HOSPITAL SURGICAL VOLUME, SURGICAL CASE MIX, AND PROFITABILITY

A Dissertation

by

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Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

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May 2017

Major Subject: Health Services Research

ABSTRACT

Surgery provision is integral to health care in the United States for patients, providers, and facilities. As the number of insured persons in the United States rises with the implementation of health care reform legislation, so does the pressure on general acute care hospitals to provide safe, high-quality care while meeting the rising demand. The purpose of this study is to understand what drives how long a surgical case takes at a given facility, which affects surgical volume; how surgical volumes affect profitability; and how this volume-profitability relationship is affected by other care providers, such as ambulatory surgical centers. The first aim of this study employs multilevel regression techniques to understand the relationship between case duration and facility, anesthesia practice, and patient characteristics. The second aim develops facility-level clusters of surgical offerings and investigates the association of cluster membership, surgical volume, and profitability. The third aim examines the effect of ambulatory surgical center presence on volumes and revenues of nearby hospitals.

Findings for these three aims are as follows. While case duration is difficult to predict accurately, facility and anesthesia-practice level variation affects case duration and is a potential source for improvement. In addition, four distinct patterns of surgical offerings are present in Texas data; however, these results do not indicate that one surgical offering grouping is more profitable than any other. Surgical volume, however, does affect the financial health of general acute care facilities. My study does not find

evidence that ambulatory surgery center penetration affects the surgical volumes or revenues of nearby hospitals. In summary, case duration differs across hospitals, which is likely part of why the volume of surgeries differs across hospitals; this is important, because surgical volume affects a hospital's profitability, which may in turn be affected by surgical provision in nearby ambulatory care facilities.

DEDICATION

Barbara Pearson, better known as Nana: Thank you for blazing the trail for women in doctoral programs and showing me that advanced academic pursuits are possible for women, even single women with four children.

Mark: No one else has seen me through the ups and the downs of this process like you have. Thank you for putting up with the late nights, the restless nights, the early mornings, and the working “lunches” that extended into working afternoons and evenings. But most of all, thank you for your relentless encouragement, optimism, and support.

Noah: Your mama loves you more than you can know. This dissertation was my “work child,” but it will never compare to the joy that my true, first child has brought to my life. Thank you for reminding me that life is more than work.

To the long list of members of the babysitter’s club: You know that I could not have done it without you. Thank you for your willingness to stay late and take care of Noah on a whim and your emotional support though all the highs and lows.

ACKNOWLEDGEMENTS

I would like to thank my committee chair, Dr. Radcliff, and my committee members, Dr. Kash, Dr. Côté, Dr. McGowan, and Dr. Miller, for their guidance and support throughout the course of this research.

Thanks also go to my friends and colleagues and the department faculty and staff for both challenging and supporting me and making my time at Texas A&M University School of Public Health a wonderful experience.

Finally, thanks to my entire family for their encouragement, support, and love.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supervised by a dissertation committee consisting of Professor Tiffany Radcliff (advisor) and Professors Bita Kash and Murray Côté of the Department of Health Policy and Management, Professor Annie McGowan of the Department of Accounting, and Dr. Thomas Miller of the American Society of Anesthesiologists.

Access to the data analyzed for Chapter II was facilitated by Dr. Thomas Miller. Access to the data analyzed for Chapters III and IV was granted by the Department of Health Policy and Management. All other work conducted for the dissertation was completed by the student independently.

Funding Sources

There are no outside funding contributions to acknowledge related to the research and compilation of this document.

NOMENCLATURE

AHA	American Hospital Association
AHRF	Area Health Resource File
AIC	Akaike Information Criterion
ANOVA	Analysis of variance
ASA	American Society of Anesthesiologists
ASC	Ambulatory surgery center
CABG	Coronary artery bypass grafting
CBSA	Core Based Statistical Area
CCS	Clinical Classifications Software
CHOL	Cholecystectomy
CMI	Case mix index
CMS	Centers for Medicare and Medicaid Services
CPT	Current Procedural Technology
DRG	Diagnosis-Related Group
HCRIS	Healthcare Cost Reporting and Information System
HCUP	Healthcare Cost and Utilization Project
HHI	Hirschman-Herfindahl Index
HRR	Health Referral Region

HRSA	Health Resources and Services Administration
HSA	Health Service Area
ICD-9	International Classification of Diseases 9th Revision
IRB	Institutional Review Board
MSA	Metropolitan Statistical Area
NACOR	National Anesthesia Clinical Outcomes Registry
OB	Obstetrical
OLS	Ordinary least squares
OR	Operating room
PCTA	Percutaneous coronary angioplasty
POS	Provider of Service
PPACA	Patient Protection and Affordable Care Act
THCIC	Texas Health Care Information Collection
TKA	Total knee arthroplasty
VIF	Variance Inflation Factors
WSS	Weighted sum of squares

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CHAPTER I

INTRODUCTION

Surgery is an integral part of the health care delivery system in the United States, considered a remedy for everything from obesity to back pain to cancer and heart disease. 21.8% of hospital stays in the US in 2012 were for non-obstetrical surgical procedures (1). This number has climbed in recent decades. For example, the percentage of hospitalizations for adults between 65 and 84 years of age undergoing total knee arthroplasty grew 59% between 1997 and 2011 (2), and even in times of economic downturn, the demand for this procedure remains stable (3). As health insurance coverage expands under the Patient Protection and Affordable Care Act (PPACA), the number of patients able to afford surgery is growing and may further expand the market (4).

Literature Review

Outpatient Surgery

In particular, the outpatient surgical sector is growing at a rapid rate, due to the increasing number of surgeries performed and the development of technologies that allow more procedures to be carried out on an outpatient basis. This is preferable for payers and policymakers, as outpatient procedures tend to be less expensive than comparable inpatient procedures without detriment to quality of care or patient safety (5). Outpatient surgeries are performed in both hospital outpatient departments and in ambulatory surgery centers (ASCs), a source of significant debate (6). ASCs, and particularly those owned by physicians, tend to have a healthier, more profitable patient mix than comparable hospital outpatient departments; critics claim that they harm social welfare by reducing the financial viability of inpatient hospitals, which in turn may reduce the quality of and access to medical care in the surrounding communities (7, 8). However, other research shows that the effect of ASC presence on hospital outpatient volumes is relatively small (9-11). The financial impact of ASC penetration on hospital finance is also tenuous. In fact, a recent study examining revenues found that while ASC revenues grew at a similar rate to medical care as a whole, hospital outpatient departments grew at a much higher rate (12).

Surgical Offerings in the US

The combination of the increase in outpatient surgery, the development of new surgical techniques for both inpatient and outpatient procedures, and the aging population has also changed the composition of surgical offerings in the US in recent years (13). Musculoskeletal procedures, particularly total knee replacement and spinal fusion, have increased by 70% and 93%, respectively, between 2001 and 2011. Most cardiac procedures, in particularly coronary artery bypass grafting, have decreased dramatically over the same time period, with the exception of percutaneous coronary angioplasty (PCTA) (13).

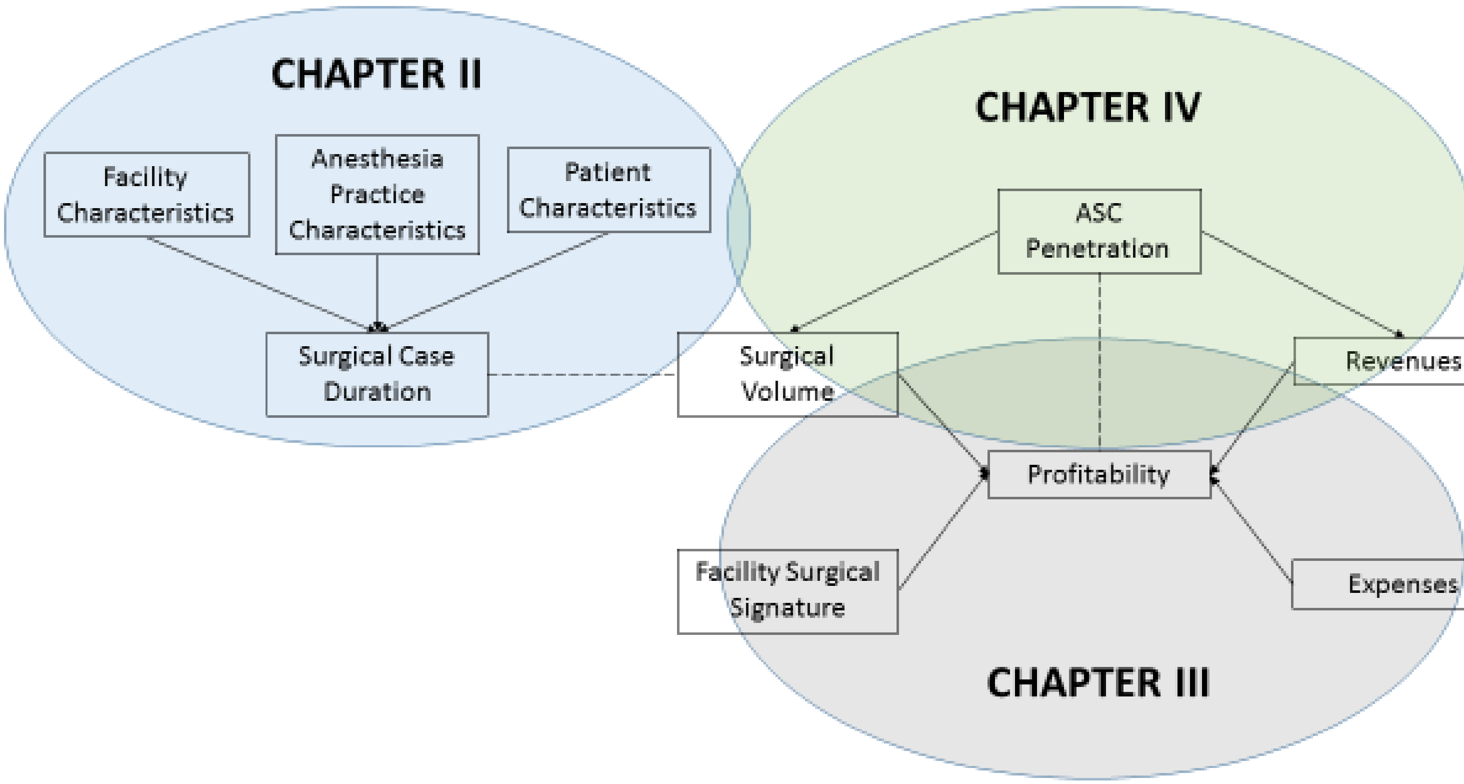
Interestingly, total knee replacement, spinal fusion, and PCTA, three procedures with high growth rates in recent years, are also procedures associated with the highest costs. Surgery is expensive. In general, non-obstetrical surgical hospitalizations accounted for approximately 25% of hospitals stays, contrasted with 50% of hospital costs between 2003 and 2012 (14), and studies have shown that operating room (OR) procedures tend to cost more than non-OR procedures (15), despite the fact that patients undergoing OR procedures, on average, are less sick than non-OR patients and are less likely to die during the hospital stay. These higher costs could be a function of a longer mean length of stay or increased intensity of care while in the hospital (16).

Surgical costs are growing more quickly than other types of hospital costs; from 2003 – 2013, average annual surgical costs grew by 2.4%, while surgical discharges decreased by 0.5% over the same period. By contrast, medical costs grew by 1.7% over the same time period, with a 0.6% increase in volumes (17). Over this period, increases in both medical and surgical costs were primarily driven by increased intensity of care during a given hospital stay (i.e. an increased number or complexity of procedures applied during hospitalization) rather than an increase in procedure utilization (18).

Surgical hospitalizations cost more than non-surgical stays, but they may also produce more revenues. In 2011, 41.3% of hospitalizations involving surgery were privately insured, while only 27.8% of non-OR stays were privately uninsured; 42.1% of these stays were funded by Medicare, compared to 34.0% for surgical stays (16). Hospitals with a higher proportion of Medicare-insured patients tend to be less profitable than hospitals with more private payer patients (19). As such, hospitals with higher surgical volume may also be more profitable. In rural hospitals, studies have shown that higher surgical volume is associated with improved hospital financial health (20, 21). There is also non-academic support for the surgical volume-profitability relationship; a consulting firm specializing in best practice implementation claims that surgeries make up “only 11% of volumes but generate 40% of hospital profits” (22).

Previous studies have established that ownership, urban or rural location, market power, teaching status, and bed size affect profitability (19). However, the interactions between these variables as they pertain to profitability are complex (23). Hospital costs are difficult to measure accurately without detailed cost accounting data, further complicating profitability measurement. Many hospitals do not have adequate cost accounting systems to capture this data, and even if they do, the data is proprietary and unavailable to external parties (24). Hospitals submit aggregate-level cost data to the Centers for Medicare and Medicaid Services (CMS) and may voluntarily respond to surveys including financial questions, such as the American Hospital Association (AHA) Annual Survey, or share audited financial information, but these sources lack patient-level granularity and, in some cases, reliability. These limitations to most sources of cost data make hospital costs and profitability difficult to measure and predict (23, 25).

Figure 1. Overall Conceptual Model



Solid lines denote relationships explicitly examined in dissertation. Dotted lines denote relationships implied but not explicitly examined.

Conceptual Model

This dissertation examines the relationship between surgical efficiency, volumes, case mix, and profitability. Figure 1 depicts the conceptual model guiding this research.

Antecedents and ramifications of surgical volume are the unifying factor in the three analyses presented here. Surgical volume is, to some extent, dependent on the time a given patient is being prepared for surgery, in surgery, and recovering from surgery; the sum of duration of each of these components of a surgical episode is sometimes referred to as case duration. Achieving ideal surgical volume at a facility requires a better understanding of variation in surgical case duration. To this end, Chapter II, titled "Understanding Case Duration in Three Surgical Procedures: A Multilevel Approach," examines variation in case duration at several levels: the patient level, provider level, anesthesia practice level, and facility level. A more nuanced understanding of sources of variation in case duration could enable policymakers and practitioners to improve efficiency via improved operating room scheduling, and may also improve patient outcomes following surgery, as long case durations may be associated with longer hospital stays, higher complication rates, and increased incidence of surgical site infections (26-28). For example, the literature shows that operative time differs across surgeons and surgical teams, and that differences in surgical time are related to complication rates (29, 30).

Increased procedural volume at a given facility is associated with improved patient outcomes in many surgical lines, but particularly for cardiac surgery, possibly due to reductions in failure-to-rescue rates in high volume facilities (31, 32). Does surgical volume also have implications for hospital financial health? A limited literature in rural hospitals has shown that increased surgical volume is associated with improved hospital financial position (20, 21). Chapter III, titled "Surgical Case Mix, Surgical Volume, and the Bottom Line: Evidence from Texas Inpatient Data," examines the link between surgical volume and profitability in a broader sample of hospitals.

My study also identifies differences in hospital surgical case mix and investigates the effect of differences in surgical case mix on profitability. Some surgical procedures are more profitable than others (10). If individual procedures differ in profitability, groupings of surgical procedures may also differ in profitability. Furthermore, there is academic evidence and practitioner guidance indicating that hospitals alter surgical offerings in response to increased completion (22, 33, 34), reinforcing the implication that surgical case mix may affect profitability and financial health, or at least practitioners may believe it does.

If surgical volume affects hospital financial position, a threat to surgical volume may also be a threat to hospital financial position. ASC penetration and ASC market entry are associated with decreases in hospital outpatient surgery volumes and, to a lesser degree, decreases in measures of hospital financial health (35). However, many of these studies were conducted before the implementation of ASC payment reform in 2008, and few explicitly examine hospital finance implications. Chapter IV, titled “Revisiting the Relationship Between Ambulatory Surgical Centers, Surgical Volume, and Revenues,” replicates and extends a previously published paper by Plotzke and Courtemanche (2010) examining the relationship between ASC penetration and surgical volumes in nearby hospitals. The replication examines data from the time period following payment reform and also extends the analysis to examine revenues.

Methods

All analyses in this dissertation are retrospective observational studies using data from several state and nationwide data sets that are, for the most part, publicly available.

Chapter II: Understanding Case Duration

Chapter II is an exploratory piece aimed toward understanding sources of variation in surgical case duration. The primary research questions examined in this piece are:

> ***RQ1***: How much variation in case duration resides at the hospital, anesthesia practice, anesthesia provider, and case level?
>
> ***RQ2***: How much of this variation can be explained by facility characteristics and other variables established in the case duration literature after accounting for the nested structure of the data?

Surgical case duration may not be independent across cases; cases are nested within providers (surgeons, anesthesiologists, nursing and support staff), within the surgical and anesthesia practices the providers belong to, and within the facilities in which the procedure is performed. The hierarchical structure of the data may mean that individual cases are not independent, violating an important assumption of ordinary least squares (OLS) regression. Chapter II uses multilevel regression to address this issue. Multilevel regression allows the researcher to explicitly incorporate nested data structures into the model by allowing error terms and, in some cases, regression coefficients, to differ within each level specified.

Case duration and other data are taken from a unique data set, the National Anesthesia Clinical Outcomes Registry (NACOR), to examine the relationship between case duration and certain facility, anesthesia practice, and patient characteristics in three surgical procedures: cholecystectomy, TKA, and CABG. A key limitation of this data set is that surgeon and surgical practice identifiers are not available; as such, only anesthesia provider and practices are incorporated into nested model structures. Individual-level variables employed in the regressions include age, sex, and American Society of Anesthesiologists (ASA) Physical Status, as well as procedure characteristics including outpatient status and type of anesthesia used. Provider-level, practice-level, and facility-level volume variables are also included. Facility characteristics in the model include facility type and facility region.

The first research question will be answered by examining intra-class correlations in case duration at each of the four levels studied (individual case, anesthesia provider, anesthesia practice, and facility) and by examining the unexplained variance at each of these levels in multilevel regressions. The second research question will be answered using the magnitude and statistical significance of multilevel regression coefficients.

Chapter III: Surgical Case Mix, Surgical Volume, and the Bottom Line

The purpose of Chapter III is to better understand the relationship between surgical volume, surgical case mix, and profitability at the hospital level. Specifically, this chapter examines the following questions and hypotheses:

> ***RQ1***: Are there distinct groupings of surgical lines ("surgical signatures") in general acute care hospitals?
>
> ***H1***: Profitability differs across "surgical signatures."
>
> ***H2***: Increased surgical volume is associated with increased profitability.

To determine whether distinct groupings of surgical lines exist in general acute care hospitals, I use k-means cluster analysis on discharges in the Texas Health Care Information Collection (THCIC) data set for 2009 – 2012 to identify native groupings in the data. The resulting clusters represent "surgical signatures" and answer the primary research question in this study. Surgical signature and surgical volume are the key independent variables in a series of three ordinary least squares regressions, each with a different dependent variable: revenues per inpatient day, expenses per inpatient day, and operating margin per inpatient day. Financial data are taken from CMS Healthcare Cost Reporting and Information System (HCRIS). Facility and area-level adjusting variables, taken from the AHA Annual Survey and the Area Health Resource File (AHRF) from Health Resources and Services Administration (HRSA), are also included in final regression models. These regressions address both hypotheses by testing the statistical significance of surgical cluster membership and surgical volume.

Chapter IV: Ambulatory Surgery Centers, Hospital Volumes, and Hospital Revenues

Chapter IV is a replication and extension of a previously published paper (Plotzke and Courtemanche, 2010), which examined the effect of ASC penetration, or the number of ASCs within a given radius of a hospital, on inpatient and outpatient surgical volumes in that hospital. The original study was conducted on data collected before 2008, when payment reform was enacted that limited payment to ASCs to 65% of reimbursement to hospital outpatient departments for the same procedure. It is possible that the observed relationships between ASC penetration and volume changed as a result of this change in policy, so this replication uses the same methods and data sets – CMS Provider of Service (POS) files and the AHA annual survey - but in more recent years (2012 – 2014). My study examines the hypothesis in the original study:

> ***H1:*** Higher ASC penetration is associated with decreased hospital-based outpatient surgical volume, with no effect on inpatient surgical volume.

I also extend the original paper by regressing the effect of ASC penetration on hospital inpatient and outpatient revenues as reported in HCRIS. A comprehensive series of sensitivity checks are performed for all regressions, including differing measures of market radius and the addition of various fixed effects and adjusting variables.

> ***H2:*** Higher ASC penetration is associated with decreased outpatient revenue, with no effect on inpatient revenue.

CHAPTER II

UNDERSTANDING CASE DURATION IN THREE SURGICAL PROCEDURES: A MULTILEVEL APPROACH

Introduction

The relationship between the length of time a patient is in surgery and postoperative outcomes is well established in the literature; longer surgeries are associated with longer hospital stays, higher complication rates, and increased incidence of surgical site infections (26-28). Understanding this relationship can be problematic, in part because most datasets contain information on case duration but may not contain a reliable measure of time in surgery. To address this issue, researchers have developed formulae that estimate surgical time from case duration (36-38). These formulae generally assume case duration is a function of time in surgery and that pre- and postoperative anesthesia prep times are constant, and other work studying operative efficiency find that reducing non-operative case duration does not yield improvements in efficiency (39). However, more recent studies have challenged this notion, showing that reduced non-operative anesthesia time in the OR can reduce cancellations and improve OR workflow (40). Clinically, recent research has shown that longer anesthesia time, not just operative time, can be associated with poorer outcomes and reductions in patient safety (41-43).

A better understanding of sources of variation in case duration may point to targets for meaningful reductions in case duration, which could improve patient outcomes. In cardiac surgery, extended operative time is associated with longer times on bypass and ventilation, which may affect patient mortality and quality of life after surgery (43). In laparoscopic general surgery, longer operative time is associated with increased 30-day surgical complication rates (42).

This analysis examines several possible sources of variation in case duration for three common surgical procedures: CABG, TKA, and laparoscopic cholecystectomy. From 2003 – 2012, cholecystectomy was the most common procedure for Medicaid and uninsured payers and TKA was the most common procedure for privately insured and Medicare patients (14). Because these procedures are performed frequently, improvements generated by increased understanding of case duration variation could generate a significant impact on patient care and providers. Cholecystectomy and TKA are frequently performed in an outpatient setting; CABG is an inpatient surgery conducted on more acute patients; as such, inclusion of CABG procedures meaningfully expands the scope of the study. Furthermore, the literature shows that extended case duration can be problematic for CABG patients (43).

In each of these procedures, we first examine the extent to which variation in case duration resides at the hospital, anesthesia practice, anesthesia provider, and patient level. Secondly, we examine the extent to which this variation can be explained by explanatory variables associated with case duration in a previous study, including type of anesthesia, whether the procedure is conducted in an inpatient or outpatient setting, patient age, patient gender, and patient ASA Physical Status Classification (44), and also explores less studied potential sources of variation in case duration such as region of the US and procedural volume.

Methods

Data

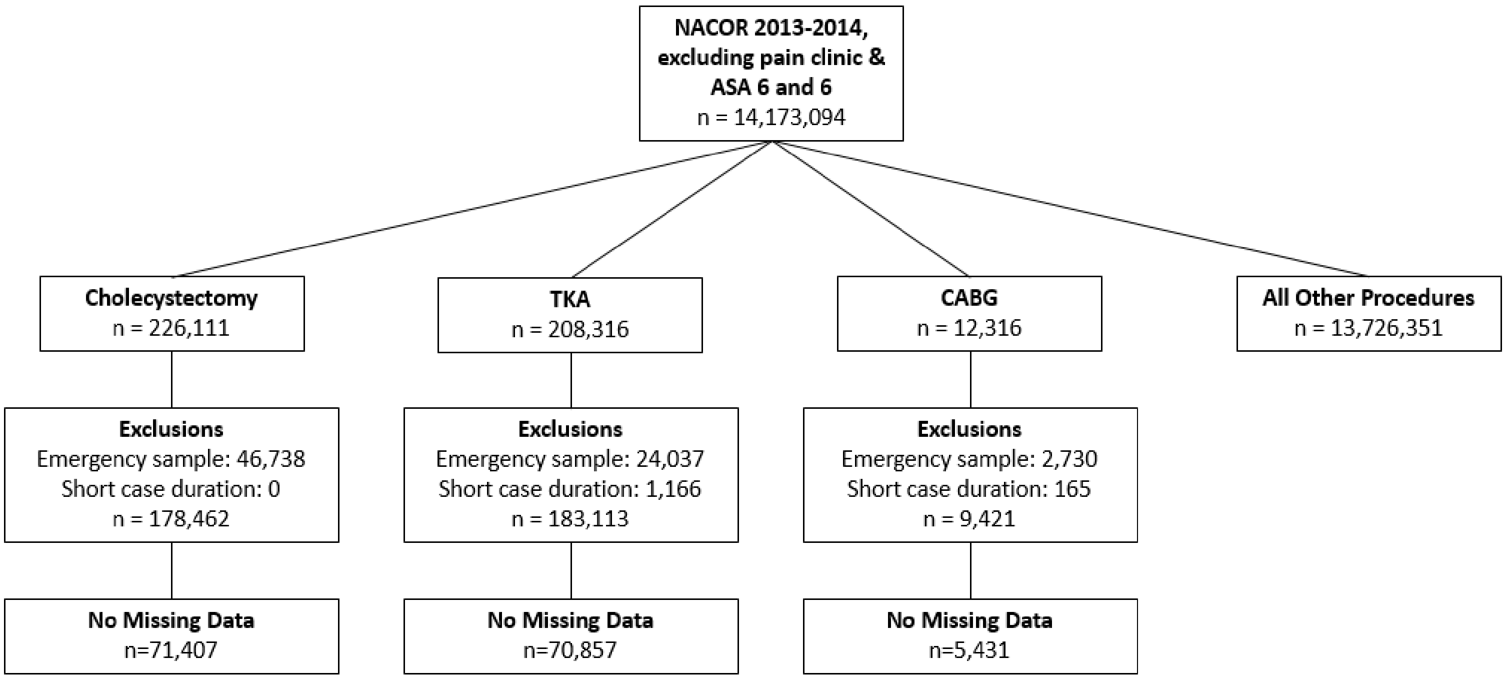
NACOR data from surgical cases in 2013 and 2014 were acquired and analyzed with the approval of the Anesthesia Quality Institute and the Institutional Review Board (IRB) of Texas A&M University. Patient consent was waived by the IRB, as obtaining consent from a large nationwide sample is problematic and risk to patients is minimal.

NACOR is a nationwide data registry that collects individual patient-level and, in some cases, outcomes data from anesthesia practices on a voluntary basis. In exchange for providing data, participating anesthesia practices can benchmark against other practice and monitor performance (45).

Sample

To obtain a surgical data set, pain clinic cases (n = 1,903) were eliminated from the complete NACOR data set for 2013 and 2014, which included 14,192,891 cases. Cases with an ASA Physical Status Classification of 5 or 6 were also excluded at this point (n=17,894). A patient's ASA Physical Status Classification is an anesthesiologist's subjective measure of the patient's overall health (46). Patients classified as a 5 or a 6 are very near death, and case durations related to these patients are likely to be very short or very long for reasons not controllable at any level studied here (46). At this point, the data were parsed to include only laparoscopic cholecystectomy, TKA, and CABG cases using CPT codes. See Appendix A for a list of CPT codes used to select the sample. Emergency cases occurring on weekends, holidays, and after 5 P.M or before 7 A.M. were eliminated from each dataset, similar to previous studies using these data (47). Very short cases in the CABG (<152 minutes) and TKA (<12 minutes) samples were eliminated because they may be non-representative (i.e. terminated due to patient death or escalation of comorbid conditions). Figure 2 summarizes the sample selection process.

Figure 2. NACOR Sample Selection



Data Cleaning

Outpatient status and facility type variables had high percentages of missing data (30% or more in all samples), and missing data for these variables resulted in extensive sample restriction in all three procedures. In the TKA sample, these variables accounted for 89.0% of the 112,256 observations lost to missing data, but only a 14.8% of the observations missing one of these data points are missing both; in the cholecystectomy sample, these variables accounted for 92.9% of the 107,055 observations lost, with 13.9% missing for both variables; in the CABG sample, outpatient status was not a model variable, but facility type accounted for 84.1% of the 3,990 observations lost. If these data are missing completely at random, listwise deletion (deleting all cases with missing data) is unbiased but inefficient (48). This is the assumption made in this analysis. However, these variables are directly reported to NACOR from anesthesia practices. It is possible that some practices systematically do not report facility or inpatient/outpatient information, or that this data is not submitted for certain types of patients. Either condition would indicate that the data is not missing completely at random. When data is not missing completely at random, listwise deletion can result in inefficient and biased estimators; the best solution in this case is some form of data imputation (48). This is a limitation of this study and an arena for future research.

Volume variables were generated on a facility, practice, and provider level by counting the number of observations in the procedure-specific dataset at each of these levels, creating a variable representing total 2-year volume for a specific procedure. Patients with ASA Physical Status Classifications of 1 or 2 were collapsed into one category, as most of the data was reported to NACOR already collapsed in this manner.

Case duration was not normally distributed as evaluated by Q-Q plots and histograms (49), and graphical techniques suggested that a log transformation of case duration fit best. In a log-level model, regression coefficients, after retransformation, can be interpreted as the percentage change in the outcome variable (in this study, case duration) attributable to a one unit change in the associated explanatory variable (49). See Table 1 for a description of variables included in this analysis and Table 2 for descriptive statistics for these variables in each procedure sample.

Table 1. Chapter II Description of Variables

Variable	Description	Values	In CABG Model	In TKA Model	In CHOL Model
Case duration	Case duration in minutes	Continuous	X	X	X
Patient age	Patient's age in years	Continuous	X	X	X
Patient sex	Male or female sex	0: Female 1: Male	X	X	X
Patient ASA score	ASA Physical Status Classification	1: ASA 1 or 2 2: ASA 3 3: ASA 4	X	X	X
Inpatient	Whether procedure is performed in inpatient or outpatient setting	0: Outpatient procedure 1: Inpatient procedure		X	X
Primary anesthesia type	Primary type of anesthesia used during procedure	1: General 2: Epidural/Spinal 3: Regional 4: Monitored Anesthesia Care/Other		X	
Provider volume	Number of cases in data set with this provider listed first	Continuous	X	X	X
Practice volume	Number of cases in data set from this practice	Continuous	X	X	X
Facility volume	Number of cases in data set from this hospital or facility	Continuous	X	X	X
Facility type	Type of hospital	1: University 2: Community 3: Specialty 4: Outpatient	X	X	X
Facility region	Region of the United States	1: Northeast 2: Midwest 3: South 4: West	X	X	X

Table 2. Chapter II Sample Characteristics

	CABG			TKA			Cholecystectomy		
	n	*Mean*	*Frequency*	*n*	*Mean*	*Frequency*	*n*	*Mean*	*Frequency*
Case Duration	5,431	314.0	---	70,857	139.2	---	71,407	95.4	---
Patient Age	5,431	65.6	---	70,857	66.4	---	71,407	49.1	---
Patient Sex									
Female	1,348	---	24.8%	43,130	---	39.1%	51,190	---	71.7%
Male	4,083	---	75.2%	27,727	---	60.9%	20,217	---	28.3%
Patient ASA Score									
ASA 1 or 2	590	---	10.9%	39,810	---	56.2%	51,709	---	72.4%
ASA 3	955	---	17.6%	30,024	---	42.4%	18,247	---	25.6%
ASA 4	3,886	---	71.6%	1,023	---	1.4%	1,451	---	2.1%
Provider Volume	5,431	27.3	---	70,857	115.3	---	71,407	59.2	---
Practice Volume	5,431	248.9	---	70,857	2280.0	---	71,407	1784.4	---
Facility Volume	5,431	163.0	---	70,857	1101.1	---	71,407	700.1	---
Facility Type									
University	557	---	10.3%	3,427	---	4.9%	5,380	---	7.5%
Community	4,488	---	82.6%	60,656	---	85.6%	59,004	---	82.6%
Specialty	386	---	7.1%	3,433	---	4.8%	298	---	0.4%
Outpatient Facility	---	---	---	3,341	---	4.7%	6,725	---	9.4%
Region of the United States									
Northeast	889	---	16.4%	17,197	---	24.3%	12,748	---	17.9%
Midwest	1,238	---	22.8%	21,766	---	30.7%	22,433	---	31.4%
South	2,538	---	46.7%	20,028	---	28.3%	24,686	---	34.6%
West	766	---	14.1%	11,866	---	16.8%	11,540	---	16.2%
Inpatient/Outpatient									
Inpatient	---	---	---	60,612	---	85.5%	22,916	---	32.1%
Outpatient	---	---	---	10,245	---	14.5%	48,491	---	67.9%
Primary Anesthesia Type									
General	---	---	---	38,940	---	55.0%	---	---	---
Epidural/Spinal	---	---	---	15,207	---	21.5%	---	---	---
Regional	---	---	---	16,077	---	22.7%	---	---	---
Monitored Anesthesia Care	---	---	---	633	---	0.9%	---	---	---

Statistical Analysis

SAS 9.3 was used to import the original dataset and pull the non-emergent surgical samples for each procedure (50). Stata/IC 14.1 was used for additional data cleaning, including necessary grouping of categorical variables, transformation of continuous variables, and exclusion of outliers, and was used for all statistical analysis (51).

Statistical Methods

The data were first analyzed using the following ordinary least squares (OLS) model: The general OLS model specification for the three samples were as follows:

$$Log(Case\ Duration) = \gamma_0 + \gamma_p Individual\ Level\ Variables +$$
$$\gamma_q Provider, Practice\ and\ Facility\ Level\ Variables + e_i$$

Where:

i represents individual observations

γ_0 is the regression intercept (a constant)

γ_p are the surgical case-level regression slopes for p -level variables

γ_q are the practice, provider, and facility-level regression slopes for *q* provider, practice, and facility-level variables

e_i are the patient-level residuals

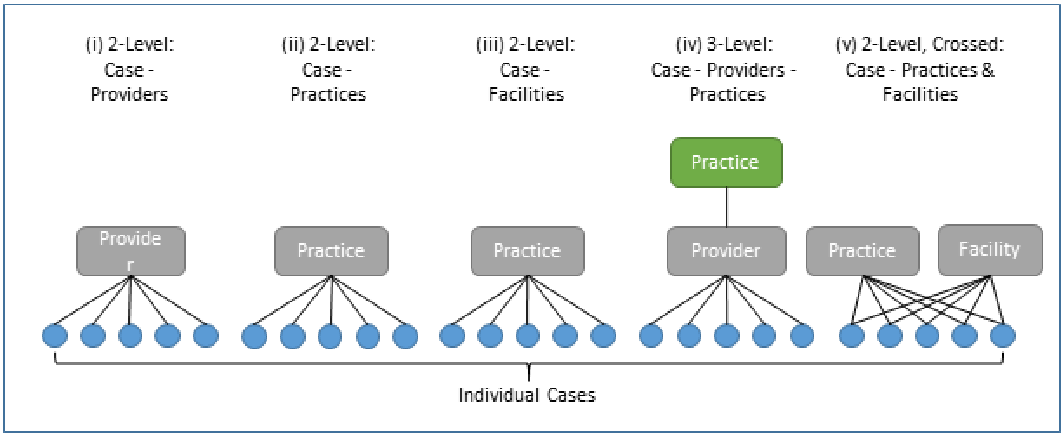
Variance inflation factors were used to assess multicollinearity, and Szroeter's and Breusch-Pagan tests were used to assess the presence of heteroscedasticity. Graphical depictions of residuals were used to assess heteroscedasticity, linearity, and the effect of influential outliers. No corrections to the model were needed, and all explanatory variables described previously were included in the final model (52). However, the ordinary least squares (OLS) models did exhibit heteroskedasticity in all three samples, which may be due in part to the nested structure of the data; cases are nested within providers, practices, and facilities, which violates the necessary OLS assumption of independence. OLS assumes that observations in the data set are independent of one another. If this assumption is violated, as is the case with hierarchical data like NACOR, OLS may generate understated standard errors and overstated statistical significance (53).

Multilevel regression can be a useful tool for hierarchical data. Multilevel regression does not attempt to correct standard errors of a model measured at one level and assuming independence (i.e. 'standard OLS'), but instead explicitly models level structures native to the data (i.e. individual patient level, or practice level, or facility level) when estimating model parameters. Multilevel models are similar to standard OLS models in that they estimate an intercept and regression coefficients for the various explanatory variables in a given model, but residual error terms are calculated not only at the level of the individual observation but also at the level of the group, i.e. the provider, practice, or facility in this sample. These second-level errors are connected to the individual-level explanatory variables in the model, meaning that for different levels of patient-level variables, the error will be explicitly different, or heteroskedastic (53).

Specifying an appropriate multilevel model requires choosing an appropriate multilevel structure. Multilevel models examining length of stay generally model provider or hospital level groupings (54-56), which are included in these models. NACOR has anesthesia practice identifiers, which are also included as a possible level in these analyses on an exploratory basis. It should be noted, however, that NACOR lacks surgeon and surgical practice identifiers, and this is a limitation of this analysis, as substantial within-surgeon and within-surgical practice variation in case duration likely does exist.

For this data, several grouping structures were plausible. The most accurate model would likely be a combination of models (iv) and (v), where cases are nested within providers which are nested within practices and cross-nested within facilities. However, modeling this relationship is computationally impossible with existing software packages in Stata and most multilevel-capable statistical software packages due to the number of error term calculations required (53). Therefore, this model is excluded from the model selection process. The other 5 grouping structures are described in Figure 3.

Figure 3. Level Structures in the NACOR Data



To select the best structure, for each of the three procedures, intercept-only multilevel models for each structure were run. The best level structure as measured by intercept-only model AIC was used for all future analyses for that procedure.

All individual-level variables (age, sex, and ASA Physical Status Classification) were added to the intercept-only model, followed by all higher-level variables (provider volume, practice volume, facility volume, facility type, and region). Model deviance, Akaike Information Criterion (AIC), and residual variances were calculated using the 'Mixed' package and post-estimation commands in StataIC 14.1. Non-nested models were compared using AIC and nested models were compared using Deviance (53). After selecting the best model from the process described above, model fit was assessed by graphically assessing residuals for patterns and outliers.

The general multilevel model specification for the three samples were as follows:

$$Log(Case\ Duration) = \gamma_{00} + \gamma_{p0} Individual\ Level\ Variables_{ij} +$$
$$\gamma_{0q} Provider, Practice\ and\ Facility\ Level\ Variables_{j} + \mu_{0j} + e_{ij}$$

Where:

i represents individual observations

j represents a higher-level unit, such as a practice or facility

γ_{00} is the regression intercept, a constant

γ_{p0} are the individual-level regression slopes for p individual-level variables

γ_{0q} are the practice, provider, and facility-level regression slopes for q provider, practice, and facility-level variables

μ_{0j} are the group-level residuals.

e_{ij} are the individual-level residuals.

Multilevel model specification differed in the three samples based on which level structure was selected for the sample and by which variables were included in the model. Level structure selection is discussed in the results section below. See Table 1 to identify which variables are included in the model for each sample; model variables included in multilevel models are the same as variables included in the OLS models.

Both OLS and multilevel regression models were run using a split sample technique to provide some measure of internal validity and because estimates of statistical significance are sensitive to sample size; as sample size increases, the magnitude of difference needed to generate a p-value of 0.05 or less decreases. As such, in very large samples like those used in this analysis, most variables will be statistically significant at with a p-value of less than 0.05. Using the split sample technique, regressions for each procedure were run on a development sample, selected randomly without replacement from the complete dataset, and the other half of the sample was used to validate the model. Coefficients reported here represent estimates from the full sample.

Results

Standard OLS Regression

Across all three procedure subsamples, model results were similar across test and validation samples in terms of both statistical significance and coefficient sign and magnitude. There was greater variation across test and development samples for the CABG sample, as expected given the smaller sample size and greater surgical complexity.

Table 3 compares OLS results across procedures.

Table 3. Results of OLS Regression across Procedures

Variable	CABG n = 5,431 Mean Case Duration: 315.16 Min.				TKA n = 70,857 Mean Case Duration: 145.39 Min.				Cholecystectomy n = 71,407 Mean Case Duration: 98.43 Min.			
	Coef	*p*	*95% CI, Min.*		*Coef*	*p*	*95% CI, Min.*		*Coef*	*p*	*95% CI, Min.*	
Patient Age	0.00	0.921	-0.07	0.06	-0.00	**0.000**	-0.24	-0.19	0.00	**0.000**	0.05	0.08
Male Sex	0.03	**0.000**	1.21	4.38	0.05	**0.000**	4.69	5.61	0.06	**0.000**	5.83	7.02
Patient ASA Score (Ref. ASA 1 or 2)												
ASA 3	0.05	**0.001**	1.90	7.48	0.03	**0.000**	2.24	3.14	0.06	**0.000**	5.97	7.26
ASA 4	0.05	**0.000**	2.87	7.76	0.05	**0.000**	3.54	7.33	0.15	**0.000**	14.09	18.24
Provider Volume	-0.00	**0.000**	-0.12	-0.06	-0.00	**0.000**	-0.02	-0.01	-0.00	**0.000**	-0.03	-0.02
Practice Volume	-0.00	**0.000**	-0.02	-0.01	0.00	**0.000**	0.00	0.00	0.00	**0.000**	-0.00	-0.00
Facility Volume	0.00	**0.000**	0.02	0.04	-0.00	**0.000**	-0.01	-0.01	-0.00	**0.000**	-0.01	-0.00
Facility Type (Ref. University Hospital)												
Community	-0.28	**0.000**	-26.04	-22.46	-0.23	**0.000**	-21.18	-19.52	-0.20	**0.000**	-19.00	-17.41
Specialty	-0.22	**0.000**	-22.37	-16.82	-0.38	**0.000**	-32.25	-30.32	-0.24	**0.000**	-24.28	-18.08
Outpatient	---	---	---	---	-0.24	**0.000**	-22.50	-20.16	-0.39	**0.000**	-33.23	-31.42
Facility Region (Ref. Northeast)												
Midwest	-0.06	**0.000**	-8.07	-3.88	-0.11	**0.000**	-11.23	-10.03	-0.14	**0.000**	-13.72	-12.41
South	-0.20	**0.000**	-19.43	-16.05	-0.07	**0.000**	-7.71	-6.39	-0.14	**0.000**	-13.36	-12.10
West	-0.09	**0.000**	-10.60	-5.99	-0.09	**0.000**	-9.67	-8.20	-0.12	**0.000**	-11.65	-10.08
Inpatient/Outpatient												
Outpatient	---	---	---	---	-0.03	**0.000**	-3.73	-2.48	-0.16	**0.000**	-14.91	-13.96
Primary Anesthesia Type												
Epidural/Spinal	---	---	---	---	0.00	0.655	-0.44	0.70	---	---	---	---
Regional	---	---	---	---	-0.07	**0.000**	-6.85	-5.77	---	---	---	---
Monitored Anesthesia Care	---	---	---	---	0.00	0.480	-1.44	3.14	---	---	---	---

The effect of patient age was very close to zero for all three procedures. Male sex was associated with longer case duration in all three samples, but this effect was largest in cholecystectomy, consistent with prior literature (57). The effect of ASA Physical Status Classification was generally positive, confirming that sicker patients generally have longer surgeries, as expected, and this is more pronounced for cholecystectomy patients with an ASA Physical Status Classification of 4. Anesthesia type was only included in the TKA model, as CABG and cholecystectomy procedures are almost exclusively carried out under general anesthesia. Procedures carried out under regional anesthesia were associated with decreased case duration relative to other types of anesthesia.

Provider, practice, and facility volume coefficient estimates were very close to zero for all three procedures. The coefficient on facility type differed more across procedures than other variables; TKA procedures in specialty hospitals tended to be significantly shorter than all other facilities, as were cholecystectomies in outpatient facilities. These findings may stem from differences in case mix severity not captured by model variables or could be related to the large percentage of missing data for this variable. Coefficient estimates on regions of the US varied significantly, complementing a stream of literature demonstrating regional differences in the incidence of various surgeries and physician practices within those surgeries (58, 59). CABG procedure case durations were most varied, with procedures included in NACOR from the South significantly shorter than all other regions. For all procedures, NACOR data demonstrates longer case duration in the Northeast compared to any other region.

Multilevel Regression

The first step in the multilevel process was to determine the most appropriate level structure for data for each procedure. In the CABG dataset, the best-fitting intercept only model was the crossed-effects model with practice and facility levels, while the providers nested within practice model fit the TKA and cholecystectomy samples best.

Table 4 shows the explained variance in the multilevel models before and after the inclusion of explanatory variables. The inclusion of explanatory variables explained between 19.3% and 25.3% of the variation observed in the dataset. After inclusion of model variables, most of the remaining variance was observed at the individual patient level (64.1%, 70.7%, and 70.7%, in CABG, TKA, and cholecystectomy, respectively).

Table 4. Explained Variance by Level

	Variance Explained				
	Provider Level	***Practice Level***	***Facility Level***	***Patient Level***	***All Levels***
CABG					
Intercept-Only Model	---	0.0292	0.0091	0.0445	0.0827
Explanatory Variable Model	---	0.0179	0.0060	0.0428	0.0668
Variance Explained by Model Variables	---	38.6%	33.9%	3.7%	19.3%
TKA					
Intercept-Only Model	0.0102	0.0370	---	0.0753	0.1225
Explanatory Variable Model	0.0065	0.0204	---	0.0647	0.0915
Variance Explained by Model Variables	36.6%	45.0%	---	14.1%	25.3%
Cholecystectomy					
Intercept-Only Model	0.0132	0.0440	---	0.1056	0.1627
Explanatory Variable Model	0.0095	0.0262	---	0.0864	0.1222
Variance Explained by Model Variables	27.8%	40.4%	---	18.1%	24.9%

Table 5. Results of Multilevel Regression across Procedures

Variable	CABG n=5,431		TKA n=70,857		Cholecystectomy n=71,407	
	Coef	*p-Value*	*Coef*	*p-Value*	*Coef*	*p-Value*
Patient Age	-0.00	0.102	-0.00	**0.000**	0.00	**0.000**
Male Sex	0.02	**0.001**	0.05	**0.000**	0.06	**0.000**
Patient ASA Score (Ref. ASA 1 or 2)						
ASA 3	-0.03	**0.032**	0.03	**0.000**	0.06	**0.000**
ASA 4	-0.01	0.722	0.06	**0.000**	0.15	**0.000**
Provider Volume	-0.00	**0.000**	-0.00	**0.000**	-0.00	**0.000**
Practice Volume	0.00	0.981	0.00	0.669	0.00	0.098
Facility Volume	-0.00	0.677	0.00	**0.000**	0.00	**0.000**
Facility Type (Ref. University Hospital)						
Community	-0.23	**0.000**	-0.12	**0.000**	-0.05	**0.000**
Specialty	-0.12	0.156	-0.27	**0.000**	-0.17	**0.000**
Outpatient	---	---	-0.20	**0.000**	-0.22	**0.000**
Facility Region (Ref. Northeast)						
Midwest	-0.05	0.306	-0.13	**0.002**	-0.13	**0.003**
South	-0.13	**0.012**	-0.09	**0.026**	-0.10	**0.027**
West	-0.00	0.958	-0.12	**0.005**	-0.13	**0.007**
Inpatient/Outpatient						
Outpatient	---	---	0.01	0.065	-0.13	**0.000**
Primary Anesthesia Type						
Epidural/Spinal	---	---	0.00	0.990	---	---
Regional	---	---	-0.06	**0.000**	---	---
Monitored Anesthesia Care	---	---	-0.03	0.021	---	---

Table 5 presents multilevel regression results for the three procedure subsamples. See Appendix B for a figure comparing OLS and multilevel regression 95% confidence intervals on explanatory variables for each of the procedures.

In the full multilevel model for all three procedures, the magnitude of estimates for facility-level variables tend to become smaller relative to OLS estimates, implying that some of the effect of these variables in the OLS model were actually incorporating within-facility, practice, or provider variation. One interesting exception to this trend is the effect of region in the TKA sample; the magnitude of these estimates actually become slightly more extreme in the after accounting for the effect of within-group variation, which implies that regional variation may stem from variation across rather than within providers or practices.

The effects of the explanatory variables were remarkably similar across procedures. All surgeries take longer in males, which is probably due to physiological differences in muscle and bone density (60). For TKA and cholecystectomy, cases of patients with ASA scores of 3 or 4 tend to be longer than cases with less sick patients, while for CABG patients, there is no difference by ASA class. Findings pertaining to anesthesia type, only relevant to the TKA sample, indicated that cases carried out under regional anesthesia were shorter than cases carried out under general, spinal, or other types of anesthesia. This finding is inconsistent with older studies (61), although the estimated effect observed in our study is small - less than 6 minutes.

Discussion

Our study found that case duration varies across levels (facility and practice levels for CABG, provider and practice levels for TKA and cholecystectomy). Consistent with the literature on case duration, facility type and facility region both have a significant effect on case duration. These findings expand on the literature by using multilevel models to parse out within-level effects and a large sample of nationwide clinical data to identify specific sources of variation in anesthesia time, such as the differences between outpatient and specialty hospitals and other facility types, or the differences of the Northeast compared to other regions. Accounting for the multilevel structure of the data tends to decrease both the statistical significance and the magnitude of most parameter estimates in the model, particularly facility-level variables like facility type or region, indicating that while these variables may still affect case duration, some of the effect observed in non-multilevel studies may come from variation within practices or facilities.

Multilevel Structures in the Data

A possible implication of these findings is that the significance of provider-level variation means that individual anesthesia providers may systematically differ from one another in terms of case duration. Cases carried out by a given anesthesia provider have case durations more similar to other cases by that provider than to cases carried out by other anesthesia providers. A small related study found that intervals between cardiac cases varied across anesthesiologists (62), which could be related to the differences in case duration across anesthesia providers studied here. If this is the case, there may be room for best practice identification across providers.

Similarly, across all three procedures, within-practice variation is an important component of the model, meaning that case duration within a given practice are more similar to one another than to those in other practices. This implies that some practices tend to take longer than other practices, consistent with the literature on the importance of small-area regional variation when looking at surgical outcomes; surgeons and anesthesiologists associated with a practice are likely to be trained in the same nearby areas. Training practices are often similar in a close geographic area, so it would not be surprising if anesthesia practices also differ across regions (59). Regardless of the mechanism by which case duration is similar within anesthesia providers and practices, these findings indicate that changes in training for anesthesia providers could be used to shorten case duration and improve patient outcomes and operating room efficiency. It should be noted, however, this anesthesia-practice could be picking up surgeon-specific or surgical practice-specific effects. Replicating this analysis in a data set that includes surgeon identifiers could parse out any effect of anesthesia providers on case duration separate from surgeon-specific effects.

When fitting the multilevel models, the best-fitting level structure was different in the CABG sample compared to TKA and cholecystectomy. For CABG cases, the most variation was explained when observations were simultaneously grouped by practices by facilities, but for TKA and cholecystectomy cases, the most variation was explained when observations were grouped by anesthesia providers within anesthesia practices. This may indicate that the within-facility variation is relatively higher for CABG cases than for other procedures. One explanation is that facility variation could incorporate some of the surgeon-specific effects not included in the dataset, and that there is more surgeon-specific variation in case duration for CABG relative to other procedures. This could be because many facilities have only a small number of surgeons who routinely perform CABG procedures. Alternatively, this could be an artifact from a facility-level variable not included in this analysis, such as operating room design or staffing structure, that is more relevant for CABG than the other procedures studied here.

Effects of Patient, Provider, Practice, and Facility Characteristics

The inclusion of explanatory variables in the multilevel model yielded a few notable results. Surprisingly, in the CABG multilevel model, very sick patients are associated with shorter surgeries than healthier patients. This could be a function of an influential outlier given the smaller sample size in the CABG case, although residual analysis did not indicate any such observations. This could also be explained by the fact that sicker patients' cases could be terminated early due to patient death, which may be more prevalent in CABG procedures than TKA or cholecystectomy. Additionally, shorter anesthesia time may be more critical for older or sicker patients, as longer anesthesia time is associated with long-term impacts on cognitive functioning (63).

Cases in teaching hospitals take longer than cases in all other types of facilities across all procedures, possibly because these facilities often take on sicker or more complex cases relative to other types of facilities, and resident operative times tend to be longer than faculty operative times (64, 65). This difference was smaller in the multilevel model, indicating that some of the facility type effect can be explained by within-facility variation.

The literature indicates that outpatient procedures tend to have decreased operative time compared to inpatient procedures, as outpatient procedures tend to be less complex procedures carried out on healthier surgical candidates (66, 67). This was reflected in the cholecystectomy sample; outpatient facilities had the shortest durations (19.7 minutes shorter in the multilevel model). However, for TKA, specialty hospitals had case durations 23.3 minutes shorter in the multilevel model, while the effect of performance in an outpatient facility was only 18.4 minutes shorter compared to an inpatient setting. Both of these effects could be due to differences in case mix not accounted for by ASA Physical Status Classification. TKA patients in specialty facilities may be more affluent and had fewer comorbidities than patients in community hospitals, and outpatient cholecystectomy is generally performed on healthier, lower-risk patients (67, 68).

This analysis demonstrated a somewhat large regional effect on case duration. Across all procedures included in this sample, those taking place in the Northeastern US tended to be longer than other regions in the US. In the Southern US, CABG cases were 11.5 minutes shorter than cases in the Northeast, which may be partially explained by the volume of cases in the region (43.4% of CABG procedures are carried out in the South, relative to 29.8% for TKA and 37.3% for cholecystectomy) (58). The literature indicates that regional variation in surgery rates is largely a function of patient demand for surgery, physician beliefs about the necessity of surgery, and the degree to which patient preferences are incorporated in to surgical decisions in different regions (58). Some of these same factors could also be influencing case duration. Differences in case duration across regions also mimics patterns in other surgical risk factors such as obesity. For example, it is possible that obesity-related health consequences could affect both patient-specific outcomes and physician practice patterns in those areas (59). It is important to note, however, that the NACOR data set may not be completely representative of the US, so these regional effects could be an artifact of the data set.

Even after the inclusion of explanatory variables and use of a multilevel model, there is still a high degree of unexplained variance in anesthesia duration. This may be because important variables are not included in the regression model (i.e. surgeon identification or more specific patient health status information), that case duration is a largely random phenomenon, or a combination of the two. These are avenues for future research.

Limitations

This research has important limitations to note. First, these findings may not hold for other types of surgery beyond the three I studied. Additionally, the dataset used for this analysis does not contain surgeon identifiers, but the individual surgeons likely exert significant influence on case duration. The staffing components of the surgical team and more specific comorbidity data are also not available, and omitted variables are particularly problematic for multilevel data (69). The data also comes with certain limitations. NACOR contains only data reported to the Anesthesia Quality Institute from ASA members, so this sample may not be representative of all surgical cases. In particular, nurse anesthetist cases are underrepresented in this dataset. This self-reported data limitation should also be taken into consideration when interpreting differences in case duration across regions, as the NACOR data set may not be nationally representative, even though it includes cases from the entire US. Two variables (facility type and outpatient status) had high percentages of missing data (<30%). If the data are not missing at random, this pattern of omission could introduce bias and compromise results.

Despite these limitations, this study identified several specific sources of variation in surgical time. The findings can be leveraged to optimize surgical time and improve surgical outcomes in future patients.

CHAPTER III

SURGICAL CASE MIX, SURGICAL VOLUME, AND THE BOTTOM LINE: EVIDENCE FROM TEXAS INPATIENT DATA

Introduction

Differences in the rates of use of surgical techniques varies across regions of the US, across hospitals in a given region, and even across providers within a given hospital. Regional variation in surgery rates was first identified in the 1970s and 1980s with the development of the concept of a regional “surgical signature,” or rate of application of a given surgical technique within a region. These studies found that the rate of specific procedures within a given region was relatively constant over time but differed from the rate of that same procedure in a different region. These regional differences in surgical technique were attributed in part to regional differences in medical training (58, 70), and regional differences in the use of surgical techniques still exist today (58, 71).

A related stream of literature examines practice patterns in surgery applications at the hospital and individual surgeon level. One recent study looked at hospital-level surgical practice patterns, measured as procedure-specific volume and frequency, in a pediatric population where disparities in access to minimally invasive surgery have previously been noted. The authors found that differences in practice patterns in minimally invasive surgery across hospitals did exist, and these differing patterns explained some of the observed difference in rates of application of minimally invasive surgery across socioeconomic strata (72). Another study examined variation in the use of radical prostatectomy for patients with low risk prostate cancer across surgeons at one academic medical center and found that surgery rates varied significantly across providers (73).

The literature on individual and hospital practice patterns combined with research on small-area variation in surgical techniques establish that the use of surgical techniques varies at many levels. The small-area variation literature also identifies specific patterns in regional variation. For example, one study found that prostatectomy rates varied nearly eightfold across Health Referral Regions in the US, with 0.64 procedures per 1,000 Medicare enrollees in Harlingen, Texas and 4.98 procedures per 1,000 Medicare enrollees in Baton Rouge, Louisiana (70). Less work has been done to identify specific patterns in variation across facilities; this is one purpose of this paper. Are there distinct, time-stable patterns in surgical offerings across facilities?

The small-area variation literature also shows that Medicare spending, like surgical utilization, varies widely across regions (74). Differences in Medicare spending across regions could be explained in part by differing care practices across regions. If this is the case, then certain “surgical signatures” could bring in more revenue than others and thus may be more profitable than others. Studies show that certain surgeries tend to be more profitable than others, so some groups of surgical offerings may also be more profitable than others (10). This paper examines this hypothesis at the facility level. Are some hospital-level surgical signatures associated with greater profitability than others?

While surgical offerings may affect hospital profitability, studies show that surgical volume may also affect profitability. Relative to medical care, more surgical care is paid for by private insurance than Medicare. In 2011, 41.3% of hospitalizations involving surgery were privately insured and 34.0% were paid for by Medicare, compared to 27.8% private funding and 42.1% Medicare funding for medical hospitalizations (16). Hospitals with a higher proportion of Medicare-insured patients are associated with lower profitability relative to hospitals with more private payers (19). If a facility's case mix is heavier on surgery than on medical care, more of the payments could be from higher-margin private sources, leading to increased profitability.

This surgical volume-profitability relationship has been noted in the non-academic sector. As part of their marketing materials, a private hospital consulting firm reports that while surgeries compose only 11% of a hospital's volume, they generate 40% of hospital revenues (22). While this number has not been academically vetted and may not be true, it does indicate the existence of a practitioner perspective that more surgery yields higher hospital profits. Two academic studies of rural hospitals showed that higher surgical volume at rural hospitals was associated with improved financial health (20, 21). The purpose of this paper is to assess the relationship between surgical volume and profitability in a sample that includes both urban and rural hospitals. Understanding the connection between a facility's surgical offerings, volumes, and profitability may become more important as more surgeries are provided on an outpatient basis. The movement toward outpatient surgery provision, particularly in freestanding ASCs, may threaten the profitability and viability of general acute care hospitals and reduce their ability to provide charity or uncompensated care (11, 75). If some surgical case mixes are more profitable than others, hospital management might consider diversifying surgical offerings to improve financial health, and policymakers may consider payment reform for less profitable but important surgeries. If surgical volume has a greater impact on profitability, hospitals may benefit from growing surgical volume on existing surgery lines. As such, the purpose of this paper is to identify prototypical hospital surgical signatures and to investigate the connection between these signatures, surgical volume, and hospital profitability.

Methods

This study received approval from the IRB of Texas A&M University. Informed consent was waived on the basis of impracticability and minimal risk to patients. Stata/MP 13.1 was used for all data preparation and analysis (51).

Data

Discharge data was used to identify patterns in surgical offerings across hospitals. Population discharge data is only publicly available for some states in the United States. Texas is one of those states. Annual discharge files for 2009 – 2012 were pulled from the Texas Health Care Information Collection (THCIC) system public use inpatient discharge file (76). THCIC is a state-mandated data collection initiative focused on hospital and health maintenance organization activity in Texas. Data are collected from all non-exempt state-licensed hospitals through the Texas Department of State Health Services. The aggregated discharge-level data file is publicly available. Additional facility-level organizational data needed for regression analysis was obtained from the AHA annual survey, which is collected via a voluntary self-reported questionnaire sent to hospital management (77). Area-level data were taken from the Health Resources and Services (HRSA) Area Health Resource File (AHRF) for 2013 (78). Financial data were taken from the Healthcare Cost Reporting and Information System (HCRIS), which contains facility-level cost and other financial data on reporting hospitals (79).

In raw form, each observation in the THCIC annual data sets represents one hospital discharge, which could contain one or more procedures. To study patterns in surgical procedures, a procedure-level data set was needed, so the discharge data were reshaped in long form such that each observation represented one procedure as represented by an International Classification of Diseases 9th Revision (ICD-9) procedure code. Blank, invalid, and nonsurgical procedures were then dropped from the data set. Invalid procedures were identified using Stata's ICD-9 check function, which identifies invalid ICD-9 codes.

Procedures were classified as surgical or non-surgical using the Healthcare Cost and Utilization Project's (HCUP) Surgery Flag program (80). The Surgery Flag software classifies either Current Procedural Technology (CPT) codes or ICD-9 codes (used here), as either non-surgical in nature, surgical under a narrow definition of surgery, or surgical under a broad definition of surgery. Classifications were made based on the academic literature and input from medical coders, clinicians, and HCUP staff. Narrow procedures are generally invasive surgical procedures; broad procedures, which encompass narrow procedures, include additional procedures often performed in a surgical setting, such as endoscopies, episiotomies, and simple wound repair. The broad definition was considered a better fit for this analysis, as the narrow definition was highly restrictive and could systematically exclude certain high-volume procedures that could be important to hospital profitability. For example, in the 2011 sample only 19.0% of the surgical procedures were narrowly surgical, composing just 7.28% of the full procedural sample.

After narrowing the sample down to only surgical procedures, observations were classified into one of 16 procedure categories using HCUP's Clinical Classifications Software (CCS) (81). CCS classifies individual ICD-9 codes into clinically meaningful categories, with separate schema for procedure codes and diagnostic codes. Classification schema are available for both procedure and diagnostic codes and as single-level files or multi-level files, where groupings are aggregated hierarchically into broader categories. The multi-level procedure groupings were used in this analysis, and procedures were classified using the most aggregated level. See Appendix C for a listing of the CCS multi-level procedure categories used to classify observations.

After CCS classification, the procedure-level surgical data set was collapsed into a facility-level data set with facility-level frequency percentages for each of the 16 procedure categories. At this point, the sample was limited to facilities identified as a "general medical and surgical" facility in the AHA Annual Survey. Pediatric hospitals, specialty hospitals, rehabilitation hospitals, and other facility types were excluded, as these facilities either do not provide many surgical procedures or provide a unique subset of surgical procedures that may hinder the cluster analysis process used to identify surgical signatures. Financial data from HCRIS were not available for a small number of the remaining facilities, so these facilities were not included in the final sample. Additionally, in each of the four years, after performing cluster analysis on the data set, a small group of facilities with high percentages of integumentary procedures emerged. Upon further examination, the procedures performed in these facilities were primarily wound care procedures typically carried out at rehabilitation facilities. As such, these facilities were removed from the sample because they differed greatly from the other general acute care facilities in the sample. Table 6 presents the sample selection process for each of the four years analyzed.

Table 6. Chapter III Sample Selection

Individual Observations	2009	2010	2011	2012
Raw discharge-level data file	2,951,296	2,978,627	2,937,579	2,965,961
Reshaped procedure-level data file	73,782,400	74,465,675	73,439,475	74,149,010
After dropping blank procedure codes	4,620,377	4,610,659	4,560,854	4,618,680
After dropping invalid procedure codes	4,617,079	4,609,616	4,401,481	4,618,347
After dropping nonsurgical procedures	1,745,355	1,747,510	1,691,132	1,721,082

Facility-Level Observations	2009	2010	2011	2012
Raw facility-level data file	446	459	462	477
After removing other facility types	260	265	265	266
After removing facilities with missing data	239	265	245	261
After removing wound care cluster	235	265	238	259

Variables

Ordinary least squares regression was used to analyze the relationship between cluster membership, or "surgical signature," and various measures of hospital financial health, including net patient revenues, operating expenses, and operating margin per inpatient day. The model was run individually for each dependent variable and year of data and was specified as follows:

$$Log(Financial\ Measure) = \beta_0 + \beta_p Surgical\ Signature + \beta_q Surgical\ Volume + \beta_r Facility\ Controls + \beta_s Area\ Controls + e_i$$

Where:

p represent the four surgical signature developed in cluster analysis

q represent facility-level adjusting variables

r represent area-level adjusting variables

Model results presented in tables pertain to 2012. The remaining years of data were used in sensitivity analysis.

Table 7. Chapter III Description of Variables

Variable	Description	Values
Operating margin per inpatient day	(CMI net patient revenues – CMI operating expenses)/Number of inpatient days	Continuous
Revenues per inpatient day	CMI net patient revenues	Continuous
Expenses per inpatient day	CMI operating expenses	Continuous
Surgical signature	Cluster membership	1: OB/general cluster 2: Cardio/musc cluster 3: Musculoskeletal cluster 4: Digestive cluster
Surgical volume per inpatient day	Number of surgical cases per year/Number of inpatient days	Continuous
Private ownership	Privately owned	0: Not privately owned 1: Privately owned
System membership	Member of a hospital system	0: Not system member 1: System member
Small bed size	Fewer than 100 beds	0: Not small 1: Small
Teaching status	Member of teaching hospital organization	0: Not teaching 1: Teaching
Mean length of stay	Mean length of stay in facility	Continuous
Proportion of population rural	Rural HSA population/total HSA population	Continuous
Proportion of the population eligible for Medicare	Medicare-eligible HSA population/total HSA population	Continuous
Proportion of the population in poverty	HSA population below poverty line/total HSA population	Continuous

Table 7 summarizes the variables used in all regression models. One of the primary explanatory variables in this analysis was a facility's surgical signature, which was identified using k-means cluster analysis (82). In k-means cluster analysis, the user selects a number of clusters (*k*). The computer begins with *k* observations; each of the remaining observations is added to the cluster with the closest group mean on clustering variables selected by the user. A new group mean is then computed for that cluster, and the process iterates for all remaining observations until all observations are classified (82). Clustering variables in this analysis included the facility-level percentages of each of the 16 procedure categories included in HCUP's clinical classification software. We developed several cluster solutions ranging from 1 cluster to 10 clusters (k=1…10) (51). The best cluster was selected using the graphical "elbow" method, in which the weighted sum of squares (WSS), a measure of distance between cluster centers, for each cluster solution is graphed against the number of clusters. At some *k*, the WSS will decrease less dramatically as the number of clusters decrease, forming an "elbow" in the curve. This is the ideal number of clusters, as the addition of another cluster reduces the overall distance between clusters to a lesser degree (83). This ideal cluster solution was transformed into a categorical variable that served as the primary explanatory variable in this analysis. The other primary explanatory variable is surgical volume per inpatient day, which measures the extent to which surgical procedures dominate a hospital's overall volume of care.

All financial variables were taken from the HCRIS and case-mix-adjusted using CMS case mix adjusting methodology to reduce variation related to differing case mixes across hospitals, similar to other studies on hospital profitability (84, 85). Historical Diagnosis-Related Group (DRG) weights were extracted from CMS data sets and applied to the principal DRG for each discharge, and then mean DRG weights were calculated for each facility. This facility-specific mean DRG weight was used as the case-mix index to adjust all financial data used in this analysis. Although CMS has historical CMI files available, they are only available for some facilities, using these would have resulted in significant sample size reduction (50/260), which may have systematically excluded certain types of facilities and biased regression results. On average, calculated CMIs were within 15% of CMS-published CMIs for facilities with this number available. CMI-adjusted results were compared to unadjusted results. There was minimal change in regression coefficient values or significance, but the use of CMI-adjusted financial measures improved model fit.

Revenues and expenses were scaled by the number of inpatient days to adjust for differences driven by volume. Alternative volume measurements included number of beds and number of discharges. Inpatient days was selected based on best fit with the research question. One of the primary hypotheses was surgical volume relative to overall hospital volume. Number of beds has more to do with facility size and may not be a good proxy for volume. While the number of discharges does measure volume, it does not take into account the intensity of a patient’s stay. Because costs differ based on intensity of stay (17), number of inpatient days was considered a better choice than number of discharges. Additionally, these alternative measures yielded poorer model fit as measured by AIC.

Adjusters included facility and area characteristics selected based on inclusion in other studies in the hospital finance literature. Private vs. non-private ownership and system membership were included, as both private ownership and system membership are associated with increased profitability (19, 25). Bed size was included, as decreased size is associated with decreased profitability (19). Teaching status was included, as more non-major teaching hospitals are associated with higher profitability (19). Mean length of stay was included, as longer length of stay may be associated with decreased profitability (86). Ownership and bed size were taken from the AHA annual survey, while all other facility-level variables were taken or derived from the THCIC inpatient file.

Area variables were measured using Health Service Areas (HSAs), which represent local health care markets. When developed, HSAs were created by grouping together zip codes in which most residents received care at the same hospitals (87). Alternatives to grouping by HSA include grouping by Core Based Statistical Areas (CBSAs), which divide areas into rural, micropolitan, and metropolitan areas, and Health Referral Regions (HRRs), which are aggregations of HSAs into markets for tertiary medical care that usually requires a referral (87, 88). HSAs were selected as the best fit for this analysis, as HRRs and CBSAs are larger than HSAs, and population data aggregated at this level may not be meaningful for financial measures for a given hospital.

HSA-level variables included in the model were the percentage of the HSA population living below the poverty level, the percentage of the population eligible for Medicare, and the proportion of the population considered rural, consistent with other studies of hospital finance (9, 19). Previous studies have found that poorer surrounding populations, older populations, rural populations, and populations with higher uninsured rates are associated with decreased profitability (19). These area-level variables were taken from the 2013 AHRF.

Statistical Analysis

Explanatory variables, which included facility cluster membership as well as facility-level and HSA-level adjusters, were examined in univariate analysis before inclusion in the final model. Listwise deletion was used for missing data as percentages of missing data were low for most variables and there was no apparent pattern of missingness. The Ramsey reset test and LINK test were used to identify model specification errors. Multicollinearity was assessed using variance inflation factors (VIFs). Shapiro-Wilk, Shapiro-Francia, and skewness-kurtosis tests were used to assess normality, supplemented by kernel density plots of residuals. Augmented component-plus-residual plots were used to assess linearity and heteroscedasticity and to identify outliers. White's test was used to formally assess heteroscedasticity, and Cameron & Trivedi's decomposition of White's test was used to evaluate skewness and kurtosis, and heteroscedasticity (52). Heteroscedasticity was detected in most of the regressions. Much of the detected heteroscedasticity was a result of high kurtosis driven by outliers in the data, as financial measures, and particularly profit measures, are highly idiosyncratic (25). Robust standard errors were used to address heteroscedasticity when present (52).

Results

The first aim of this analysis was to determine whether distinct groupings of surgical procedures were present in the data and if these groupings were consistent over time. Based on the cluster selection criteria described previously, the ideal cluster solution reached in all four years of data was five clusters. Upon examination, one of the clusters represented facilities performing wound-related procedures. This cluster was eliminated from further analysis. The four remaining clusters included an obstetrical (OB)-heavy general cluster, a cardiovascular/musculoskeletal general cluster, a musculoskeletal-focused cluster, and a digestive-focused cluster. 79.0% of facilities belonged to the same cluster for all years in the data set. 10.0% switched between the two “general” categories. Only 2.6% of the facilities switched between more than two categories across the four years. The remaining 8.4% switched between general and focused clusters or focused clusters.

Table 8 shows the mean percentages of CCS categories within each cluster relative to a nationwide average for all facilities. Appendix D contains box plots showing the distributions of CCS category percentages within each cluster.

Table 8. CCS Percentages within Surgical Clusters

CCS Category	OB/General Cluster 2012	Cardio/Musc Cluster 2012	Musc Cluster 2012	Digestive Cluster 2012
Nervous	1.7%	4.5%	15.4%	1.3%
Endocrine	0.2%	0.3%	0.2%	0.1%
Eye	0.0%	0.1%	0.2%	0.0%
Ear	0.1%	0.1%	0.0%	0.0%
Nose, mouth, and pharynx	0.3%	0.5%	0.4%	0.4%
Respiratory	1.4%	3.2%	0.1%	2.9%
Cardiovascular	6.2%	18.3%	0.4%	2.2%
Hemic and lymphatic	0.5%	1.0%	0.7%	0.7%
Digestive	19.3%	20.3%	4.0%	59.3%
Urinary	2.4%	3.2%	1.0%	0.6%
Male genital	10.9%	5.0%	0.2%	0.7%
Female genital	10.6%	5.9%	3.2%	4.3%
Obstetrical	29.4%	11.5%	0.0%	0.5%
Musculoskeletal	13.1%	21.7%	69.6%	14.2%
Integumentary	2.4%	3.1%	4.6%	8.9%
Miscellaneous	1.5%	1.2%	0.1%	3.8%

Facilities in HSAs containing only one acute-care hospital were almost exclusively OB/general facilities. 63% of HSAs with two facilities had two general facilities, either OB-focused or cardiovascular/musculoskeletal; the remaining 37% had one general and one focused facility. Musculoskeletal facilities were only present in HSAs with four or more facilities, with one exception. The five HSAs with the most facilities, representing San Antonio, Austin, Dallas/Fort Worth, and Houston, comprised 50% of the acute care facilities in the state, but 72.7% of the musculoskeletal facilities and only 30.3% of the digestive-focused facilities. Figure 4 demonstrates the percentages of each surgical signature across four HSA groupings selected by natural breaks in the data.

Figure 4. Surgical Signature by HSA Facility Density

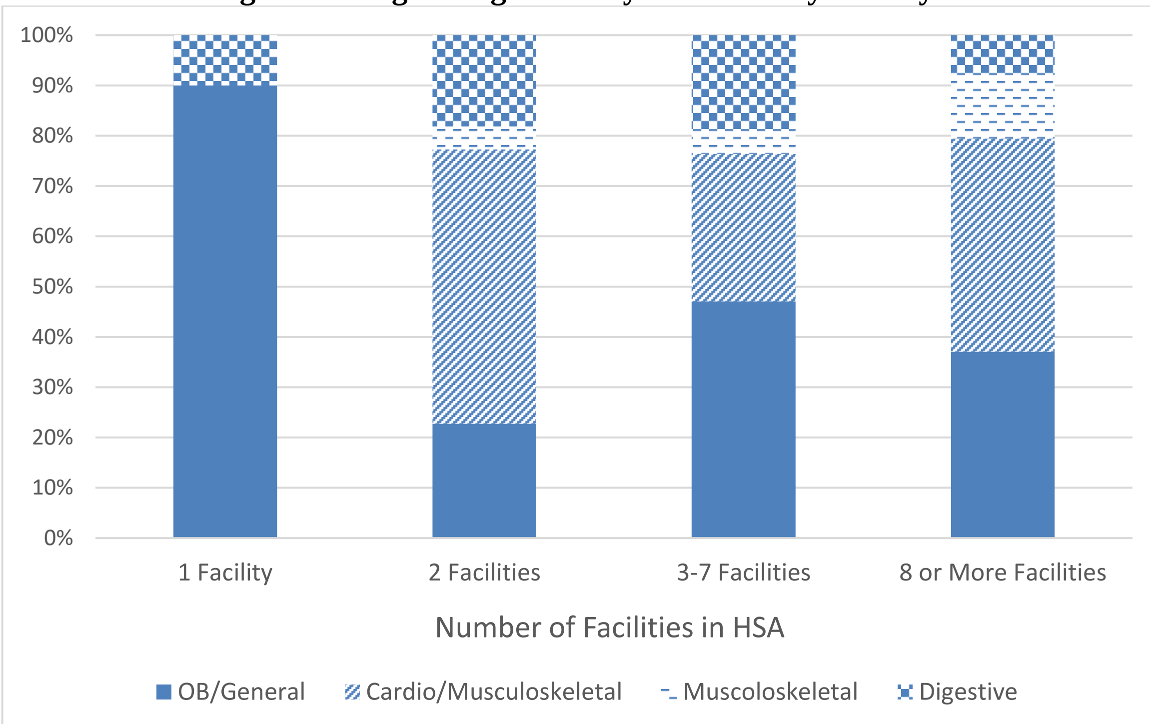


Table 9. Chapter III Sample Characteristics by Cluster, 2012

	All Clusters n=264		OB/General Cluster n=110		Cardio/Musc Cluster n=99		Musculoskeletal Cluster n=33		Digestive Cluster n=22	
	Mean	Freq.	Mean	Freq.	Mean	Freq.	Mean	Freq.	Mean	Freq.
Dependent Variables										
Log of Net Patient Revenue per Inpatient Day	9.1	---	8.8	---	9.0	---	10.2	---	9.2	---
Log of Operating Expense per Inpatient Day	9.1	---	8.9	---	9.0	---	10.1	---	9.3	---
Operating Margin per Inpatient Day	-0.1	---	-0.1	---	-0.1	---	0.1	---	-0.3	---
Facility Characteristics										
Private Ownership	---	46.6%	---	43.6%	---	42.4%	---	95.4%	---	39.4%
System Membership	---	15.8%	---	10.9%	---	10.1%	---	59.1%	---	18.2%
Small Bed Size	---	45.5%	---	43.6%	---	18.2%	---	100.0%	---	93.9%
Teaching Status	---	11.7%	---	3.6%	---	26.3%	---	0.0%	---	3.0%
Facility Mean Length of Stay	4.9	---	4.2	---	6.1	---	2.6	---	5.5	---
Surgical Volume/Inpatient Day	0.2	---	0.2	---	0.2	---	0.9	---	0.1	---
Area Characteristics										
HSA Proportion Rural	0.5	---	0.5	---	0.5	---	0.5	---	0.5	---
HSA Proportion Medicare Eligible	0.2	---	0.2	---	0.2	---	0.2	---	0.2	---
HSA Proportion in Poverty	0.2	---	0.2	---	0.2	---	0.2	---	0.	---

Table 9 shows that case-mix-adjusted revenues and expenses per inpatient day are similar across all clusters. Revenues are slightly higher than expenses, except for digestive cluster facilities, where expenses are slightly higher than revenues.

OB/general facilities tend to have fewer beds than the cardiovascular/musculoskeletal facilities, with a shorter length of stay, close to the typical obstetrical length of stay of 3-4 days. Cardiovascular/musculoskeletal facilities include most of the teaching facilities. They are not usually a part of a hospital system, comprise most of the large facilities, and have a longer mean length of stay than other clusters. Musculoskeletal facilities are almost exclusively small, privately owned, non-teaching hospitals, usually a part of a hospital system, with high surgical volume relative to inpatient days and a short mean length of stay. They tend to be located in more urban areas, with a younger, wealthier patient base. Digestive facilities are almost exclusively small, non-academic facilities with public or nonprofit ownership. These facilities have the lowest ratio of surgical volume to inpatient days and are located in poorer, more rural, older areas than other facility types.

Table 10. Results of OLS Regression for Revenues and Expenses, 2012

	Log of Net Patient Revenue per Inpatient Day						Log of Operating Expense per Inpatient Day					
	Before Adjustment [a, b]		***After Adjustment*** [a, b]		***Including Surgical Volume*** [a, b]		***Before Adjustment*** [a, b]		***After Adjustment*** [a, b]		***Including Surgical Volume*** [a, b]	
	Coef.	*p-value*	*Coef.*	*p-value*	*Coef.*	*p-value*	*Coef.*	*p-value*	*Coef.*	*p-value*	*Coef.*	*p-value*
n	258		258		258		259		259		259	
Adjusted R^2	0.2951		0.4675		0.5307		0.2667		0.4516		0.5200	
Cluster												
Cardiac/Musculoskeletal	0.13	0.088	0.36	0.000	0.30	0.000	0.12	0.099	0.30	0.000	0.25	0.001
Musculoskeletal	1.39	0.000	0.96	0.000	0.48	0.002	1.25	0.000	0.82	0.000	0.41	0.058
Digestive	0.40	0.005	0.40	0.001	0.37	0.001	0.48	0.002	0.39	0.016	0.37	0.015
Facility Characteristics												
Private Ownership	---	---	0.09	0.192	0.03	0.600	---	---	0.01	0.894	-0.04	0.515
System membership	---	---	-0.01	0.946	-0.12	0.206	---	---	-0.01	0.963	-0.10	0.417
Small Bed Size	---	---	0.33	0.000	0.34	0.000	---	---	0.45	0.000	0.45	0.000
Teaching Status	---	---	-0.04	0.716	-0.09	0.407	---	---	0.20	0.087	0.16	0.144
Facility Mean Length of Stay	---	---	-0.08	0.000	-0.05	0.014	---	---	-0.07	0.002	-0.05	0.035
Surgical Volume/Inpatient Day	---	---	---	---	0.87	0.000	---	---	---	---	0.74	0.003
Area Characteristics												
HSA Proportion Rural	---	---	-0.47	0.135	-0.33	0.265	---	---	-0.41	0.094	-0.29	0.196
HSA Proportion Medicare eligible	---	---	-1.48	0.329	-0.88	0.537	---	---	-0.97	0.515	-0.45	0.740
HSA Proportion in Poverty	---	---	-2.88	0.000	-2.46	0.000	---	---	-2.75	0.000	-2.39	0.000

[a] Robust standard errors reported to address heteroscedasticity

Table 11. Results of OLS Regression for Profitability, 2012

	Operating Margin					
	Before Adjustment[a, b]		**After Adjustment**[a, b]		**After Adjustment, Including Surgical Volume**[a, b]	
	Coef.	p-value	Coef.	p-value	Coef.	p-value
n	0.0126		254		254	
Adjusted R^2	0.0126		0.1295		0.1415	
Cluster						
Cardiac/Musculoskeletal	0.07	0.223	0.10	0.068	0.09	0.130
Musculoskeletal	0.17	0.004	0.19	0.023	0.06	0.508
Digestive	(0.06)	0.478	0.10	0.36	0.09	0.376
Facility Characteristics						
Private Ownership	---	---	0.13	0.011	0.12	0.026
System Membership	---	---	0.01	0.926	(0.02)	0.781
Small Bed Size	---	---	(0.24)	0.000	(0.23)	0.000
Teaching Status	---	---	(0.30)	0.005	(0.31)	0.003
Facility Mean Length of Stay	---	---	(0.01)	0.449	(0.00)	0.812
Surgical Volume/Inpatient Day	---	---	---	---	0.23	0.064
Area Characteristics						
HSA Proportion Rural	---	---	(0.07)	0.799	(0.03)	0.916
HSA Proportion Medicare Eligible	---	---	(1.15)	0.365	(0.98)	0.435
HSA Proportion in Poverty	---	---	(0.32)	0.436	(0.21)	0.626

[a] Robust standard errors reported to address heteroscedasticity
[b] Outliers removed to improve model fit

Regression Results

Coefficients in Table 10 and 11 represent 2012 results. To interpret these coefficients, exponentiate the coefficient and subtract one. The resulting number is the percentage increase in revenues, expenses, or operating margin associated with a one-unit change in the variable associated with the coefficient. Table 10 shows that cardiovascular/musculoskeletal, musculoskeletal, and digestive facilities tend to generate higher revenues and expenses than the OB/general cluster, with the musculoskeletal differences most pronounced. Before covariate adjustment, the revenues and expenses per inpatient day for the two general facility clusters do not differ significantly. After adjusters are included in the model, however, cardiovascular/musculoskeletal facilities generate higher revenues and expenses than the OB-centric general facilities, although the magnitude of this difference is less than either of the two focused facility types.

Of particular interest is the change in the magnitude of the effects of cluster membership after inclusion of surgical volume in the model, which increases the explanatory power of both models - by 6.8% for expenses and 6.3% for revenues. Above and beyond other adjusters, inclusion of surgical volume reduces the increase in musculoskeletal revenues above the base case from 160.9% to 61.3%, indicating that the cause for this increase in revenues has less to do with the revenues generated from musculoskeletal procedures and more to do with the volume of surgeries carried out at these facilities. The mean ratio of surgeries to inpatient days for musculoskeletal facilities is 0.866, but around 0.150 for all other clusters, and the mean length of stay is between two and four days shorter than all other facility types. This trend also holds for expenses; in fact, after inclusion of the surgical volume variable, expenses at musculoskeletal facilities no longer differ significantly from OB/General facilities.

Profitability regression results indicate that cluster membership and most other variables do not explain a significant degree of variation; the variance explained by the model is just 1.3% before adjustment and 14.2% after. This may be because profitability is a highly idiosyncratic phenomenon, or because the increases in revenues tend to offset increases in expenses and vice versa, yielding much smaller differences across facilities than revenues or expenses taken separately. Similar to the revenue and expense regressions, while profitability differs significantly for the musculoskeletal cluster, this difference is insignificant after inclusion of surgical volume in the model.

Sensitivity Analyses

Alternative categorizations of adjusting variables were used, including a public/private/non-profit ownership grouping and a small/medium/large bed size grouping, but these groupings yielded decreased model fit relative to the model described previously. HSA-level Hirschman-Herfindahl Indices (HHIs) based on surgical volume were also included in the model but introduced additional heteroscedasticity without improving model fit. Weighted least squares using poverty as the weighting variable and the square of the error as the weight type was used instead of robust standard errors for regressions demonstrating heteroscedasticity, as the sample size is somewhat small, which can be problematic when using robust standard errors (52). Results were relatively similar, but robust standard errors were selected because they are less sensitive to user assumptions.

This process was replicated for 2009 and 2011; complete financial data was not available for 2010 due to a CMS reporting transition, so only cluster analysis and descriptive statistics were computed for this year. Regression results conducted for 2009 and 2011 were similar, although each year demonstrated idiosyncrasies in profitability. In particular, in 2009, the digestive cluster was significantly more profitable than the OB-general cluster. This finding was not replicated in any other year.

Discussion

The descriptive results from our cluster analysis provide a remarkably consistent picture of surgical service offerings and acute care market structure across HSAs in Texas. First, these results demonstrate that there is significant consistency in cluster membership over time. Most facilities that moved between one cluster or another were low volume in terms of both total discharges and surgical procedures performed.

Second, there was a distinct pattern of cluster membership within HSAs. HSAs with only one facility are almost exclusively OB/General facilities. More complex procedures from these regions may be outsourced to facilities with higher procedural volume, where more specialists and specialized facilities are available, and where quality may be higher due to increased procedural volume (89). Digestive facilities are concentrated in HSAs with more than one facility but fewer than eight, and most are located in small cities in rural areas. These facilities could be magnet facilities that take on digestive procedures not performed at very small rural hospitals (i.e. facilities in HSAs with only one facility) in the surrounding areas (90). Musculoskeletal facilities are almost exclusively located in urban areas and probably represent facilities that are similar to orthopedic specialty hospitals.

Another important finding is that differences in surgical mix did not explain differences in hospital profitability. One practitioner suggestion for improving hospital profitability is to add a new surgery line, since some surgical lines are more profitable than others (22, 91). If changing an entire surgical profile doesn't significantly increase profitability, adding a surgical line may not either. Additionally, research shows that adding surgery lines dilutes the quantity of procedures performed at any given facility, leading to lower average procedural volume and poorer quality of care and patient outcomes (89).

Improving volume of surgeries already performed at the facility rather than adding new surgery lines may be a better strategy for profit maximization. Surgical volume had much more explanatory power for all financial measures studied here relative to surgical cluster; higher surgical volume relative to inpatient days was associated with higher revenues, higher expenses (but to a lesser degree than revenues), and increased profitability in 2012 and all other years studied, consistent with previous studies conducted in rural hospital settings (20, 21).

The mean ratio of surgical volume to inpatient days differed significantly across profitable and not-profitable hospitals ($p = 0.0007$); the mean ratio was 0.27 in the profitable facilities in the sample, but just 0.15 in the not-profitable subsample. Similarly, overall surgical volume was 6,461 procedures/year in the profitable subsample, but 4,130 procedures/year in the not-profitable subsample ($p = 0.0028$). This suggests that hospital profitability could be linked to the quantity of surgeries provided at that facility.

One important implication of this is that the increasing number of surgeries performed in outpatient surgery centers could reduce the profitability and viability of inpatient acute care hospitals which would have provided these surgeries otherwise. This bolsters similar claims from the hospital industry (8, 10). Research shows that an increase in the number of ASCs per 100,000 population reduces volume in hospital outpatient departments and that as a result the profitability of hospital outpatient departments decreases (7, 11). This is particularly important to consider, as 65% of all surgeries are now performed on an outpatient basis and this number is expected to increase (5). Health care organization leadership may consider strategies to manage this trend such as joint ventures with ambulatory surgery centers to reduce competition, although such strategies may decrease overall welfare by increasing prices for patients (33, 92). Policymakers may want to consider payment reform for inpatient facilities, especially for financially vulnerable facilities like Critical Access Hospitals, to encourage viability without relying as heavily on surgical volume, above and beyond previous reforms to ambulatory surgery center reimbursement, which reduced reimbursement to ASCs but did not assist inpatient facilities with covering the unprofitable care the lost surgical volume may have compensated for (10, 93).

The effect of surgical volume is particularly pronounced when examining musculoskeletal-focused facilities. Orthopedic procedures have a reputation for higher profitability than other surgery lines, but these results indicate that on an aggregate level much of this profitability is actually explained by the higher volume of surgical procedures common to these facilities. Many orthopedic procedures are same-day surgeries, and those that are not completed same-day are not usually associated with a long length of stay or high complication rates (94).

Limitations

The results shown here are limited to Texas hospitals and may not generalize to other states or outside the US. In addition, the sample was limited to inpatient facilities; results for outpatient facilities may be (and likely are) very different, which is important, as an increasing number of surgeries are carried out in outpatient settings. The data sets included in this analysis also levy limitations. The sample was based on hospitals reporting to the THCIC. Certain hospitals, including certain rural hospitals and hospitals not seeking government reimbursement, are specifically exempted from this data by statute. These findings may not generalize to exempt hospitals. AHA data is self-reported by hospitals, and while some data cleaning is performed by the AHA, the data may be inconsistent or misreported. 2012 data was not available for all area-level adjusters in the 2013 AHRF, so 2011 data was used for some measures.

These results are presented with a few statistical limitations as well. First, because profitability is highly idiosyncratic, results may be compromised by outliers in the data. Residuals were non-normal for all regressions, which could yield inflated standard errors and decreased statistical significance. Finally, cluster membership is most likely endogenous to the financial measures used in this analysis. Logistic regressions with each cluster as the dependent variable show several significant relationships between surgical signature and other model variables. See Appendix E for results of these logistic regressions. This endogeneity may lead to inconsistent estimators (95). One possible solution to this problem is to use an instrument in two-stage least squares regression, which is an avenue for future research.

Conclusion

General acute care facilities tend to fall into one of four clusters based on surgical procedure volume: OB-related general, cardiovascular/musculoskeletal general, musculoskeletal, or digestive. An HSA-level pattern in market structures also exists. Cluster membership differs based on facility and area-level characteristics, in particular teaching status, bed size, system membership, and ownership. While clusters differ significantly in terms of revenues and expenses, profitability does not differ significantly across clusters. Increasing surgical volume rather than changing surgical signature may be a better strategy for improving profitability; however, maintaining this ratio may be a challenge given the current trend toward surgery provision in ambulatory surgical centers.

CHAPTER IV

REVISITING THE RELATIONSHIP BETWEEN AMBULATORY SURGICAL CENTERS AND HOSPITAL SURGICAL VOLUME AND REVENUES

Introduction

The proliferation of Ambulatory Surgery Centers (ASCs) has been the subject of debate since CMS began reimbursing these facilities for surgical procedures on Medicare patients in 1982 (96). Proponents say that ASCs are more efficient, safer, and lower cost than inpatient surgery and that they stimulate healthy competition; opponents say that ASCs rob inpatient facilities of high-profit outpatient procedures, reducing their ability to cover the costs of charitable care and other unprofitable care activities that contribute less to the hospital's bottom line but significantly to societal welfare (7-9).

There is empirical evidence to support both positions. Studies on volume show that ASC penetration is associated with a modest decrease in outpatient volumes, with no effect on inpatient volumes (9, 11). However, studies examining the effect of ASC entry into the market found evidence of a more dramatic decrease in outpatient volumes (9, 97). There is ample evidence of "cherry picking" of profitable procedures and healthier patients by ASCs, implying reduced profitability for inpatient hospitals (10, 93, 96). There is less evidence as to whether this effect is large enough to detract from overall profitability, but the limited literature on this topic implies that ASC presence does tend to reduce revenues, costs, and profitability (35). Understanding the effect on profitability at the facility level and not just the procedure-level effect is also important, as the narrative in much of the anecdotal evidences blames ASCs for reductions in *overall* profitability, not just per-procedure profitability (8).

Regardless of public opinion, ASCs are more pervasive than ever and continue to open; in Texas, for example, the number of ASCs grew by an average of 2.79% over 2010-2015; there were 482 ASCs operating in the state in 2010 and 553 in 2015, an increase of 71 facilities over the course of five years (98). However, this is not to say that the concerns of ASC opponents have been ignored. In 2008, to reduce “cherry picking” of profitable cases by ASCs, payment reform was implemented that reduced reimbursement for ASCs to approximately 65% of the reimbursement hospitals receive for the same procedure. Growth since 2008 has slowed but not stalled, possibly because of this reform. (99). The passage of the PPACA may have also affected the market for ambulatory surgery. Some non-academic pundits opine that ASC proliferation is more critical in the post-PPACA era, as expansion of access to health insurance coverage will expand demand for medical care in general and elective outpatient surgery in particular (4).

Much of the research on ASCs was conducted before the passage of Medicare ASC payment reform and the PPACA, so the relationships observed in those studies may have changed. This study replicates Plotzke and Courtemanche (2010) using more recent data and also extends the analysis to examine the effect of ASC penetration on overall hospital inpatient and outpatient revenues in addition to volumes. Specifically, this paper tests the following hypotheses:

> *H1*: Higher ASC penetration is associated with decreased hospital-based outpatient surgical volume, with no effect on inpatient surgical volume.
>
> *H2*: Higher ASC penetration is associated with decreased outpatient revenue, with no effect on inpatient revenue.

Methods

This study was conducted under the approval of the IRB of Texas A&M University. Patient consent was waived as obtaining consent for retrospectively collected data is impractical and the risk posed to patients was minimal.

Data

Data on ASC penetration were collected from the Center for Medicaid and Medicare Services (CMS) Provider of Services (POS) files for 2012 through 2014 (98). Data on hospital characteristics and surgical volumes were taken from the AHA annual survey for 2012 through 2014, which were only available for the state of Texas, limiting the sample to Texas hospitals (77). Revenue data were taken from CMS Healthcare Cost Reporting Information System files for 2012-2014 (79). County-level area data were taken from HRSA Area Health Resource File (AHRF) for 2013 (78). The most recent AHRF data available for these characteristics came from 2011, so this year of data was used for all models.

The AHA survey file for Texas included 615 facilities in 2012, 627 in 2013, and 617 in 2014. Hospitals that were not general acute-care hospitals or that served pediatric populations were removed, yielding a total of 1,128 hospital-year observations representing 394 unique hospitals. The sample was further limited to 713 of the 1,128 observations located in metropolitan statistical areas (MSAs), consistent with the original study, as urban facilities are more likely to be located near ASCs than rural facilities. Missing data were negligible (<5%) for all variables, so listwise deletion was used to handle missing data, leaving a final sample of 625 facility-years representing 226 unique facilities.

Variables

The primary independent variable in this analysis is ASC penetration, measured as the number of ASCs within a given radius of a hospital. To calculate the distance between two hospitals and between each hospital and each ASC, addresses for all facilities were taken from the AHA survey and CMS POS files. These addresses were converted to latitude and longitude coordinates using Texas A&M University Geoservices Geocoding Services (100). Stata’s geodist function was employed to calculate the distance between latitude and longitude coordinates of (a) each hospital with each of the other hospitals and (b) each hospital with every ASC. These distances were used to measure ASC penetration, to measure the number of other hospitals within a given radius of that hospital, and to calculate the Herfindahl-Hirschman Index (HHI) within a given radius of a hospital.

One contribution of the Plotze and Courtemanche (2010) study not replicated here is their investigation into the appropriate hospital market size. This replication originally used one-third of the mean fixed radius for hospitals (3.83 miles), as the original study found no significant effect for ASC penetration beyond this radius (9). We employed other radii (3 miles, 5 miles, 10 miles, and 20 miles) as a sensitivity check. In the course of the sensitivity checks, we found that a 5-mile radius was most meaningful for this sample. This is further discussed in the results and discussion.

Adjusting variables were selected based on inclusion in the original Plotzke & Courtemanche (2010) paper. Most variables are sourced and calculated in much the same way as the original paper; one distinction is the HHI in this paper is calculated based on total surgical volume, while the HHI in the original paper was based on hospital admissions. Table 12 summarizes model variables.

Table 12. Chapter IV Description of Variables

Variable	Description	Values
Outpatient surgical volume	Number of outpatient surgical operations reported to AHA	Continuous
Inpatient surgical volume	Number of inpatient surgical operations reported to AHA	Continuous
Outpatient revenues	Net outpatient revenues reported in HCRIS	Continuous
Inpatient revenues	Net inpatient revenues reported in HCRIS	Continuous
ASC penetration	Number of ASCs within 5 miles of hospital. Other radii used in sensitivity analysis	Continuous
Small bed size	Fewer than 100 beds	
Ownership	Type of hospital control	1: Public 2: Not-for-profit 3: Private
Teaching	Membership of teaching hospital organization	0: Not teaching 1: Teaching
Hospital outpatient department	Hospital has a hospital outpatient department (HOPD)	0: No HOPD 1: HOPD
Operating rooms	Number of operating rooms	Continuous
Privileged physicians	Number of privileged physicians	Continuous
Herfindahl Hirschman Index (HHI)	HHI within a 5-mile radius	Continuous
Hospitals within 5 miles	Number of other hospitals within 5 miles	Continuous
Proportion eligible for Medicare	Proportion of HSA population eligible for Medicare	Continuous
Total population (100,000)	Total HAS population in 100,000s	Continuous
Proportion uninsured	Proportion of HSA population uninsured	Continuous
Unemployment rate	Proportion of HSA population over 18 unemployed	Continuous
Log of median household income	Natural log of HSA median household income	Continuous
Proportion in poverty	Proportion of HSA living below the poverty line	Continuous

Statistical Analysis

Stata/MP 13.1 was used for all data cleaning and analysis (51). Individual variables were regressed on the four outcome variables (hospital-based outpatient surgical volume, inpatient surgical volume, outpatient revenues, and inpatient revenues) to examine need for inclusion in the final model. The models were specified as follows:

$$Log(Fincial\ or\ Volume\ Measure) = \beta_0 + \beta_1 ASC\ penetration + \beta_p Facility\ Controls + \beta_q Market\ Controls + \beta_f Area\ Controls + \beta_s Year + \beta_t Facility + e_i$$

Where:

p represent facility-level adjusting variables

q represent market-level adjusting variables

r represent area-level adjusting variables

s represent year fixed effects

t represent facility fixed effect

Linearity of regressors in the outcome variable was assessed using augmented component-plus-residual plots with lowess lines. Heteroscedasticity was examined using the Breusch-Pagan test; when present, robust standard errors were used (52). VIFs were used to assess multicollinearity. Certain variables, in particular median household income and percentage in poverty, were highly collinear, but omitting either variable did not dramatically improve model fit or alter estimates or significance to a large degree, so both were included in the model to be consistent with the original study. Residual plots were used to identify outliers; kernel density plots of residuals were used to assess normality. The Ramsey RESET test and Stata's linktest were used to identify model specification errors. Model fit was assessed using R-squared or adjusted R-squared, and models were compared using AIC (52). Several sensitivity analyses were conducted, including the use of differing hospital market definitions and the addition of MSA fixed effects, as well as one-year lagged and leading ASC penetration. The inclusion of prior year ASC penetration could provide evidence of an ASC entry effect on volumes. A positive, significant coefficient on subsequent year ASC penetration could indicate reverse causality – ASCs open in response to increased demand for surgery in an area instead of taking existing market share.

Results

Table 13 summarizes the facility, market, and area characteristics of the sample.

Table 13. Chapter IV Sample Characteristics
n = 625 facility-years

Level	Variable	Mean	Std. Dev.
	Dependent Variables		
Facility	Annual number of outpatient surgeries	4,161	4,375
	Annual number of inpatient surgeries	2,765	3,555
	Annual outpatient revenue ($100,000)	$ 3,561.81	$ 4,321.50
	Annual inpatient revenue ($100,000)	$ 4,753.38	$ 6,489.78
	Independent Variables		
	ASCs within 3 miles	4.63	5.31
	ASCs within 3.83 miles	4.93	6.31
	ASCs within 5 miles	6.99	7.54
	ASCs within 10 miles	14.45	15.55
	ASCs within 20 miles	34.29	31.80
	Adjusting Variables		
	<100 beds	44.18%	0.50
	Ownership: government	13.18%	0.34
	Ownership: not-for-profit	37.59%	0.48
	Ownership: for-profit	49.23%	0.50
	Teaching	23.77%	0.43
	Hospital outpatient department	35.62%	0.48
	Number of operating rooms	11.30	11.33
	Number of privileged physicians	447.36	441.11
Market	Herfindahl Hirschman Index (HHI)	0.62	0.32
	Number of hospitals within 3 miles	0.87	1.28
	Number of hospitals within 3.83 miles	1.06	1.39
	Number of hospitals within 5 miles	1.69	1.90
	Number of hospitals within 10 miles	4.35	4.36
	Number of hospitals within 20 miles	12.45	11.54
County	Percentage eligible for Medicare	11.94	3.03
	Total population (100,000)	12.97	14.02
	Percentage uninsured	25.61	5.14
	Unemployment rate	7.88	1.33
	Log of median household income	10.83	0.23
	Percentage in poverty	17.75	6.21

Sample means were somewhat similar to results presented in Plotzke & Courtemanche (2010), although the samples are not directly comparable. In particular, the number of ASCs within the hospital's market were larger in the replication sample, possibly a function of the number of ASCs opened between 2004, the last year in the original sample, and 2012, the first year included in this sample. The mean number of ASCs within 3.83 miles of a hospital was 4.93, compared to 2.225 in the original study; however, the median in the replication sample was 3 ASCs, closer to the mean of the original study. Hospitals in this sample are also smaller than the original sample, with fewer other hospitals within their market and lower HHIs. Counties included in this sample also have a higher percentage of people living below the poverty line and higher uninsured rates than the nationwide sample used in Plotzke & Courtemanche (2010).

Table 14. Results of OLS Regression on Outpatient Surgical Volume
n = 625 facility-years

	Coefficient	**Robust p-Value**
ASCs within 5 miles	-0.08	0.102
ASCs between 5 and 10 miles	-0.01	0.832
ASCs between 10 and 20 miles	0.00	0.964
Small bed size	0.18	0.226
Ownership – not-for-profit	-0.20	0.338
Ownership – for-profit	-0.11	0.668
Teaching status	-0.11	0.156
Hospital outpatient department	0.03	0.672
Number of operating rooms	0.01	0.147
Number of privileged physicians	0.00	0.065
HHI - 5 miles	**-0.13**	**0.015**
Number of hospitals within 5 miles	0.04	0.417
Percent eligible for Medicare	**0.01**	**0.000**
Total population (100,000)	**1.53**	**0.000**
Percent uninsured	**0.01**	**0.000**
Percent unemployed	0.00	0.978
Log of median household income	**7.33**	**0.015**
Percent below poverty line	-0.00	0.984
Year – 2013	0.13	0.099
Year – 2014	0.13	0.146

[a] Robust standard errors used to mitigate heteroscedasticity.
[b] Facility fixed effects included in this regression but omitted for brevity.

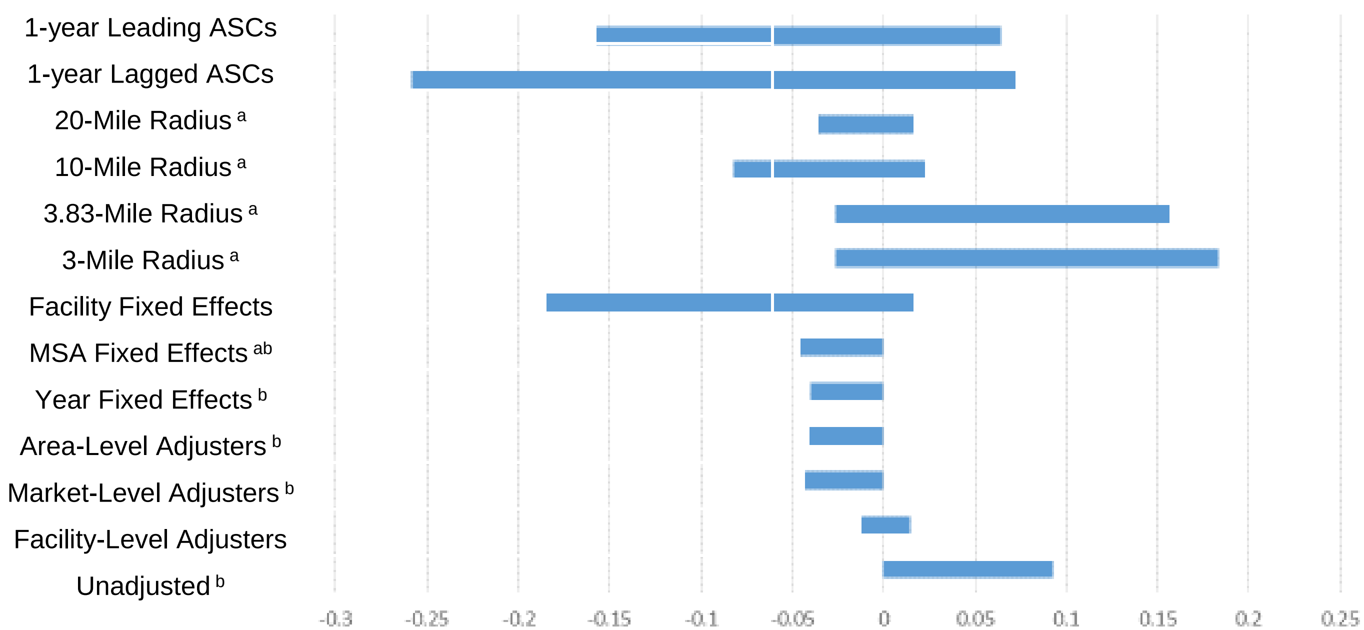
Table 14 presents full regression results for the outpatient operations model. Both model coefficients and statistical significance differed from the original study for independent and adjusting variables. The coefficient on ASC penetration is negative, consistent with the original study, but it is not statistically significant. Additionally, no facility-level adjusting variables were significant at 5%. However, the original sample is more than 20 times larger than our sample, as it contains five years of nationwide data rather than three years of Texas data, so the difference in significance could be a function of sample size.

The sign and magnitude of the coefficient on ASC penetration is somewhat similar to the original study: -0.08 in our sample vs. -0.03 in the original sample. It should be noted, though, that the market radii is not directly comparable in the two studies. The original study used a fixed market radius of 3.83 miles, while this replication used a radius of 5 miles. We used this radius as a starting point for our analysis; however, this radius yielded some unexpected results.

Using a 3.83-mile radius definition, increasing ASC penetration was associated with an *increase* in outpatient volume although this was not statistically significant (p=0.102). One additional ASC within 3.83 miles was associated with an increase in outpatient volumes equal to 7.93% at the mean number of outpatient operations in the sample. However, the number of ASCs within 3.83 exhibited non-linearity in this model, so as a further sensitivity test, the number of ASCs within 3.83 miles was categorized based on natural breaks in the data: the base category had no ASCs within 3.83 miles, the second category had between one and three ASCs within market, and the third category contained facilities with four or more ASCs within market. When the categorized variable was included in the regression, the resulting coefficients were even more positive. In fact, hospitals with between one and three ASCs within 3.83 miles are associated with a statistically significant increase in outpatient volume (13.36% at the mean, p=0.004).

Per Figure 5, which presents results of sensitivity analyses across different definitions of a hospital's market, with radii less than five miles, the extent of ASC penetration was associated with an increase in hospital-based outpatient surgical volume. At five miles or greater, however, an increase in ASC penetration was associated with a decrease in the number of hospital-based outpatient operations, as expected based on prior studies. Sensitivity analysis for other dependent variables, shown in Appendix F, shows that, consistent with our expectation, ASC penetration had very little effect on the number of inpatient operations and almost no effect on inpatient revenues. The effect of ASC penetration on outpatient revenues was also small and insignificant.

Figure 5. Results of Sensitivity Tests on Outpatient Volume OLS Regression



The x-axis of each figure represents the untransformed regression coefficients of the regressions on the outcome variable specified in the figure. The y-axis identifies the sensitivity test results presented directly to the right. The "base case" used for analysis is the model titled "Facility Fixed Effects." Each bar is a 95% confidence interval for that variable.

[a] Models are additive, with the exception of MSA fixed effects and measures of market radii. The sample size is inadequate to include both MSA and facility fixed effects, and facility fixed effects yield better fitting models based on AIC.

[b] ASC penetration significant at 5%.

Discussion

On the whole, these findings indicate that ASC penetration does not have a statistically significant effect on inpatient or outpatient volumes or revenues detectable in a sample of this size. However, the magnitude and direction of the effect of ASC penetration are similar to those found in prior studies (9, 11).

These results demonstrate that, as predicted by the literature coming out in the late 2000s, the number of ASCs in metropolitan areas has increased, at least in Texas. This increase is in part a function of the trend moving surgeries from inpatient to outpatient settings (5). This increase could also reflect an increase in population or in the "size of the pie" with the advent and implementation of the Patient Protection and Affordable Care Act (PPACA). As more patients are insured, the pool of potential patients becomes larger, particularly for elective outpatient surgeries. To our knowledge, the effect of insurance expansion on surgical volumes has not been explicitly tested (97). Although these results do not speak directly to this question, coefficients on the 2013 and 2014 year fixed effects (0.04 and 0.05, respectively) are both positive but insignificant at 5%.

An interesting finding from this study is that increasing ASC penetration is associated with a counterintuitive but statistically insignificant increase in the number of outpatient operations within a small radius (three miles and 3.83 miles), while associated with an expected decrease in the number of outpatient operations within a larger radius (five miles and larger). This relationship holds to a lesser degree for inpatient operations as well. The small-radius findings differ from the original study and other nationwide studies from the early 2000s, which found a significant but smaller negative effect of ASC penetration on the number of outpatient operations, even using the same or similar market radii (9, 11).

This result could be completely spurious, or it could be explained by an unidentified phenomenon, such as a “medical center” effect that is present in Texas but not in all states across the nation. Outpatient volumes could be higher in hospitals with a high number of ASCs nearby (within 3.83 miles) because these areas that are “destinations” for surgical patients from other areas. As the radius expands to five miles, the “medical center” effect dissipates, instead representing a higher degree of competition without the “destination” status, resulting in decreased outpatient volumes. Houston, Texas is an internationally recognized medical center and a destination for surgical patients, so it could be driving this “medical center” effect (101, 102). However, when Houston hospitals were eliminated from the sample, the coefficient on ASC penetration at 3.83 and 3 miles were smaller in magnitude and insignificant, but still positive.

An alternative explanation to the “medical center” effect would be that the five-mile radius is simply more meaningful in Texas as compared to the nationwide sample used to develop the 3.83-mile radius in Plotzke & Courtemanche (2010), although the 3.83-mile radius model fit the data better (AIC 69.93 vs. 114.36). The regressions on inpatient volumes also favor the use of a five-mile radius; the effect of the number of ASCs is very close to zero for all models other than the five-mile radius model.

Overall, however, ASC penetration did not significantly affect volumes or revenues in any of our final model specifications. A power analysis assuming 80% power indicated that this sample should be able to detect an 11% effect size at a significance level of 5%; the original study by Plotzke and Courtemanche with a much larger sample would be able to detect an effect size of approximately 2.5%. These power analyses indicate that if ASC penetration does effect volumes or revenues, the effect size is likely less than 11%.

The fact that sensitivity analysis indicates that most of the coefficients on ASC penetration are very close to zero in all regressions provides further evidence that any effect of ASC penetration on volumes and particularly on revenues is small. Despite the fact that previously published evidence shows that ASCs may "cherry pick" the more profitable procedures and patients, these findings demonstrate that this effect may not be large enough to affect overall revenues or profitability. However, larger studies have found a downward trend in revenues associated with ASC penetration, so further analysis with a larger, more robust nationwide sample is warranted (35).

Limitations

The findings in this paper are subject to a number of limitations. Because the sample differs temporally and geographically from that in Plotzke and Courtemanche (2010), results are not directly comparable. This sample is limited to Texas and may not generalize to other states or outside the United States. Inpatient and outpatient volumes and most of the facility characteristics are taken from the AHA annual survey, which is self-reported and subject to biases and inaccuracies. Surgical volumes and revenues are both highly complex phenomena; important variables could be omitted which could produce biased estimates, although the suite of adjusting variables employed here are consistent with the original paper and other literature on hospital revenues and volumes (9, 19). This analysis did not examine the effect of ASC entry or a first-mover ASC effect due to the limited sample size; findings related to ASC penetration may not hold for these phenomena.

Conclusions

Key implications from these results are twofold. First, the degree of ASC penetration does not appear to have a large effect on nearby hospital volumes or revenues. However, these findings do provide evidence confirming the proliferation of ASCs predicted in previous years, and suggests the possibility of a “medical center” effect on hospital surgical volumes, where facilities in highly concentrated medical centers actually generate increased volume relative to their counterparts in non-medical center urban areas, despite the increased competition, due to the draw of the medical center as a destination for surgical procedures. Both of these findings may merit examination in larger, more broadly representative samples.

CHAPTER V

SUMMARY AND CONCLUSIONS

Summary of Findings

Results from Chapter II, exploring the sources of variation in case duration within and across facilities, anesthesia practices, and anesthesia providers, demonstrate that the time a patient is in surgery is a highly idiosyncratic phenomenon. Facility type, teaching status, and facility region all affect case duration, but above and beyond these variables, significant variation in case duration persists at the anesthesia practice and hospital level. The hospital-level findings are unsurprising, but the unexplained variation at the anesthesia practice level is less established in the literature. This result could be a function of the omitted surgeon level. Further research including this data is needed.

Chapter III illustrates that there are four distinct "surgical signatures" for general acute care hospitals that are consistent over time, answering the first research question of the study: OB-related general hospitals; cardiovascular/musculoskeletal-related general hospitals; musculoskeletal-focused hospitals; and digestive-focused hospitals. Small, rural health services areas generally have one or two facilities from one of the two general categories; larger rural areas sometimes host "magnet" digestive-focused hospitals; cardiovascular/musculoskeletal facilities are often teaching hospitals located in more urban areas; and musculoskeletal-focused facilities appear to be similar to specialty hospitals, with a large number of outpatient procedures and an urban location.

After adjusting for other facility- and area-level adjusters, profitability did not differ across clusters, providing no evidence for the first hypothesis of the study. Surgical volume, not surgical case mix, had the greatest effect on profitability; more surgeries were associated with more profit, consistent with prior findings in rural hospitals and confirming the second hypothesis of the study (20, 21).

Chapter IV examined the association between ASC penetration and changes in surgical volume and revenues at nearby hospitals and found no significant effect, providing no evidence to support either of the two hypotheses posited in the study.This may be partially a result of an underpowered sample. The findings pertaining to revenues are an interesting complement to previous evidence showing that ASCs "cherry pick" profitable procedures; while this is probably occurring given the extent to which it is documented in the literature, it may not be frequent or large enough to affect hospital revenues in aggregate. Another interesting finding of this chapter is that the direction of the effect of ASC penetration within a small market radius is positive, not negative as expected; higher ASC penetration is associated within increased volume, although this increase is not significant at 5% (p=0.102). This may be a spurious result, or it could be the result of a "medical center" phenomenon present in Texas as a result of the high number of cities with "destination" medical centers for surgical procedures. Hospitals near many ASCs are likely located in medical centers, and these medical centers may draw disproportionately large numbers of surgical patients, generating higher surgical volumes despite competition from ASCs.

Implications for Management and Policymakers

Improved Management of Case Duration

In the predominant mentality, anesthesia practices do not have much effect on overall case duration or time in surgery. However, if anesthesia practices do differ in case duration, as implied in this study, some anesthesia practices keep patients under anesthesia for longer than other practices. Although this study does not quantify the extent of that difference, it does challenge the opinion that anesthesia is a fixed component of a surgical episode and implies that reductions in case duration, which may benefit both the patient outcomes and hospital efficiency, could be generated by identifying and implementing best practices from anesthesia practices with shorter case durations.

This study also reinforces previous research identifying regional variation in surgery provision (58, 70, 103), and echoes the calls made in those studies for an improved understanding of *why* surgeries take longer in some regions than others. If case duration has detrimental long-term outcomes for patients, particularly elderly patients, then significant regional variation should not be acceptable (26-28). More research should be conducted and policies implemented to identify and address the sources of regional variation.

Improved Payment Policy and Management Strategies for Profitability

The identification of the four unique surgical clusters is one of this dissertation's key contribution to the literature, and understanding these clusters may also have implications for managers and policymakers. The literature linking procedure-specific volume and higher quality of care imply that procedure specialization is not a bad thing (104); implementing policies that try to "level the playing" field for facilities of different types or management practices intended to grow new surgical lines may have detrimental effects on the quality of care and patient safety, and this study provides evidence that these strategies may not have the intended effect on profitability. If changing an entire surgical profile doesn't significantly increase profitability, adding a surgical line possibly does not either. However, because higher surgery volume is associated with higher profitability, maximizing the number of surgeries conducted within a hospital's existing surgical offerings may be a good strategy to maximize profitability.

Informing Future ASC Policy

Payment reform for ASCs was implemented in 2008 that reduced reimbursement for ASCs to 65% of reimbursement for a similar procedure to nearby hospitals, with the goal of reducing "cherry picking" of profitable patients by ASCs and allowing hospitals to compete with ASCs for lucrative outpatient procedures. These findings provide evidence that this policy may be working; ASC penetration does not significantly affect the revenues of nearby hospitals in a post-2008 sample. The relationship between ASC penetration and volumes was not as straightforward in this sample; future research is needed to understand if the surprising effect of ASC penetration within a small market radius on nearby hospital surgical volumes was spurious or the result of a previously unidentified phenomenon such as the “medical center” effect described in the discussion of Chapter IV. This explanation may be of interest to management of medical center hospitals and could also have policy and reimbursement ramifications.

Avenues for Future Research

Research investigating the sources of differences on case duration across anesthesia practices and quantification of these differences is necessary before best practices can be identified and disseminated to other anesthesia practices to reduce case duration and improve outcomes and efficiency. The cluster analysis conducted in Chapter III should be replicated in samples from other states to ascertain whether cluster delineations differ in other regions of the United States, and the profitability analysis should be conducted using an approach that can handle the endogeneity of surgical cluster membership to profitability.

More research is needed to understand the link between surgical volume and profitability to properly inform payment policy and policies intended to maintain outpatient surgery volumes at general acute care hospitals. The effect of ASC penetration on volumes and revenues should be replicated on a larger sample covering other regions of the United States to better understand the magnitude and significance of the effect of ASC penetration on volumes, and in particular to provide a context for the surprising increase in hospital volumes associated with nearby ASC penetration documented in Chapter IV.

Conclusion

Surgery is an integral part of hospital-based health care in the United States, for both the patients undergoing surgery and the delivery systems providing surgery. This dissertation explores the relationship between case duration, surgical volumes, hospital profitability, and outside influences on volumes and profitability using observational study design methods and secondary data sources. Hospitals differ in mean surgical case duration; case duration affects the volume of surgeries conducted at a given hospital; and surgical volume affects a hospital profitability, which may in turn be affected by volumes at nearby facilities. These relationships have implications for both payment policy and hospital management strategies.

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APPENDIX A

CPT CODES USED TO PULL PROCEDURE SUBSAMPLES

CABG CPT Codes
33510
33511
33513
33514
33516
33517
33518
33519
33521
33522

TKA CPT Codes
27440
27441
27442
27443
27444
27445
27446
27447
27486
27487

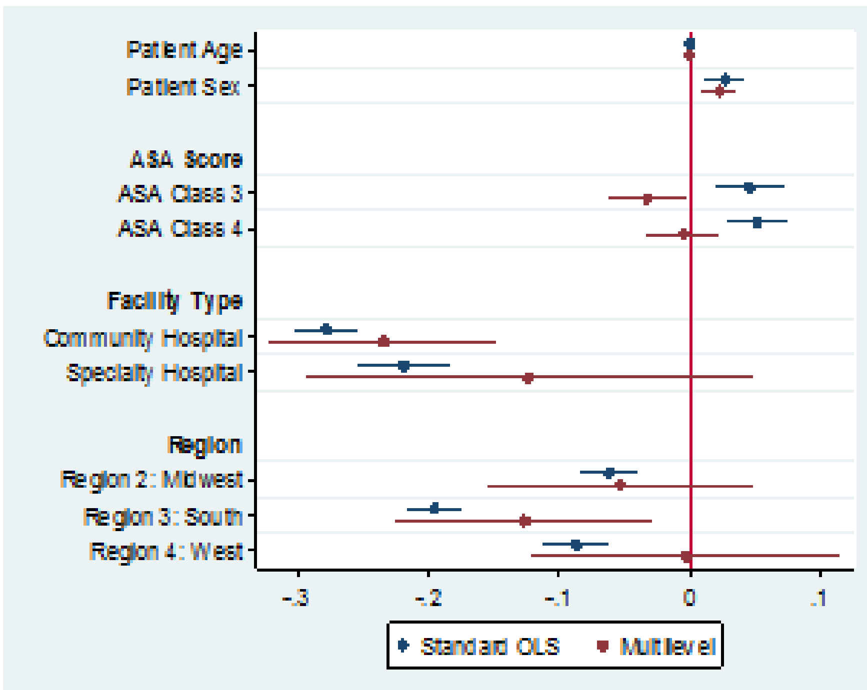
Cholecystectomy CPT Codes
47562
47563
47564
47600
47605
47610

APPENDIX B

CONFIDENCE INTERVALS FOR OLS AND MULTILEVEL REGRESSION

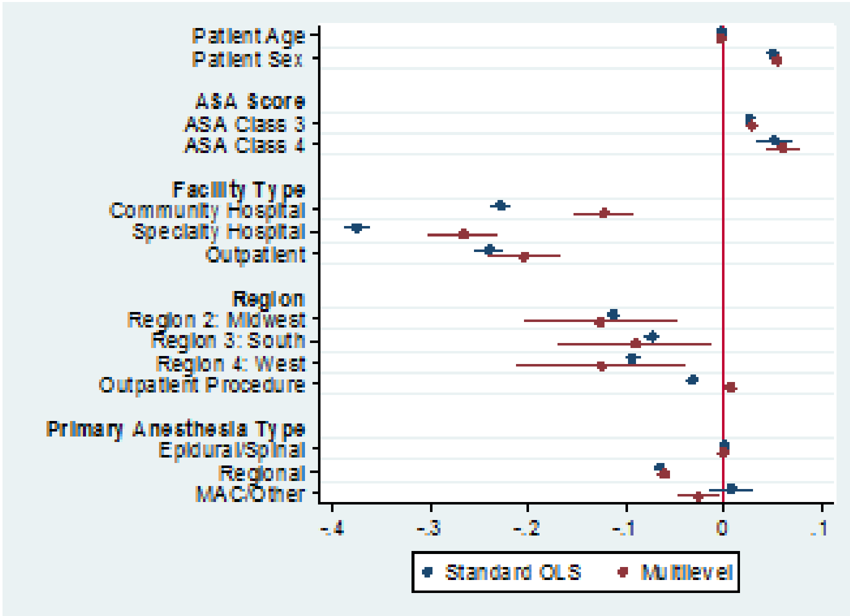
The following figures compare 95% confidence intervals for OLS and multilevel regression coefficients in each of the three procedure subsamples examined in Chapter II. In interpreting these figures, it is important to note that confidence intervals for multilevel regression will be larger than standard OLS even in the same sample with the same number of observations. When assumptions of independence are violated, standard errors tend to be too small, and smaller standard errors generate more narrow confidence intervals (53).

CABG



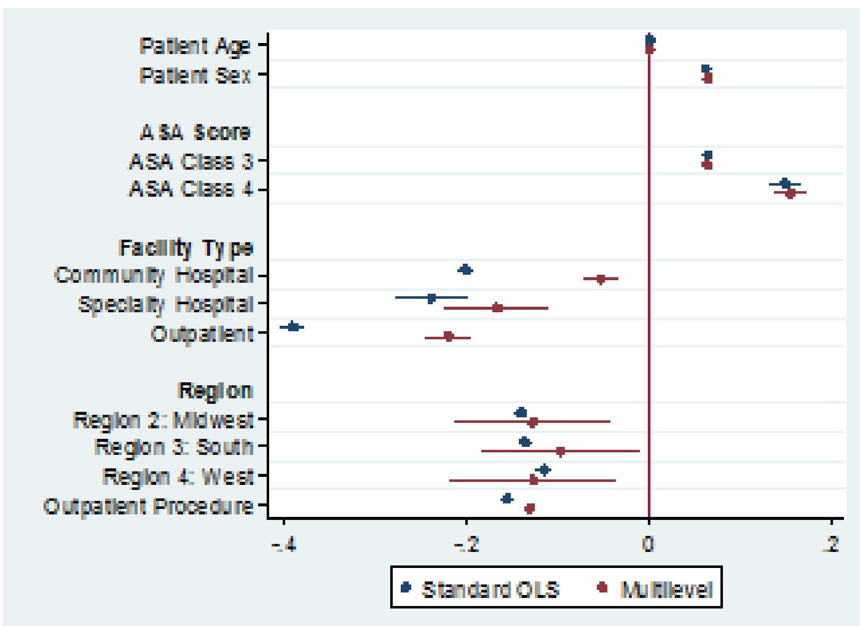
The range of the x-axis in minutes is -25.92 to 10.52.

TKA



The range of the x-axis in minutes is -32.97 to 10.52.

Cholecystectomy



The range of the x-axis in minutes is -32.97 to 22.14.

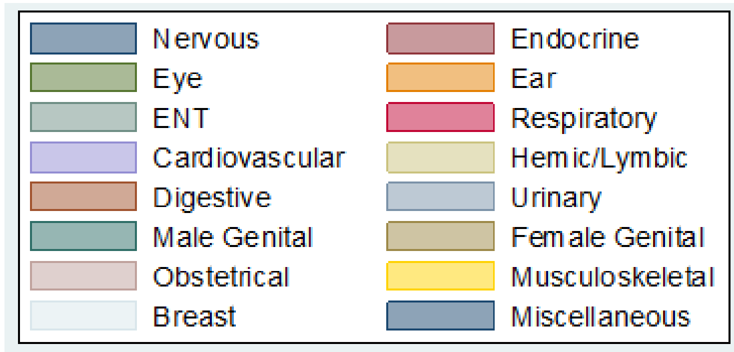
APPENDIX C

LIST OF CLINICAL CLASSIFICATION SYSTEM PROCEDURE CATEGORIES

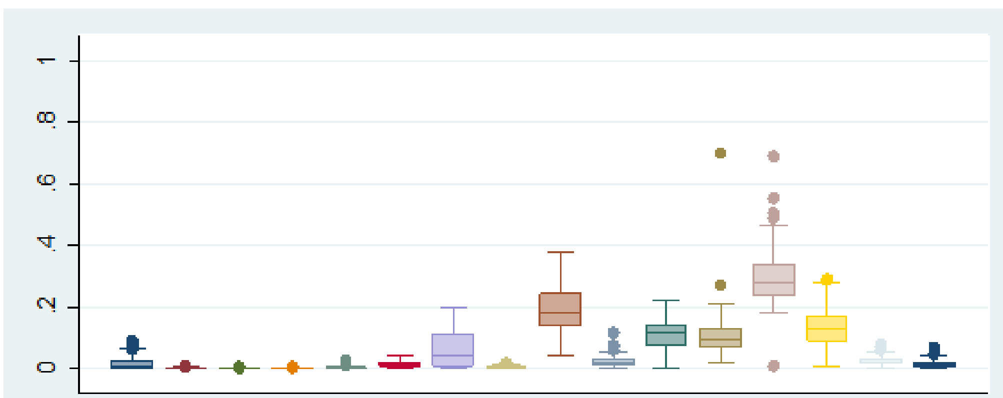
CCS Category	**Category Name**
1	Operations on the nervous system
2	Operations on the endocrine system
3	Operations on the eye
4	Operations on the ear
5	Operations on the nose; mouth; and pharynx
6	Operations on the respiratory system
7	Operations on the cardiovascular system
8	Operations on the hemic and lymphatic system
9	Operations on the digestive system
10	Operations on the urinary system
11	Operations on the male genital organs
12	Operations on the female genital organs
13	Obstetrical procedures
14	Operations on the musculoskeletal system
15	Operations on the integumentary system
16	Miscellaneous diagnostic and therapeutic procedures

APPENDIX D

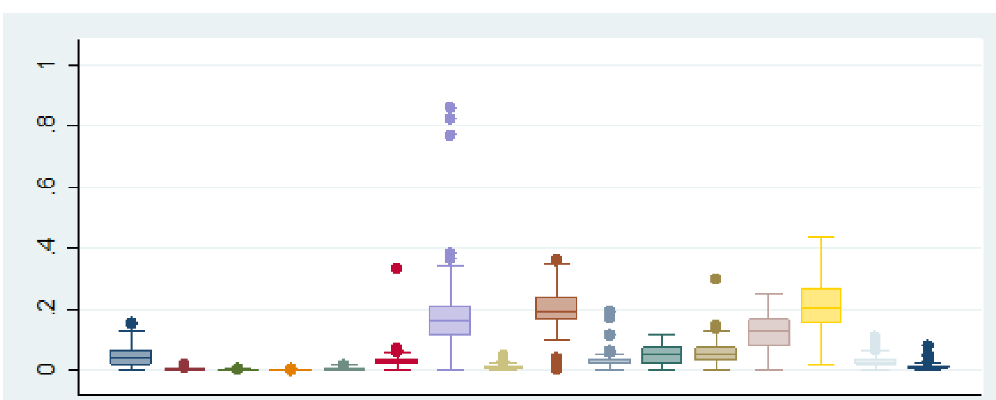
CCS PERCENTAGE DISTRIBUTIONS ACROSS CLUSTERS, 2012



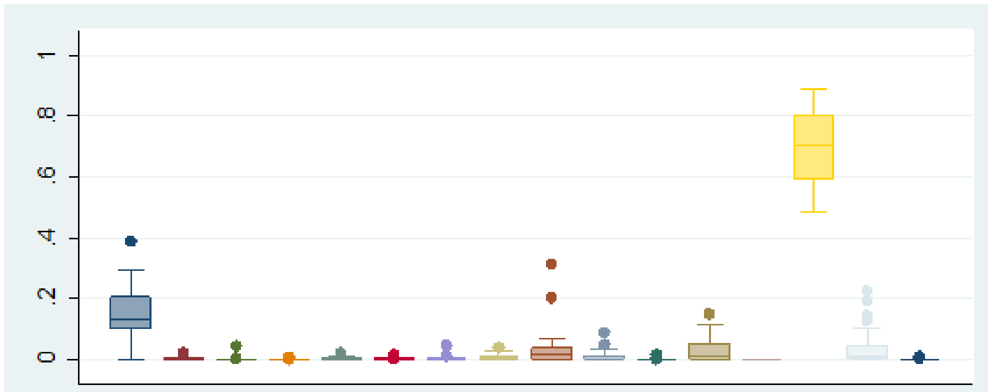
OB/General Cluster



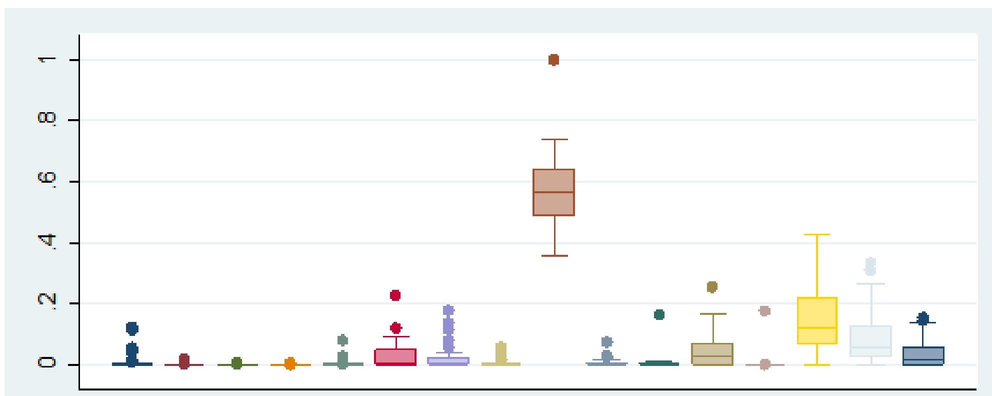
Cardiovascular/Musculoskeletal General Cluster



Musculoskeletal-Focused Cluster



Digestive-Focused Cluster



APPENDIX E

EXPLORATION OF ENDOGENEITY OF CLLUSTER MEMBERSHIP

OB/General Cluster

```
Logistic regression                               Number of obs   =        266
                                                  LR chi2(8)      =      54.27
                                                  Prob > chi2     =     0.0000
Log likelihood = -153.24548                       Pseudo R2       =     0.1504
```

clus_obgen	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
private	-.7049737	.2974502	-2.37	0.018	-1.287965	-.1219821
_system	-1.015764	.4352922	-2.33	0.020	-1.868921	-.1626071
bed_small	-1.051186	.3541461	-2.97	0.003	-1.7453	-.3570725
teaching_ind	-1.499172	.6251906	-2.40	0.016	-2.724524	-.2738213
log_fac_mean_LOS2	-2.242136	.5095427	-4.40	0.000	-3.240822	-1.243451
log_hsa_pct_rural	-.8922988	.4833997	-1.85	0.065	-1.839745	.0551472
log_hsa_pct_elig_medicare	-1.093492	1.037219	-1.05	0.292	-3.126404	.9394195
log_hsa_pct_pov_11	.4537511	.6138211	0.74	0.460	-.7493162	1.656818
_cons	2.13261	1.959443	1.09	0.276	-1.707828	5.973047

Cardiovascular/Musculoskeletal Cluster

```
Logistic regression                               Number of obs   =        266
                                                  LR chi2(8)      =      99.40
                                                  Prob > chi2     =     0.0000
Log likelihood = -125.88857                       Pseudo R2       =     0.2830
```

clus_cardmusc	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
private	.4549812	.3289131	1.38	0.167	-.1896766	1.099639
_system	.0506997	.5057341	0.10	0.920	-.9405209	1.04192
bed_small	-1.236648	.3608031	-3.43	0.001	-1.943809	-.5294867
teaching_ind	1.416463	.6058201	2.34	0.019	.2290774	2.603848
log_fac_mean_LOS2	2.314813	.5547132	4.17	0.000	1.227595	3.40203
log_hsa_pct_rural	1.21453	.5637958	2.15	0.031	.1095103	2.319549
log_hsa_pct_elig_medicare	1.255021	1.134299	1.11	0.269	-.9681646	3.478206
log_hsa_pct_pov_11	-1.063885	.7208892	-1.48	0.140	-2.476802	.3490314
_cons	-2.679	2.147882	-1.25	0.212	-6.888771	1.530771

Musculoskeletal Cluster

```
Logistic regression                               Number of obs   =        120
                                                  LR chi2(6)      =      44.89
                                                  Prob > chi2     =     0.0000
Log likelihood = -34.723756                       Pseudo R2       =     0.3926
```

clus_musc	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
private	2.829254	1.144519	2.47	0.013	.5860379	5.07247
system	1.165814	.6627723	1.76	0.079	-.133196	2.464824
bed_small	0	(omitted)				
teaching_ind	0	(omitted)				
log_fac_mean_LOS2	-3.013878	1.090655	-2.76	0.006	-5.151522	-.876234
log_hsa_pct_rural	.4401177	1.299272	0.34	0.735	-2.106409	2.986645
log_hsa_pct_elig_medicare	.3622087	2.672816	0.14	0.892	-4.876414	5.600832
log_hsa_pct_pov_11	1.07417	1.555215	0.69	0.490	-1.973995	4.122336
_cons	2.203486	4.856159	0.45	0.650	-7.31441	11.72138

Teaching and small bed size omitted because they predicted failure perfectly.

Digestive Cluster

```
Logistic regression                               Number of obs   =        266
                                                  LR chi2(8)      =      66.64
                                                  Prob > chi2     =     0.0000
Log likelihood = -66.414321                       Pseudo R2       =     0.3341
```

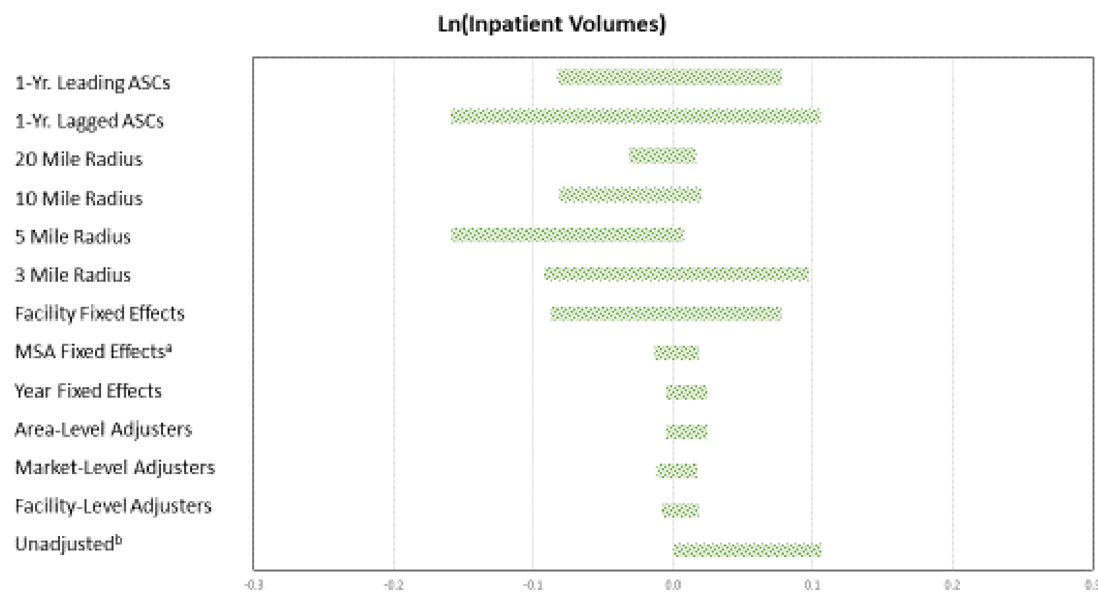
clus_dig	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
private	-.2238565	.4828658	-0.46	0.643	-1.170256	.7225431
_system	.0281944	.5853378	0.05	0.962	-1.119047	1.175435
bed_small	4.355414	.9063042	4.81	0.000	2.57909	6.131737
teaching_ind	-.1652547	1.290182	-0.13	0.898	-2.693964	2.363455
log_fac_mean_LOS2	2.599805	.6680686	3.89	0.000	1.290414	3.909195
log_hsa_pct_rural	-.0184768	.966889	-0.02	0.985	-1.913544	1.876591
log_hsa_pct_elig_medicare	1.18128	1.813159	0.65	0.515	-2.372448	4.735007
log_hsa_pct_pov_11	.9544405	1.057967	0.90	0.367	-1.119137	3.028018
_cons	-4.99843	3.151751	-1.59	0.113	-11.17575	1.178888

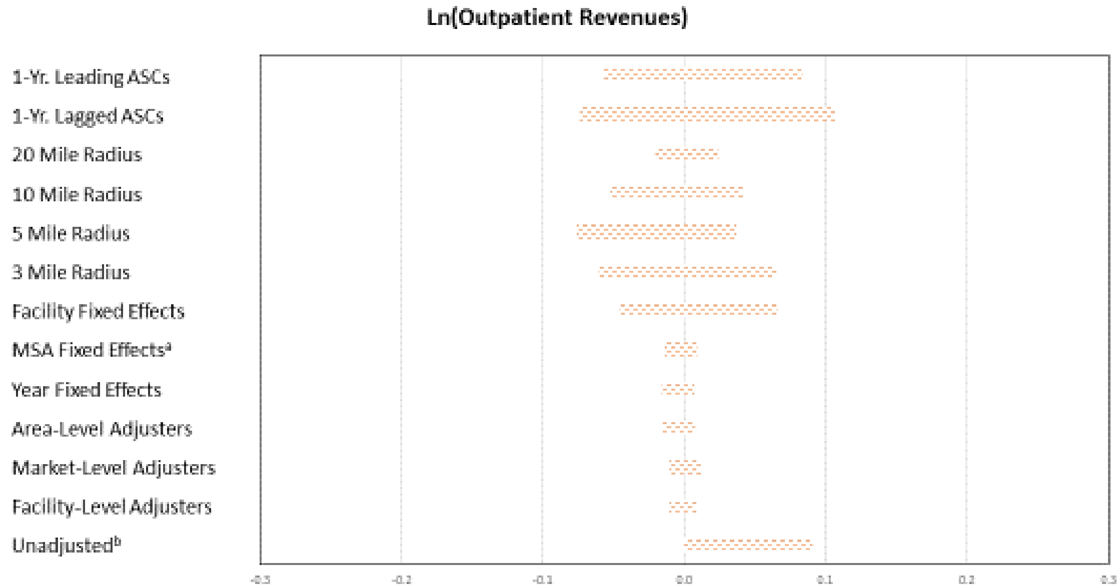
APPENDIX F

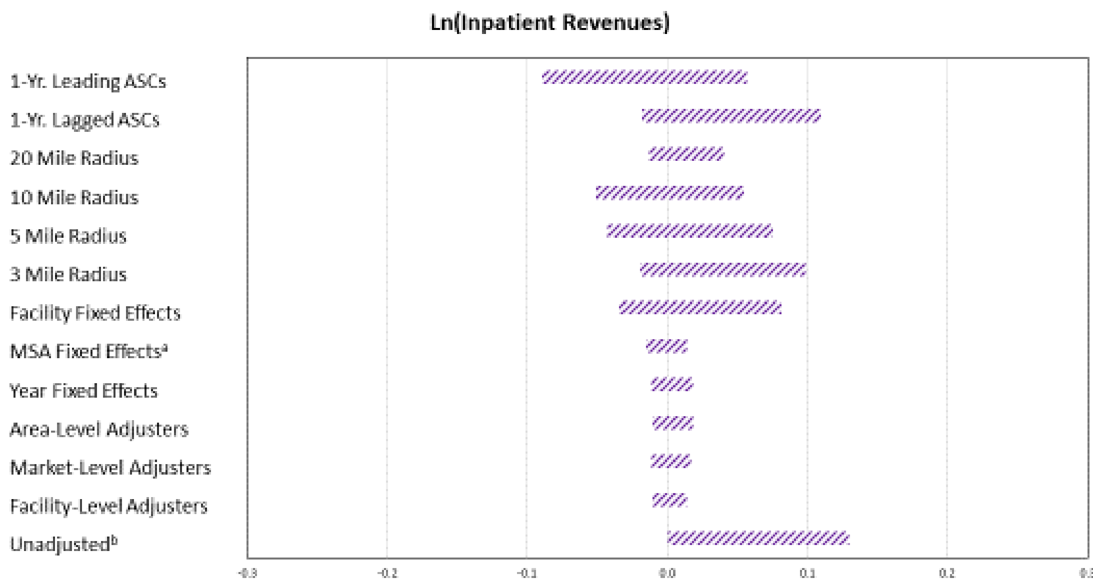
RESULTS OF SENSITIVITY TESTS ON INPATIENT VOLUMES, INPATIENT REVENUES, AN OUTPATIENT REVENUES

The x-axis of each figure represents the untransformed regression coefficients of the regressions on the outcome variable specified on the figure. The y-axis represents the identifies the sensitivity test results presented directly to the right. The "base case" used for analysis is the model titled "Facility Fixed Effects."

Models are additive, with the exception of MSA fixed effects and differing market radii models. The sample size is inadequate to include both MSA and facility fixed effects, and facility fixed effects yield better fitting models based on AIC. Only "Unadjusted" models are significant at a significance level of 5%.




Ln(Outpatient Revenues)
1-Yr. Leading ASCs
1-Yr. Lagged ASCs
20 Mile Radius
10 Mile Radius
5 Mile Radius
3 Mile Radius
Facility Fixed Effects
MSA Fixed Effects[a]
Year Fixed Effects
Area-Level Adjusters
Market-Level Adjusters
Facility-Level Adjusters
Unadjusted[b]
-0.3
-0.2
-0.1
0.0
0.1
0.2
0.3


Ln(Inpatient Revenues)
1-Yr. Leading ASCs
1-Yr. Lagged ASCs
20 Mile Radius
10 Mile Radius
5 Mile Radius
3 Mile Radius
Facility Fixed Effects
MSA Fixed Effects[a]
Year Fixed Effects
Area-Level Adjusters
Market-Level Adjusters
Facility-Level Adjusters
Unadjusted[b]
-0.3
-0.2
-0.1
0.0
0.1
0.2
0.3