure of hospital costs, and the cost of empty hospital beds. *Journal of health economics*. **14**(3): 291-317.
- Gaynor, M. and Town, R.J., 2011. *Competition in health care markets*. No. w17208. *National Bureau of Economic Research*.
- Gaynor, M., 2006. What do we know about competition and quality in health care markets? No. w12301. *National Bureau of Economic Research*.
- Gaynor, M., 2014. Competition policy in health care markets: Navigating the enforcement and policy maze. *Health Affairs*. **33**(6): 1088-93.
- Gerteis J., Izrael D., Deitz D., LeRoy L., Ricciardi R., Miller T., Basu J., 2014. Multiple Chronic Conditions Chartbook. AHRQ Publications No,Q14-0038. Rockville, MD.
- Goldman, D. and Romley, J.A., 2008. Hospitals as hotels: the role of patient amenities in hospital demand. No. w14619. *National Bureau of Economic Research*.
- Gordon, T.A., Burleyson, G.P., Tielsch, J.M. and Cameron, J.L., 1995. The effects of regionalization on cost and outcome for one general high-risk surgical procedure. *Annals of surgery*. **221**(1): 43.
- Gravelle, H., Santos, R. and Siciliani, L., 2014. Does a hospital's quality depend on the quality of other hospitals? A spatial econometrics approach. *Regional science and urban economics*. **49**(11): 203-216.
- Green, L.V. and Nguyen, V., 2001. Strategies for cutting hospital beds: the impact on patient service. *Health services research*. **36**(2): 421-442.
- Greenwald, L., Cromwell, J., Adamache, W., Bernard, S., Drozd, E., Root, E. and Devers, K., 2006. Specialty versus community hospitals: referrals, quality, and community benefits. *Health affairs*. **25**(1): 106-118.
- Grönroos, C., 1990. *Service management and marketing: managing the moments of truth in service competition*. *Jossey-Bass*.
- Halvorson, G.C. and Isham, G.J., 2003. *Epidemic of care: A call for safer, better, and more accountable health care*. San Francisco: *Jossey-Bass*.
- Harrison, T. D. 2008. On the bias and consistency of OLS for an endogenous interaction coefficient. Working paper, Drexel University, Philadelphia.
- Hausman, J., and McFadden, D. 1984. Specification tests for the multinomial logit model. *Econometrica*. **52**(5): 1219–1240.
- Hausman, J.A., 1978. Specification tests in econometrics. *Econometrica*. **46**(6): 1251-1271.

- Hayes, L.J., O'Brien-Pallas, L., Duffield, C., Shamian, J., Buchan, J., Hughes, F., Laschinger, H.K.S., North, N. and Stone, P.W., 2006. Nurse turnover: a literature review. *International journal of nursing studies*. **43**(2): 237-263.
- Health Affairs. 2005. Health Information Technology (special issue) 24(5): entire issue.
- Hendricks, K.B. and Singhal, V.R., 1996. Quality awards and the market value of the firm: An empirical investigation. *Management science*. **42**(3): 415-436.
- Heskett, J. L. 1983. Shouldice Hospital Limited. HBS Case 9-683-068. Harvard Business School, Boston.
- Hewner, S., 2014. A Population-Based Care Transition Model For Chronically III Elders. *Nursing Economics*. **32**(3): 109.
- HHS. 2009. <http://www.hhs.gov/>.
- Hibbard, J.H. and Peters, E., 2003. Supporting informed consumer health care decisions: data presentation approaches that facilitate the use of information in choice. *Annual Review of Public Health*. **24**(1): 413-433.
- Hirsch, B.T. and Schumacher, E.J., 1995. Monopsony power and relative wages in the labor market for nurses. *Journal of Health Economics*. **14**(4): 443-476.
- Hoechle, D., 2007. Robust standard errors for panel regressions with cross-sectional dependence. *Stata Journal*. **7**(3): 281
- Hopp, W.J., Iravani, S.M. and Yuen, G.Y., 2007. Operations systems with discretionary task completion. *Management Science*. **53**(1): 61-77.
- Huckman, R.S., Pisano, G.P., 2006. The Firm Specificity of Individual Performance: Evidence from Cardiac Surgery. *Management Science*. **52**(4): 473-488.
- Hyer, N.L., Wemmerlöv, U. and Morris, J.A., 2009. Performance analysis of a focused hospital unit: The case of an integrated trauma center. *Journal of Operations Management*. **27**(3): 203-219.
- Ingwersen, P.E.R., 1992. *Information Retrieval Interaction*. Taylor Graham.
- Jack, E.P. and Powers, T.L., 2004. Volume flexible strategies in health services: a research framework. *Production and Operations Management*. **13**(3): 230-244.
- James, J., 2012. Health policy brief: pay-for-performance. *Health Affairs*. **11**: 2043-2050.
- Janiszewski Goodin, H., 2003. The nursing shortage in the United States of America: an integrative review of the literature. *Journal of advanced nursing*. **43**(4): 335-343.
- Jha, A. K. 2006. Measuring hospital quality what physicians do? How patients fare? Or both? *JAMA J. Am. Med. Assoc*. **296**(1): 95-97.

- Jha, A.K., E.J. Orav, A. Dobson, R.A. Book, and A.M. Epstein. 2009. Measuring efficiency: The association of hospital costs and quality of care. *Health Affairs*. **28**(3): 897-906.
- Jha, A.K., Orav, E.J., Li, Z. and Epstein, A.M., 2007. The inverse relationship between mortality rates and performance in the Hospital Quality Alliance measures. *Health affairs*. **26**(4): 1104-1110.
- Joint Commission on Accreditation of Healthcare Organizations, 2002. Health care at the crossroads: strategies for addressing the evolving nursing crisis. *Joint Commission on Accreditation of Healthcare Organizations*. Oakbrook Terrace, Ill.
- Jones, S.S., Adams, J.L., Schneider, E.C., Ringel, J.S. and McGlynn, E.A., 2010. Electronic health record adoption and quality improvement in US hospitals. *The American journal of managed care*, 16(12 Suppl HIT) SP64-71.
- Joynt, K.E. and Rosenthal, M.B., 2012. Hospital Value-Based Purchasing Will Medicare's New Policy Exacerbate Disparities?. *Circulation: Cardiovascular Quality and Outcomes*. **5**(2): 148-149.
- Kamakura, W.A., Mittal, V., de Rosa, F. and Mazzon, J.A. 2002. Assessing the Service-Profit Chain. *Marketing Science*. **21**(3): 294-317.
- Katz, J.N., Barrett, J., Mahomed, N.N., Baron, J.A., Wright, R.J. and Losina, E., 2004. Association between hospital and surgeon procedure volume and the outcomes of total knee replacement. *Journal of Bone and Joint Surgery*. **86**(9): 1909-1916.
- Kc, D.S. and Terwiesch, C., 2009. Impact of workload on service time and patient safety: An econometric analysis of hospital operations. *Management Science*. **55**(9): 1486-1498.
- Kc, D.S. and Terwiesch, C., 2012. An econometric analysis of patient flows in the cardiac intensive care unit. *Manufacturing & Service Operations Management*. **14**(1): 50-65.
- Kenagy, J.W., Berwick, D.M. and Shore, M.F., 1999. Service quality in health care. *JAMA*. **281**(7): 661-665.
- Kessler, D.P. and Geppert, J.J., 2005. The effects of competition on variation in the quality and cost of medical care. *Journal of Economics & Management Strategy*. **14**(3): 575-589.
- Kessler, D.P. and McClellan, M.B., 1999. *Is hospital competition socially wasteful?* No. w7266. *National Bureau of Economic Research*.
- Kline, D.S., 2003. Push and pull factors in international nurse migration. *Journal of nursing scholarship*. **35**(2): 107-111.
- Konetzka, R.T., Stearns, S.C. and Park, J., 2008. The staffing–outcomes relationship in nursing homes. *Health services research*. **43**(3): 1025-1042.

- Lang, T.A., Hodge, M., Olson, V., Romano, P.S. and Kravitz, R.L., 2004. Nurse–patient ratios: a systematic review on the effects of nurse staffing on patient, nurse employee, and hospital outcomes. *Journal of Nursing Administration*. **34**(7-8): 326-337.
- Li, L. and Benton, W.C., 2006. Hospital technology and nurse staffing management decisions. *Journal of Operations Management*. **24**(5): 676-691.
- Lindenauer, P.K., Remus, D., Roman, S., Rothberg, M.B., Benjamin, E.M., Ma, A. and Bratzler, D.W., 2007. Public reporting and pay for performance in hospital quality improvement. *New England Journal of Medicine*. **356**(5): 486-496.
- Litvak, E. and Bisognano, M., 2011. More patients, less payment: Increasing hospital efficiency in the aftermath of health reform. *Health Affairs*. **30**(1): 76-80.
- Locke, E.A., Shaw, K.N., Saari, L.M. and Latham, G.P., 1981. Goal setting and task performance: 1969–1980. *Psychological bulletin*. **90**(1): 125.
- Luft, H.S., Garnick, D.W., Mark, D.H., Peltzman, D.J., Phibbs, C.S., Lichtenberg, E. and McPhee, S.J., 1990. Does quality influence choice of hospital?. *Jama*. **263**(21): 2899-2906.
- Luft, H.S., Hunt, S.S. and Maerki, S.C., 1987. The volume-outcome relationship: practice-makes-perfect or selective-referral patterns?. *Health services research*. **22**(2): 157.
- Luke, R.D., Luke, T. and Muller, N., 2011. Urban hospital ‘clusters’ do shift high-risk procedures to key facilities, but more could be done. *Health Affairs*. **30**(9): 1743-1750.
- Maddala, G. S. 1983. Limited-Dependent and Qualitative Variables in Econometrics. Cambridge University Press, Cambridge, UK
- Manary, M.P., Boulding, W., Staelin, R. and Glickman, S.W., 2013. The patient experience and health outcomes. *New England Journal of Medicine*. **368**(3): 201-203.
- Marshall MN, Shekelle PG, Leatherman S, Brook RH. 2000. The public release of performance data: What do we expect to gain? A review of the evidence. *JAMA*. **283**(14): 1866–1874
- May, J.H., Bazzoli, G.J. and Gerland, A.M., 2006. Hospitals’ responses to nurse staffing shortages. *Health Affairs*. **25**(4): W316-W323.
- McAleese, P. and Odling-Smee, W., 1994. The effect of complications on length of stay. *Annals of surgery*. **220**(6): 740.
- McCabe, C., Kirchner, C., Zhang, H., Daley, J. and Fisman, D.N., 2009. Guideline-concordant therapy and reduced mortality and length of stay in adults with community-acquired pneumonia: playing by the rules. *Archives of Internal Medicine*. **169**(16): 1525-1531.

- McConnell, K.J., Lindrooth, R.C., Wholey, D.R., Maddox, T.M. and Bloom, N., 2013. Management practices and the quality of care in cardiac units. *JAMA internal medicine*, **173**(8): 684-692.
- McCue, M., Mark, B.A. and Harless, D.W., 2003. Nurse staffing, quality, and financial performance. *Journal of health care finance*. **29**(4): 54-76.
- McCullough, J.S., Casey, M., Moscovice, I. and Prasad, S., 2010. The effect of health information technology on quality in US hospitals. *Health Affairs*. **29**(4): 647-654.
- McCullough, J.S., Parente, S. and Town, R., 2013. *Health information technology and patient outcomes: The role of organizational and informational complementarities*. No. w18684. National Bureau of Economic Research.
- McDermott, C.M. and Stock, G.N., 2011. Focus as emphasis: conceptual and performance implications for hospitals. *Journal of Operations Management*. **29**(6): 616-626.
- McKinsey 2008. Service Line Strategies for US Hospitals. http://healthcare.mckinsey.com/sites/default/files/737801_Serviceline_strategies_for_US_hospitals_.pdf
- Mckinsey, 2014. Optimizing the nursing skill mix: A win for nurses, patients, and hospitals <http://healthcare.mckinsey.com/optimizing-nursing-skill-mix-win-nurses-patients-and-hospitals>
- Mechanic, D., 2008. Rethinking medical professionalism: the role of information technology and practice innovations. *Milbank Quarterly*. **86**(2): 327-358.
- Miller D.J., Fern M.J., Cardinal L.B., 2007. The use of knowledge for technological innovation within diversified firms. *Academy of Management Journal*. **50**(2): 307-325.
- Miller, A.R. and Tucker, C., 2011. Can healthcare IT save babies?. *Available at SSRN 1080262*.
- Miller, S. 2008. Kudzu.com survey reveals online reviews significantly impact consumer spending. Available at <http://www.reuters.com/article/idUS159105+09-Dec-2008+PRN20081209>
- Monstad, K., Engesæter, L.B. and Espehaug, B., 2006. Patients' preferences for choice of hospital. *Health Economics Bergen Working Paper*. **5**(06).
- Montgomery, H. and Svenson, O., 1989. A think-aloud study of dominance structuring in decision processes. *Process and structure in human decision making*, 135-150.
- Mukherjee, A.S., Lapré, M.A. and Van Wassenhove, L.N., 1998. Knowledge driven quality improvement. *Management Science*. **44**(11-part-2): S35-S49.

- Needleman, J., Buerhaus, P., Mattke, S., Stewart, M., Zelevinsky, K., 2002. Nurse Staffing Levels and the Quality of Care in Hospitals. *New England Journal of Medicine*. **346**(22): 1715-1722
- Needleman, J., Buerhaus, P.I., Stewart, M., Zelevinsky, K. and Mattke, S., 2006. Nurse staffing in hospitals: is there a business case for quality?. *Health Affairs*. **25**(1): 204-211.
- New York Times, 2014. F.T.C. Wary of Mergers by Hospitals. *The New York Times*. http://www.nytimes.com/2014/09/18/business/ftc-wary-of-mergers-by-hospitals.html?_r=0
- Newby, L.K., LaPointe, N.M.A., Chen, A.Y., Kramer, J.M., Hammill, B.G., DeLong, E.R., Muhlbaier, L.H., Califf, R.M., 2006. Long-term adherence to evidence-based secondary prevention therapies in coronary artery disease. *Circulation*. **113**(2): 203-212.
- Osborne, N.H., Nicholas, L.H., Ghaferi, A.A., Upchurch, G.R. and Dimick, J.B., 2010. Do popular media and internet-based hospital quality ratings identify hospitals with better cardiovascular surgery outcomes?. *Journal of the American College of Surgeons*. **210**(1): 87-92
- Palmer, R.H., 1997. Process-based measures of quality: the need for detailed clinical data in large health care databases. *Annals of Internal Medicine*. **127**(8_Part_2): 733-738.
- Parasuraman, A., Zeithaml, V.A. and Berry, L.L., 1985. A conceptual model of service quality and its implications for future research. *The Journal of Marketing*. 49(4): 41-50.
- Payne, J.W. 1976. Task Complexity and Contingent Processing in Decision Making: An Information Search and Protocol Analysis. *Organizational Behavior and Human Performance*. **16**(2): 366–87.
- Pope, D.G., 2009. Reacting to rankings: evidence from “America's Best Hospitals”. *Journal of health economics*. **28**(6): 1154-1165.
- Pronovost, P.J., Jenckes, M.W., Dorman, T., Garrett, E., Breslow, M.J., Rosenfeld, B.A., Lipsett, P.A. and Bass, E., 1999. Organizational characteristics of intensive care units related to outcomes of abdominal aortic surgery. *Jama*. **281**(14): 1310-1317.
- Propper, C., Burgess, S. and Gossage, D., 2008. Competition and quality: Evidence from the NHS internal market 1991–9*. *The Economic Journal*. **118**(525): 138-170.
- PwC Consulting, 2012. <http://www.pwc.com/us/en/press-releases/2012/moment-of-truth-for-healthcare.html>
- Queenan, C.C., Angst, C.M. and Devaraj, S., 2011. Doctors’ orders—If they’re electronic, do they improve patient satisfaction? A complements/substitutes perspective. *Journal of Operations Management*. **29**(7): 639-649.

- Queenan, C.C., Kull, T.J. and Devaraj, S., 2016. Complements or Substitutes? Culture–Technology Interactions in Healthcare. *Decision Sciences*.
- Rathore, S.S., Epstein, A.J., Volpp, K.G. and Krumholz, H.M., 2005. Regionalization of care for acute coronary syndromes: more evidence is needed. *JAMA*, **293**(11): 1383-1387.
- Richardson, W.C., Berwick, D.M., Bisgard, J., Bristow, L.R., Buck, C.R. and Cassel, C.K., 2001. Crossing the quality chasm: a new health system for the 21st century
- Rivers, P.A., Tsai, K.L. and Munchus, G., 2004. The financial impacts of the nursing shortage. *Journal of health care finance*. **31**(3): 52-64.
- Robinson, J.C., 1988. Hospital quality competition and the economics of imperfect information. *The Milbank Quarterly*. **66**(3): 465-481.
- Robinson, J.C., 1988. Market structure, employment, and skill mix in the hospital industry. *Southern Economic Journal*. **55**(2): 315-325.
- Roche, J.J.W., Wenn, R.T., Sahota, O. and Moran, C.G., 2005. Effect of comorbidities and postoperative complications on mortality after hip fracture in elderly people: prospective observational cohort study. *Bmj*. **331**(7529): 1374.
- Rodak, 2013. <http://www.beckershospitalreview.com/hospital-key-specialties/is-center-of-excellence-investment-the-silver-bullet-healthcare-has-been-looking-for.html>
- Roques, F., Nashef, S.A.M., Michel, P., Gauducheau, E., De Vincentiis, C., Baudet, E., Cortina, J., David, M., Faichney, A., Gavrielle, F. and Gams, E., 1999. Risk factors and outcome in European cardiac surgery: analysis of the EuroSCORE multinational database of 19030 patients. *European Journal of Cardio-thoracic Surgery*. **15**(6): 816-823.
- Rubin, H.R., Pronovost, P. and Diette, G.B., 2001. The advantages and disadvantages of process based measures of health care quality. *International Journal for Quality in Health Care*. **13**(6): 469-474.
- Rudolph, J.W. and Repenning, N.P., 2002. Disaster dynamics: Understanding the role of quantity in organizational collapse. *Administrative Science Quarterly*. **47**(1): 1-30.
- Rust, R.T. and Zahorik, A.J., 1993. Customer satisfaction, customer retention, and market share. *Journal of retailing*. **69**(2): 193-215.
- Salop, S.C., 1979. Strategic entry deterrence. *The American Economic Review*. **69**(2): 335-338.
- Schultz, M.A., van Servellen, G., Chang, B.L., McNeese-Smith, D. and Waxenberg, E., 1997. The relationship of hospital structural and financial characteristics to mortality and length of stay in acute myocardial infarction patients. *Outcomes Management for Nursing Practice*. **2**(3): 130-136.

- Senot, C., Chandrasekaran, A. and Ward, P.T., 2015. Role of Bottom-Up Decision Processes in Improving the Quality of Health Care Delivery: A Contingency Perspective. *Production and Operations Management*. **25**(3): 458-476
- Senot, C., Chandrasekaran, A., Ward, P.T., Tucker, A.L. and Moffatt-Bruce, S.D., 2015. The Impact of Combining Conformance and Experiential Quality on Hospitals' Readmissions and Cost Performance. *Management Science*. **62**(3): 829:848.
- Sharma, L., Chandrasekaran, A., Boyer, K., and McDermott, C., 2016. The Impact of Health Information Technology Bundles on Performance: An Econometric Study. *Journal of Operations Management*. **41**(1): 24-41.
- Shen, Y.C., 2003. The effect of financial pressure on the quality of care in hospitals. *Journal of health economics*. **22**(2): 243-269.
- Shwartz, M., A.B. Cohen, J.D. Restuccia, Z.J. Ren, A. Labonte, C. Theokary, R. Kang, and J. Horwitt. 2011. How Well Can We Identify the High-Performing Hospital? *Medical Care Research and Review*. **68**(3): 290-310.
- Silow-Carrol S, Alteras T, Meyer JA. *Hospital Quality Improvement: Strategies and Lessons From U.S. Hospitals*. New York, NY: The Commonwealth Fund; 2007
- Sirmon, D.G., Gove, S. and Hitt, M.A., 2008. Resource management in dyadic competitive rivalry: The effects of resource bundling and deployment. *Academy of Management Journal*. **51**(5): 919-935.
- Skinner, Jonathan S. 2011. "Causes and Consequences of Regional Variations in Health Care." In *Handbook of Health Economics*. Vol. 2, ed. Mark V. Pauly, Thomas G. McGuire and Pedro P. Barros, 45–93. Elsevier
- Skinner, W., 1974. The focused factory. *Harvard Business Review*. **52**(3): 113–121.
- Sloan, F.A., Picone, G.A., Taylor, D.H. and Chou, S.Y., 2001. Hospital ownership and cost and quality of care: is there a dime's worth of difference?. *Journal of health economics*. **20**(1): 1-21.
- Sofaer, S., Crofton, C., Goldstein, E., Hoy, E. and Crabb, J., 2005. What do consumers want to know about the quality of care in hospitals?. *Health services research*. **40**(6p2): 2018-2036.
- Spear, S.J., 2005. Fixing health care from the inside, today. *Harvard business review*. **83**(9):78.
- Staw, B.M., Sandelands, L.E. and Dutton, J.E., 1981. Threat rigidity effects in organizational behavior: A multilevel analysis. *Administrative science quarterly*. **26**(4): 501-524.
- Tay, A., 2003. Assessing competition in hospital care markets: the importance of accounting for quality differentiation. *RAND Journal of Economics*. **34**(4): 786-814.

- Teisberg, E.O., Porter, M.E. and Brown, G.B., 1993. Making competition in health care work. *Harvard Business Review*. **72**(4): 131-141.
- The Economist, 2014. <http://www.economist.com/blogs/democracyinamerica/2014/07/health-care-jobs>
- The New York Times, 1996. <http://www.nytimes.com/1996/08/19/nyregion/once-in-big-demand-nurses-are-targets-for-hospital-cuts.html?pagewanted=all>
- The New Yorker. 2011. Ask the Author Live: Atul Gawande on Medical Costs. *The New Yorker*. January 14. <http://www.newyorker.com/books/ask-the-author/ask-the-author-live-atul-gawande-on-medical-costs>.
- Thungjaroenkul, P., Cummings, G.G., Embleton, A., 2007. The impact of nurse staffing on hospital costs and patient length of stay: a systematic review. *Nursing Economics*. **25**(5): 255-265.
- Tirole, J., 1988. The theory of industrial organization. MIT press.
- Tucker, A.L. and Edmondson, A.C., 2003. Why hospitals don't learn from failures: Organizational and psychological dynamics that inhibit system change. *California Management Review*. **45**(2): 55-72.
- Tucker, A.L., 2007. An empirical study of system improvement by frontline employees in hospital units. *Manufacturing & Service Operations Management*. **9**(4): 492-505.
- Umesh, U.N. and Cote, J.A., 1988. Influence of situational variables on brand-choice models. *Journal of Business Research*. **16**(2): 91-99.
- Vahey, D.C., Aiken, L.H., Sloane, D.M., Clarke, S.P. and Vargas, D., 2004. Nurse burnout and patient satisfaction. *Medical care*. **42**(2 Suppl): II57.
- Van de Ven, A.H. and Ferry, D.L., 1980. *Measuring and assessing organizations*. John Wiley & Sons.
- Varkevisser, M., van der Geest, S.A. and Schut, F.T., 2012. Do patients choose hospitals with high quality ratings? Empirical evidence from the market for angioplasty in the Netherlands. *Journal of Health Economics*. **31**(2): 371-378.
- Victoor, A., Delnoij, D.M., Friele, R.D. and Rademakers, J.J., 2012. Determinants of patient choice of healthcare providers: a scoping review. *BMC health services research*. **12**(1):1
- Wang, G., Li, J., Hopp, W.J., Fazzalari, F.L. and Bolling, S., 2015. Hospital Quality and Patient Choice: An Empirical Analysis of Mitral Valve Surgery. *Available at SSRN*.
- Washington Post, 2013. Design flaws in the Affordable Care Act. https://www.washingtonpost.com/opinions/design-flaws-in-the-affordable-care-act/2013/12/13/905571ce-636e-11e3-aa81-e1dab1360323_story.html

- Wayne, A., 2014. Obamacare Rate Increases Low as Insurer Competition Grows [WWW Document]. Bloomberg.com. URL <http://www.bloomberg.com/news/articles/2014-10-31/obamacare-rate-increases-low-as-insurer-competition-grows>.
- Weiner, B. J., J. A. Alexander, S. M. Shortell, L. C. Baker, M. Becker, and J. J. Geppert. 2006. Quality improvement implementation and hospital performance on quality indicators. *Health Services Research*. **41**(2): 307-34.
- Weissman, J.S., Rothschild, J.M., Bendavid, E., Sprivulis, P., Cook, E.F., Evans, R.S., Kaganova, Y., Bender, M., David-Kasdan, J., Haug, P. and Lloyd, J., 2007. Hospital workload and adverse events. *Medical care*. **45**(5): 448-455.
- Werner, R.M., 2010. Does pay-for-performance steal from the poor and give to the rich?. *Annals of internal medicine*, **153**(5): 340-341.
- Werner, R.M., Bradlow, E.T. and Asch, D.A., 2008. Does hospital performance on process measures directly measure high quality care or is it a marker of unmeasured care?. *Health services research*. **43**(5p1):1464-1484.
- Wood, R. E., 1986. Task Complexity: Definition of the Construct. *Organizational Behavior and Human Decision Processes* **37**(1): 60–82.
- Wooldridge, J.M., 2010. *Econometric analysis of cross section and panel data*. MIT press.
- Xu T., Wu A.W., Makary M.A., 2015 The Potential Hazards of Hospital Consolidation: Implications for Quality, Access, and Price. *JAMA*. **314**(13): 1337-1338.
- Zeithaml, V.A., 1988. Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence. *The Journal of marketing*, **52**(3): 2-22.
- Zhang, D.J., Gurvich, I., Mieghem, V., A, J., Park, E., Young, R.S., Williams, M.V., 2015. Hospital Readmissions Reduction Program: An Economic and Operational Analysis. *Management Science*, *Forthcoming*

APPENDIX A

SUMMARY OF KEY PAPERS ON THE IMPACT OF EHRS AND INFORMATION TECHNOLOGY

Study	Study Period	Main Independent Variable	Quality Dimensions	Findings
Agha 2011	1998 - 2005	EMR Adoption	Medical Expenditure, LOS, Readmission	No change in outcomes even after several years of adoption
Angst et al. (2011)	NA	Technologies for Cardiology	Cost/Patient, LOS	Sequence of adoption impacts costs and LOS
Angst et al. (2012)	NA	Cardiology and Administrative Technologies	Process Quality, Patient Satisfaction, Mortality	Administrative technology impacts patient ratings while cardiology technologies impact process quality
Appari et al (2012)	2009	EMR and CPOE Adoption	Process Quality	Mixed, adopters benefit from EMR but not CPOE adoption.
Appari et al (2013)	2006 - 2010	EMR Capability	Process Quality	Positive
Aron et al. (2011)	NA	Automation of sensing, control and monitoring systems	Error Rates	Automation of error prevention functions reduces medical errors
Devara j et al (2013)	NA	IT Investment	Mean and Standard Deviation of LOS, Patient Revenues	Patient Flow is an important mediating variable in improving financial performance
Drano ve et al. (2012)	1996 - 2009	EHR Adoption	Hospital Operating Costs	Mixed, No reduction in costs in the first three years of adoption. Cost reduces in later years only after certain conditions are met

Freedman et al (2014)	2003 - 2010	Adoption of CPOE and Physician Documentation	Patient Safety Indicators	Mixed, no impact on the mean patient. Benefits accrue for younger, less sick and low mortality risk patients
Furukawa (2011)	2006	EMR Capability	Emergency Department Throughput	Mixed. Advanced EMRs improve efficiency, no effect found with adoption of basic EMRs
Hydari et al (2014)	2005 - 2012	Adoption of Basic and Advanced EMRS	Patient Safety Indicators	Positive, Advanced EMRs reduce errors
Jones et al (2010)	2004 - 2007	EHR Capability	Process Quality	Mixed, Basic and Advanced EHRs have differential impact on various process quality measures
McCullough (2010)	2004 - 2007	EHR and CPOE Adoption	EHR and CPOE Adoption	Mixed, Adoption improved only few process quality measures
McCullough (2013)	2002 - 2007	Use of EHRs and CPOE	Mortality, LOS, Readmission	Mixed, No effect on LOS and readmissions but reduces mortality for the sickest pneumonia patients
Miller and Tucker (2011)	1995 - 2006	EHR Adoption	Neonatal Mortality	Positive
Queenan et al. (2011)	2008	CPOE Use, Technology Infrastructure	Patient Satisfaction	CPOE Use increases patient satisfaction
Sharma et al (2016)	2007-2012	EHR Adoption Sequence and Speed	Operating cost, Patient Satisfaction	Sequence and speed have a differential impact on satisfaction and costs

Note: EMR = Electronic medical records, CPOE = Computerized Physician Order Entry, LOS = Length of Stay

APPENDIX B

PROCESS OF CARE COMPONENTS

Process of Care Components (Number of Hospitals = 308)		Mean	Standard Deviation
Heart Attack (AMI)			
AMI2	Patients given aspirin at discharge	95.87	8.22
AMI7	Patients given fibrinolytic medication within 30 minutes of arrival	69.27	26.78
AMI8	Patients given PCI within 90 minutes of arrival	83.08	19.32
Heart Failure (HF)			
HF1	Patients given discharge instructions	84.92	19.12
HF2	Patients given an evaluation of LVS function	95.23	10.99
HF3	Patients given ACE inhibitor or ARB for LVSD	93.13	9.26
Pneumonia (PN)			
PN3	Patients whose initial ER blood culture was performed prior to administration of first antibiotic	93.71	6.39
PN6	Patients given the most appropriate initial antibiotic(s)	91.54	8.27
Surgical Care Improvement Project (SCIP)			
SCIP1	Surgery patients who received preventative antibiotic(s) 1 hour prior to incision	91.84	12.16
SCIP2	Surgery patients who received appropriate preventative antibiotic(s) for surgery antibiotic(s) 1 hour prior to incision	95.02	7.00
SCIP3	Surgery patients with previous antibiotic(s) stopped within 24 hours after surgery	88.06	14.71