Entry Decisions and Incumbents' Responses: Evidence from the Outpatient Surgery Market*

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Abstract

This paper examines the impact of competition on access to care, patients' welfare and hospitals' quality in the outpatient surgery market when prices are regulated. To do that, I exploit a Medicare reimbursement change for a major type of surgery provider, ambulatory surgery centers (ASCs). The new reimbursement rates change the likelihood of ASCs performing different surgeries and also lead to exogenous variations in the level of competition across surgeries. The resulting incentives for the other type of provider, hospitals, to invest in quality change differentially based on the level of competition they face. Threatened by potential ASC entrants, each incumbent hospital commits a fixed investment toward quality, which increases its revenue through both the channel of direct competition and the channel of entry deterrence. The latter is more salient in markets facing a median level of entry threat.

To estimate the model, I use the outpatient discharge and facility certificate data from Florida for 2006 and 2008 and employ a Markov chain Monte Carlo (MCMC) method. The results suggest that, on average, a one-standard-deviation increase in the reimbursement rate ($18.2) leads to a 12.5 percent increase in the entry probability of an ASC, which intensifies competition. Hospitals respond by spending $2,551 more annually on quality. The effect of entry deterrence explains 47 percent of the increase, which demonstrates how ignoring strategic entry-deterrence investments may lead to an underestimation of the effect of competition induced by the reimbursement change. Patients benefit from the intensified competition by having more surgery-location choices and receiving care of higher quality. Counterfactual analyses are conducted to evaluate the impact of policy changes on welfare, accounting for ASCs' endogenous entry decisions, which change the market structure and level of competition.

JEL Codes: I11, I18, L11, L51
Key Words: Outpatient Surgery Market, Access to Care, Entry Deterrence, Patient Welfare, MCMC Estimation

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1 Introduction

Increasing market competition to achieve better clinical outcomes is often the goal of health care reform in the United States. When prices are highly regulated in the health care market, facilities engage in non-price competition such as quality levels. Some previous studies provide evidence that competition among health care providers under regulated prices induces better clinical outcomes for inpatient care (Cooper et al., 2011; Gaynor and Town, 2011; Kessler and McClellan, 2000). However, despite the fact that outpatient surgery has grown in popularity in the past 30 years and has become the key profit generator for hospitals, scarce information exists on the impact of competition in the outpatient surgery market.[1] In this paper, I provide evidence of the impact of competition on hospitals' surgery outcomes, cost of investing in quality level and patients' welfare. To do that, I exploit a payment schedule change in the outpatient surgery market that leads to exogenous changes in the level of competition.

Outpatient surgery is surgery that does not require an overnight hospital stay. Hospital outpatient departments[2] and ambulatory surgery centers (ASCs) are the major providers in the outpatient surgery market. Compared with the traditional hospitals, which provide a wide range of services, ASCs are smaller and specialize in providing a selected number of outpatient procedures. To prove its quality and safety level to the public, an ASC can join and be evaluated by one of the accreditation programs.[3]

ASCs became increasingly popular facility choices for outpatient surgeries. The number of Medicare-certified ASCs in the U.S. rose from 400 in 1983 to 5316 in 2010. The percentage of outpatient surgeries performed by ASCs rose from 10 percent in 1983 to 47 percent in 2010.[4] The rapid growth in the number of ASCs provides patients better access to the outpatient surgery

[1]Improved technology and advances in anesthesia have allowed more surgical procedures to be performed as outpatient surgeries. According to Hall et al. (2017), in 1980, 20 percent of all surgeries performed in the U.S were outpatient surgeries. This number grew to more than 70 percent by 2010. In 2010, gross revenue from outpatient procedures totaled $887.4 billion, which was up 10.5 percent from 2009.

[2]In the rest of the paper, I use hospital and hospital outpatient department interchangeably.

[3]Accreditation associations offer accreditation programs that assess whether an ASC's policies and procedures hold to a certain quality and safety standard. The leading accreditation associations in the U.S. include the Accreditation Association for Ambulatory Health Care (AAAHC) and The American Association for Accreditation of Ambulatory Surgery Facilities, Inc. (AAAASF).

[4]All the historical numbers cited in this paragraph are from Hall et al. (2017).

market and generates significant competition against the hospitals. Carey et al. (2011) and Courtemanche and Plotzke (2010) found downward pressure on hospitals' outpatient volume, revenues, costs, and profits associated with the presence of the ASCs in the market. In this paper, I exploit the Medicare outpatient facility fee change for ASCs in 2008 across five surgery categories to study the impact of competition on hospitals' surgery quality levels. Specifically, I study how each ASC makes its entry decision for each surgery market, and how each hospital chooses a quality level to compete with ASCs and possibly deter ASCs from entering the market.

In 2008, the Centers for Medicare and Medicaid Services (CMS) implemented a new payment system which significantly changed how much Medicare paid ASCs for each outpatient surgery. As a result of this payment schedule change, there was substantial variation in the change of profitability across different procedures performed in ASCs.[5] In general, high-acuity procedures, which required advanced technologies and equipment, became more profitable, while low-acuity and traditionally high-volume procedures became less profitable for ASCs. The payment schedule change provided exogenous variation in ASCs' incentive for performing different surgeries over time and across procedures. The payment change encouraged ASCs to invest in their equipment and enter the surgery market that became more profitable. However, hospitals could respond to the emerging competition from ASCs in high-end outpatient surgery markets by investing in surgical quality to retain patients and to deter entry.

To properly evaluate the impact of the payment change on the surgery volume and surgery quality, I build a two-stage static equilibrium model that takes both hospitals' and ASCs' responses into account.

On the demand side, I assume a patient and her surgeon act as an agent. Each agent decides whether to have a surgery and in which facility to have a surgery. The agent's utility from having a surgery in a facility depends on her own observed characteristics, traveling distance to the facility, and facility-surgery-specific quality levels.

On the supply side, I analyze a two-stage game for hospitals and ASCs in the outpatient surgery market. In the first stage, each hospital decides its quality level for each surgery category,

[5] See Background and Data section (section 2) for details.

while accounting for other hospitals' choices as well as its impact on ASCs' entry decisions. In the second stage, each ASC observes all hospitals' choices and determines whether to enter the market based on its expected profits, conditional on rational beliefs about other ASCs entry probabilities.

An important feature of this model is that increasing surgery quality level in each hospital can affect its profit through two different channels. First, it increases each patient's utility from choosing a hospital conditional on ASCs' entry decisions, hence increasing demand (effect of direct competition). Second, it can potentially deter ASCs from entering the market (effect of entry deterrence), which results in a higher demand for the hospital and stronger bargaining power against insurance companies, allowing the hospital to enjoy a higher markup.

Facilities' surgery quality levels cannot be observed directly by econometricians. I construct a surgery-specific quality level for each hospital in each year based on the 14-day readmitted rate after receiving an outpatient surgery. The quality measurement is adjusted for the observed characteristics and the unobserved severity of illness of the patients treated in the facility.

To estimate the model, I use outpatient discharge data and facility certificate data from Florida in 2006 and 2008. I focus on five categories of surgeries: knee arthroscopy surgery, breast lesion removal surgery, tonsil and adenoid removal surgery, retina surgery, and hernia repair.

I adopt a Bayesian Markov Chain Monte Carlo approach to estimate my model. My estimates show that a higher Medicare reimbursement rate for ASCs can encourage ASCs to enter the market. Averaged across all ASCs, a one-standard-deviation ($18.17 dollar) increase in the Medicare reimbursement rate for ASCs increases an ASC's entry probability by 2.01 percentage points. Given the average entry probability of 16.04 percent, a one-standard-deviation increase in the Medicare reimbursement rate results in a 12.5 percent increase in the average entry probability. The average elasticity of entry probabilities with respect to the Medicare reimbursement rate is 0.26. Meanwhile, hospitals invest in surgery quality levels to compete with ASCs. Averaged across hospitals, a one-tenth-standard-deviation increase in the hospital's surgery quality level leads to 5 more patients for a surgery in a year. The effect of entry deterrence explains 47 percent of the increase, and the effect of direct competition explains 53 percent of the increase in quantity. Averaged across facilities, a hospital pays $1,315 dollars to increase its surgery quality level by a one-tenth-standard-deviation. Averaged across all hospitals, a one-standard-deviation increase in ASCs' reimbursement rate results in a 0.17-standard-deviation increase in hospital's optimal quality level, or equivalently, a $2,551 increase in its surgery quality level.

Using the estimates from the model, I conduct a policy simulation, in which I decrease the Medicare reimbursement rates for hospitals by 10% from the Medicare reimbursement in 2008. When facing such a policy, each hospital chooses an optimal quality level for each surgery market to maximize its profit with the understanding that ASCs' entry decisions are affected by the hospital's quality choice. The results show that, when facing a lower Medicare reimbursement rate, averaged across all hospitals, the quality level decreases by 4.18% (0.31 standard deviations). On average, hospitals spend $4,076 less on their investment in quality level. On the other hand, ASCs are more likely to enter the market, averaged across all ASCs, the entry probability increases by 1.3 percent.

This paper contributes to the literature on the effect of competition on quality in the health-care market, where most of the existing empirical evidence focuses on the inpatient care market (Gowrisankaran and Town, 2003; Ho and Hamilton, 2000; Kessler and McClellan, 2000; Mukamel et al., 2002; Tay, 2003).[6] This paper examines the competition among hospitals and ASCs in the outpatient surgery market, suggesting that both entry threat and direct competition from ASCs can lead to higher surgery quality levels in hospitals. When evaluating the impact of different levels of competition on hospitals' outcomes, studies from earlier years consider market competitiveness and actions that determine the competition intensity, such as facilities' entry, exit and merging decisions, as exogenous (Courtemanche and Plotzke, 2010; Ho and Hamilton, 2000; Mukamel et al., 2002; Tay, 2003). Recent studies start to exploit exogenous variations that explain the difference in market competitiveness (Cooper et al., 2011; Volpp et al., 2003), which provides stronger evidence for the causal relationship between level of competition and hospitals' outcomes. In this paper, I endogenize ASCs' entry decisions. The 2008 payment schedule change provided exogenous variations in ASCs' profitability and ASCs' incentives for entering different surgery markets. In particular, ASCs had a stronger incentive to perform surgeries that became more profitable, and

[6] Gaynor (2007) provides a general review of the literature in this field.

hospitals faced a greater increase in the intensity of competition in such surgery markets.

This paper also belongs to the literature on market entry. Most applications of entry models do not use post-entry quantities and prices due to lack of data (Bresnahan and Reiss, 1990; Ciliberto and Tamer, 2009; Mazzeo, 2002; Seim, 2006). Typically, these studies characterize the expected profits of potential entrants as a reduced linear function of other players' entry decision. These studies do not attempt to separately identify the effects of markup, quantity demanded and fixed cost on entry decisions. More recently, a few studies incorporate entry decisions and post-entry outcomes in the same framework (Ciliberto et al., 2016; Ellickson and Misra, 2012; Roberts and Sweeting, 2014). This approach allows researchers to recover deep structural parameters that drive strategic entry decisions. This paper models each facility's expected profit as a nonlinear function of its markup, expected surgery volume and fixed cost. Incorporating post-entry demand estimation in this model allows me to form a more accurate expected volume for each ASC. Since the expected volume is determined by the quality levels of hospitals and other ASCs' entry decisions, this model explicitly shows how each ASC's entry decision is affected by its competitors.

This paper also contributes to the literature of entry deterrence. Most of the previous literature focuses on showing the existence of entry-deterring investment (Cookson, 2017; Dafny, 2005; Ellison and Ellison, 2011; Goolsbee and Syverson, 2008). I take a more structural approach to quantify the magnitude of entry-deterring investment. Estimates from the model suggest that 43 percent of hospitals' quality investment can be explained by hospitals' motive of deterring ASCs from entering the market.

The rest of the paper proceeds as follows. In section 2, I provide background information and data description. I present my model in section 3 and describe the estimation strategy in section 4. I present the estimates of my structural parameters and a policy simulation in section 5 and section 6. I conclude the paper in section 7.

2 Background and Data

2.1 Overview of Medicare Payment

Medicare Part B covers medical services and supplies for eligible patients. In particular, outpatient surgery providers, namely hospitals and ASCs, receive facility payments from Medicare. The payment is determined by the Medicare and Medicaid Service Center (CMS), according to the cost of performing the surgery. The reimbursements for outpatient surgeries differ across facility settings. In general, hospitals receive higher reimbursements than ASCs. In the U.S., states establish and administer their own Medicaid programs and determine the scope of services and the reimbursement within broad federal guidelines. In Florida, Medicaid covers the outpatient services for eligible patients. The reimbursement rates for hospitals and ASCs are closely related to the Medicare reimbursement rates and further adjusted for the local costs of performing the surgery. In this section, I focus on the Medicare reimbursement rate.

The reimbursement schedules for ASCs and hospitals has changed over time. In the period relevant to this research, hospitals were paid according to the Outpatient Prospective Payment System (OPPS). OPPS had 177 different Ambulatory Payment Classifications (APCs) based on the cost. All procedures within the same classification received the same payment, which did not vary based on patients' health conditions. The payments to hospitals were set nationally and adjusted according to a local wage index. ASCs were paid under a different system before 2008. The payment system for ASCs had only 9 categories. Like the OPPS, all procedures within the same category were paid the same amount.

In 2006, a study published by the Government Accounting Office (GAO) showed that the relative costs of surgeries were similar in ASCs and hospitals and they should be paid under the same classification system. ASCs were systematically underpaid for procedures requiring advanced surgical equipments and technologies, while they were overpaid in low-end procedures. The GAO suggested that both ASCs and hospitals should be paid under the OPPS, which correctly reflected the relative costs of performing surgeries in both settings.

Medicare started to phase in a new payment system for ASCs in 2008 according to the GAO report. All procedures performed in ASCs received payment according to the OPPS. The CMS estimated that the labor costs were higher in hospitals than in ASCs. Therefore, ASCs should receive about 59 percent of the payments paid to hospitals for all procedures.

Different procedures performed in ASCs experienced different payment changes. Some surgeries in ASCs, such as tonsil and adenoid removal surgery, did not experience a large change in the Medicare reimbursement rate. On the other hand, surgeries requiring high equipment investment, such as retina surgery, experienced an increase in the Medicare facility payment.

2.2 Data Description

2.2.1 Categories of Surgeries

My study focuses on five categories of surgeries: knee arthroscopy (CPT codes: 29875-29887), breast lesion removal surgery (CPT codes:19120, 19125, 19140, 19160, 19162, 19180 and 19182), tonsil and adenoid removal surgery (CPT codes: 42820-42826, 42830 and 42831), retina surgery (CPT codes: 67036-67045, 67108, 67228) and hernia repair (CPT codes: 49495-49507, 49560, 49561, 49585 and 49587).[7]

All of these surgeries satisfy the following requirements. First, the number of surgeries performed in each year should be large enough. The least popular surgery in my study is retina surgery. More than 30,000 patients received retina surgeries per year. Second, both hospitals and ASCs should have non-negligible market shares for the surgery. I exclude some high volume procedures, such as cataract surgery, from my sample due to this reason. In Florida, in 2006, less than 5 percent of the cataract surgeries were performed in hospitals. Third, the surgery should not be used as a diagnostic tool. I exclude colonoscopy and other high volume surgeries due to this reason. While these procedures have complications that might result in inpatient admission, they also reveal more severe diseases that could result in inpatient admission. Since I cannot observe the reason for inpatient admission, I cannot construct a reliable quality measurement for diagnostic surgeries.

[7]Procedures in my dataset are coded using Current Procedural Terminology (CPT) code. CPT code is a medical code set that is used to report medical, surgical, and diagnostic procedures and services for electronic medical billing process.

2.2.2 Patients

Each patient in my model makes a decision on whether to receive a surgery and in which facility to have the surgery. There are two groups of patients in my model. The first group includes all patients who received surgery. The second group includes all patients who chose the outside option (not to have surgery).

I obtain individual-level information on patients who received surgery from the State Ambulatory Surgery and Services Databases (SASD) of Florida from 2006 and 2008, which is a part of the Healthcare Cost and Utilization Project (HCUP). The SASD includes encounter-level discharge data for ambulatory surgeries from hospitals and ASCs. The dataset includes all outpatient surgery visits in hospitals and ASCs.[8] For each outpatient surgery visit, I observe the patient's zip code, an identifier for the facility in which she received the surgery, an identifier for her surgeon, the main diagnosis and the treatment. I also observe the patient's characteristics, including her gender, age, race and health insurance coverage. Using the identifiers for the surgeons, I create two variables for each surgeon: the number of outpatient procedures performed by the surgeon and the percentage of surgeries performed in ASCs by the surgeon.

I present the summary statistics for patients in Table 1a and Table 1b. The majority of the patients for breast lesion removal surgeries are females (96.2%), and the majority of the patients for hernia repair surgeries are males (94%). For these two surgeries, I only keep female patients and male patients, respectively. For the rest of the surgeries, females account for about half of the patients. I classify each patient into one of the five age categories, under 45, 45-54, 55-64, 65-75 and >75. In my sample, more than half of the patients who received retina surgeries are over age 64 and eligible for Medicare.[9] For hernia repair surgeries and breast lesion removal surgeries, the patients are younger. Around 30 percent of the patients who received breast lesion removal surgeries are older than 64 and eligible for Medicare. For knee arthroscopy, patients between age

[8] Some outpatient surgeries are performed in physician offices. The SASD does not include these patients. However, this is not a problem for the surgeries investigated in this paper. All the surgeries studied in this paper require a certain level of anesthesia, which makes it almost impossible to perform in a physician office.

[9] From the dataset, I observe the first payer for each patient who received a surgery. Generally, Medicare is available for people age 65 or older, younger people with disabilities and people with End Stage Renal Disease. In most cases, a patient over 64 uses Medicare as her first payer. However, if a patient over 64 is still working, she might be covered by a employer-provided health insurance plan.

45 and 64 account for around 45 percent of the patients. For tonsil and adenoid removal surgery, the majority of the patients are children, so I use different age categories. About a quarter of the patients who received tonsil and adenoid removal surgeries are Medicaid beneficiaries. Five age categories are under 3, 4-7, 7-12, 13-18 and over 18. Patients in my sample are younger than the average patient in the outpatient surgery market, and their Medicare coverage rates are also lower. Most of the patients in my sample are covered by private insurance. Around 25 percent of the patients in my sample are non-white, which is similar to the percentage of the non-white population in Florida.

The number of surgeries performed by the surgeon varies across different surgeries. While the average tonsils and adenoids removal surgeon around 640 surgeries per year, other surgeons perform fewer cases. This is because it takes only about 30 minutes to one hour to perform a tonsillectomy, which is significantly less time-consuming than other surgeries. Surgeons performing different surgeries also have varied preferences for performing a surgery in an ASC. In may sample, on average, a surgeon takes 53 percent of her cases to ASCs for knee arthroscopy, while takes only 17 percent of her cases to ASCs for hernia repair. From 2006 to 2008, surgeons shifted their retina surgeries from hospitals to ASCs. Around 30 percent of the retina surgeries were performed in ASCs in 2006, while this number grew to 37 percent in 2008.

The SASD provides a revisit variable that can be used to track sequential visits for a patient within a state and across facilities and hospital settings. I assume a patient experiences an adverse medical event if she is re-admitted into the hospital inpatient setting or visited an emergency room within 14 days following the surgery.[10] The readmission rate is used to construct facility-specific surgery quality levels. Table 2 reports the means and the standard deviations by surgeries for patients in hospitals and ASCs. For knee arthroscopy, tonsil and adenoid removal, and hernia repair, the average readmission rates are higher for patients in hospitals than patients in ASCs. This is because patients with severe illness are more likely to choose a hospital that is better equipped to deal with complicated situations during the surgery. For retinal surgery, the average readmission rate was lower for patients in ASCs than patients in hospitals in 2006, but was higher

[10]Readmission rates are common measures for surgery outcomes in previous literature. I detail the reasons for constructing surgery quality levels based on the readmission rate in section (4.1.1.2)

Table 1a: Summary Statistics
Patients, 2006

Surgery	Knee Arthroscopy		Breast Lesion Removal		Tonsil and Adenoid Removal		Retina Surgery		Hernia Repair	
Variables	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Female	0.49	0.50	–	–	0.53	0.50	0.50	0.50	–	–
Age Group 2	0.23	0.42	0.22	0.41	0.22	0.11	0.12	0.33	0.18	0.38
Age Group 3	0.22	0.41	0.19	0.40	0.42	0.08	0.22	0.41	0.17	0.38
Age Group 4	0.14	0.35	0.17	0.38	0.13	0.05	0.27	0.44	0.16	0.37
Age Group 5	0.06	0.24	0.14	0.34	0.05	0.03	0.29	0.46	0.14	0.35
African-American	0.08	0.27	0.11	0.31	0.11	0.32	0.13	0.34	0.10	0.30
Other Races	0.13	0.33	0.14	0.35	0.22	0.41	0.22	0.42	0.15	0.36
Medicare	0.20	0.40	0.31	0.46	0.01	0.08	0.52	0.50	0.29	0.45
Medicaid	0.02	0.13	0.04	0.19	0.25	0.43	0.05	0.22	0.07	0.25
Private Insurance	0.65	0.48	0.59	0.49	0.69	0.46	0.31	0.46	0.53	0.50
Other Types of Insurance	0.13	0.33	0.04	0.20	0.04	0.20	0.08	0.27	0.09	0.29
Numbers of Diagnoses	2.61	2.34	4.62	3.48	2.57	2.23	3.38	2.49	3.32	2.96
Number of procedures performed by the surgeon	0.36	0.52	0.45	0.31	0.64	0.75	0.44	0.63	0.40	0.28
Percentage of surgeries performed in ASCs by the Surgeon	0.53	0.38	0.17	0.27	0.41	0.34	0.30	0.42	0.17	0.26
Obs	59,109		27,423		29,333		17,790		30,421	

Note: The data is provided by the Center of Medicare and Medicaid Service (CMS). In this sample, I exclude patients who do not live in Florida or do not provide a zip code location.Note that for tonsils and adenoids removal surgery, age group 2 represent age 4-7, group 3 represents age 7-12, age group 4 represents age 13-18 and age group 5 represents age > 18. The omitted age category is the youngest age group, age 0-3. For other surgery categories, age group 2, 3, 4, 5 represent age 45-54, 55-64, 65-75 and >75, respectively. The unit for the number of surgery performed by the surgeon is 100 cases.

for patients in ASCs in 2008. This is because, in 2008, more ASCs started providing retina surgeries. These new entrants were less experienced in providing services for retina surgeries. As a result, there was an increase in the readmission rate for patients in ASCs. The average readmission rates are higher for breast lesion removal surgery for patients in ASCs than for patients in hospitals. There is no clear explanation for this. One of the possible explanations is that, though breast lesion removal surgery is not designed as a diagnostic procedure, it is possible to discover more severe symptoms during the surgery. ASCs cannot predict these complications before the surgery and cannot deal with them during the surgery. As a result, ASCs send these cases to hospitals for inpatient care.

I also report the standard deviations among facilities and within facilities, for each surgery. Surgery outcome differences within each facility can explain most of the variations among patients' readmissions. However, there are variations among facilities, which reflect the variations in surgery quality levels across facilities. The standard deviation among hospitals varies across different

Table 1b: Summary Statistics
Patients, 2008

Surgery	Knee Arthroscopy		Breast Lesion Removal		Tonsil and Adenoid Removal		Retina Surgery		Hernia Repair	
Variables	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Female	0.48	0.50	–	–	0.53	0.50	0.52	0.50	–	–
Age Group 2	0.23	0.42	0.22	0.42	0.21	0.11	0.10	0.30	0.18	0.38
Age Group 3	0.22	0.41	0.20	0.40	0.46	0.08	0.21	0.40	0.18	0.38
Age Group 4	0.15	0.35	0.19	0.39	0.11	0.05	0.28	0.45	0.18	0.38
Age Group 5	0.06	0.24	0.15	0.35	0.04	0.03	0.34	0.47	0.15	0.35
African-American	0.08	0.27	0.11	0.32	0.12	0.32	0.12	0.32	0.10	0.30
Other Races	0.13	0.33	0.15	0.36	0.22	0.41	0.25	0.43	0.16	0.36
Medicare	0.20	0.40	0.34	0.47	0.01	0.08	0.57	0.50	0.31	0.46
Medicaid	0.02	0.14	0.04	0.19	0.28	0.45	0.04	0.21	0.07	0.26
Private Insurance	0.65	0.48	0.56	0.50	0.66	0.47	0.28	0.45	0.51	0.50
Other Types of Insurance	0.12	0.32	0.04	0.20	0.05	0.22	0.06	0.24	0.08	0.27
Numbers of Diagnoses	2.71	2.45	4.91	3.62	2.67	2.25	3.22	2.57	3.84	3.33
Number of procedures performed by the surgeon (by 100)	0.33	0.22	0.44	0.27	0.65	0.67	0.47	0.41	0.42	0.27
Percentage of surgeries performed in ASCs by the Surgeon	0.55	0.37	0.19	0.28	0.41	0.33	0.37	0.44	0.18	0.26
Obs	58,206		25,662		28,305		19,756		31,198	

Note: The data is provided by the Center of Medicare and Medicaid Service (CMS). In this sample, I exclude patients who do not live in Florida or do not provide a zip code location.Note that for tonsils and adenoids removal surgery, age group 2 represent age 4-7, group 3 represents age 7-12, age group 4 represents age 13-18 and age group 5 represents age > 18. The omitted age category is the youngest age group, age 0-3. For other surgery categories, age group 2, 3, 4, 5 represent age 45-54, 55-64, 65-75 and >75, respectively. The unit for the number of surgery performed by the surgeon is 100 cases.

surgeries. The standard deviation among hospitals that performed knee arthroscopy in 2008 is 0.016, while the standard deviation among hospitals that performed tonsil and adenoid removal is 0.045. Compared to 2006, the standard deviations among hospitals increased for tonsil and adenoid removal, and hernia repair. For the rest of surgeries in my sample, the standard deviations among hospitals decreased.

I cannot observe the patients who choose not to have surgeries. I simulate these patients using detailed Florida population estimates.[11]. In each year, the Office of Economic and Demographic Research provides the population in each zip code area and the population in each county by gender, race and age group. I assign each zip code area to a county based on the location of the zip code's population center. I assume that the distribution of the population's characteristics in each zip code area is the same as the distribution of the population's characteristics in the corresponding county. For each zip code area and each surgery market in each year, I draw a set

[11]The detailed information about Florida demographics is provided by the Florida Legislature's Office of Economic and Demographic Research

Table 2: Readmission Rates in Hospitals and ASCs, 2006 and 2008

			Readmission Rate in Hospitals	
			Year 2006	
Surgery	Mean	Std	Within Hospital Std	Between Hospital Std
Knee Arthroscopy	0.032	0.175	0.174	0.017
Breast Lesion Removal	0.057	0.232	0.231	0.042
Tonsil and Adenoid Removal	0.064	0.245	0.243	0.042
Retina Surgery	0.049	0.216	0.215	0.024
Hernia Repair	0.044	0.206	0.205	0.024
			Year 2008	
Surgery	Mean	Std	Within Hospital Std	Between Hospital Std
Knee Arthroscopy	0.034	0.182	0.181	0.016
Breast Lesion Removal	0.056	0.230	0.229	0.035
Tonsil and Adenoid Removal	0.066	0.248	0.247	0.045
Retina Surgery	0.044	0.205	0.205	0.022
Hernia Repair	0.049	0.216	0.215	0.028
			Readmission Rate in ASCs	
			Year 2006	
Surgery	Mean	Std	Within ASC Std	Between ASC Std
Knee Arthroscopy	0.029	0.168	0.168	0.014
Breast Lesion Removal	0.070	0.255	0.246	0.067
Tonsil and Adenoid Removal	0.041	0.199	0.197	0.037
Retina Surgery	0.045	0.208	0.206	0.050
Hernia Repair	0.034	0.180	0.179	0.022
			Year 2008	
Surgery	Mean	Std	Within ASC Std	Between ASC Std
Knee Arthroscopy	0.029	0.168	0.167	0.013
Breast Lesion Removal	0.063	0.244	0.239	0.047
Tonsil and Adenoid Removal	0.047	0.211	0.209	0.046
Retina Surgery	0.056	0.230	0.226	0.060
Hernia Repair	0.028	0.165	0.164	0.025

of patients based on the joint distribution of the local population's characteristics (race, gender and age group) conditional on not receiving the surgery.

In order to calculate the utility of receiving a surgery in a facility for each simulated patient, I need to know her insurance coverage and the observed characteristics for her surgeon. These variables cannot be obtained directly from the Florida population demographic research.

First, I simulate the insurance coverage status for each potential patient. I use a multivariate probit framework to model the insurance coverage and estimate the model using data from the American Community Survey (ACS) in 2006 and 2008. The American Community Survey includes a survey for health insurance coverage in each year. Each respondent provides information on his/her health insurance coverage, county, race, gender, and age. I use the health insurance coverage (Medicare, Medicaid, private insurance, other types of insurance or no insurance) for each respondent as the outcome variable for the multivariate probit model. By regressing the outcome variables on the respondents' age group, gender, race, county and the survey year, I obtain estimates of the multivariate probit model and predict the insurance coverage for each potential patient I simulated.

Second, I simulate the characteristics of the surgeon (number of surgeries per year and the percentage of surgeries performed in ASCs) for each patient. The process of seeking a surgeon is beyond the scope of this paper. I assume that the chosen surgeon's characteristics are determined by the observed characteristics of the patient and are not affected by whether the patient chooses to have a surgery. I model the number of surgeries performed by the surgeon under a negative binomial regression framework and the percentage of surgery performed by the surgeon in ASCs under a linear regression framework. I estimate both models using patients observed in the SASD discharge files, controlling for patient's age group, gender, race, county, insurance coverage and a year fixed-effect. Using the estimates from the model, I predict the surgeon's characteristics for each simulated patient.

2.2.3 Hospitals and ASCs

I use the facility identifier in the discharge file to calculate the number of hospitals and ASCs and the percentage of surgeries performed in ASCs in each surgery category. Table 3 shows the number of hospitals and ASCs that provided the relevant surgeries in 2006 and 2008. In general, more ASCs entered the outpatient surgery market over time. For example, the number of ASCs performing retina surgery has increased by 30.9 percent.

Although I do not model hospitals' entry and exit decisions, I do observe that a few hospitals left the market. From 2006 to 2008, the ASCs' market shares in different surgery categories changed. The market share for ASCs in the retina surgery market increased by 36 percent; for the knee arthroscope market, it decreased by 7 percent. At the same time, the market share for ASCs in tonsil and adenoid removal surgery, hernia repair, and the breast lesion removal surgery stayed almost unchanged.

Table 3: The Numbers and the Market Shares of Hospitals and ASCs

	Hospitals			
	Number		Market Share	
	Year 2006	Year 2008	Year 2006	Year 2008
Surgery				
Knee Arthroscopy	117	113	0.58	0.61
Breast Lesion Removal	156	150	0.83	0.83
Tonsil and Adenoid Removal	97	92	0.55	0.53
Retina Surgery	40	37	0.75	0.66
Hernia Repair	149	145	0.80	0.78
	ASCs			
	Number		Market Share	
	Year 2006	Year 2008	Year 2006	Year 2008
Surgery				
Knee Arthroscopy	101	110	0.42	0.39
Breast Lesion Removal	54	56	0.17	0.17
Tonsil and Adenoid Removal	75	82	0.45	0.47
Retina Surgery	42	55	0.25	0.34
Hernia Repair	56	67	0.20	0.22

Notes: The data comes from the State Ambulatory Surgery and Services Databases (SASD): Florida (2006 and 2008). I exclude all the facilities that performed less than 15 cases within the surgery category in the year.

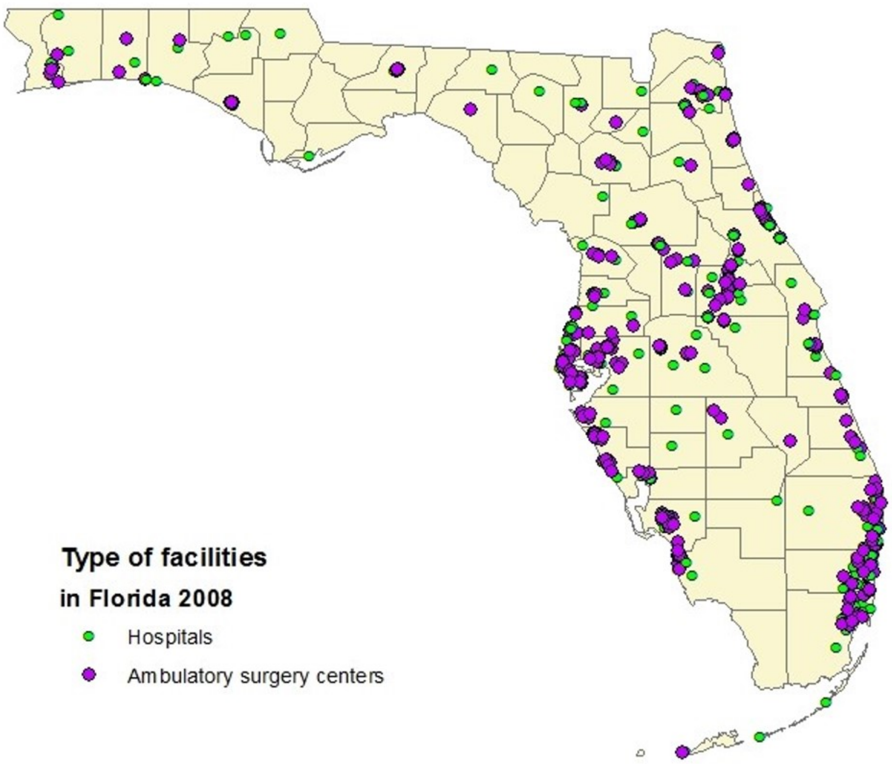


Figure 1: ASCs and Florida in the Florida

I obtain hospitals' characteristics, such as ownership, teaching status, the number of outpatient visits each year and location from the American Hospital Association's Annual Survey (AHA). For ASCs, the Provider of Services File (PSF) provides their locations as well as their accreditation status. Figure 1 is a map of outpatient facilities in Florida in 2008.

Table 4 presents hospitals' and ASCs' observed characteristics. In general, hospitals in different surgery markets are similar along their observed dimensions, with a few exceptions. Hospitals that are performing retina surgeries have larger numbers of outpatient visits per year and are more likely to be teaching hospitals. Compared with 2006, more ASCs have accreditations to prove their surgery quality level and safety in 2008.

Table 4: Summary Statistics
Facilities, 2006 and 2008

	Knee Arthroscopy		Breast Lesion Removal		Tonsil and Adenoid Removal		Retina Surgery		Hernia Repair	
Facilities' Observed Characteristics, 2006										
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Hospitals' Characteristics										
Number of HMO Contracts	16.30	12.13	16.06	12.71	15.98	12.95	15.70	11.90	16.14	12.88
Number of Total Outpatient Visits per Year (by 10,000)	1.43	1.46	1.30	1.33	1.65	1.55	2.09	1.75	1.32	1.35
Teaching Hospital	0.06	0.24	0.05	0.22	0.06	0.24	0.15	0.36	0.05	0.21
Within a Hospital Network	0.44	0.50	0.40	0.49	0.43	0.50	0.40	0.50	0.41	0.49
For Profit	0.45	0.50	0.43	0.50	0.51	0.50	0.55	0.50	0.42	0.50
Not For Profit, Private	0.41	0.49	0.46	0.50	0.34	0.48	0.23	0.42	0.46	0.50
Number of Hospitals	117		156		97		40		149	
ASCs' Characteristics										
With Accreditation	0.22	0.42	0.28	0.45	0.27	0.45	0.29	0.46	0.20	0.40
Number of ASCs	101		54		75		42		56	
Facilities' Observed Characteristics, 2008										
	Knee Arthroscopy		Breast Lesion Removal		Tonsil and Adenoid Removal		Retina Surgery		Hernia Repair	
Hospitals' Characteristics	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Number of HMO Contracts	15.69	14.04	15.47	13.50	16.82	14.61	15.08	9.09	15.46	13.53
Number of Total Outpatient Visits per Year (by 10,000)	1.58	1.75	1.40	1.54	1.88	1.90	2.27	1.90	1.40	1.56
Teaching Hospital	0.06	0.24	0.05	0.23	0.09	0.28	0.16	0.37	0.05	0.22
Within a Hospital Network	0.48	0.50	0.42	0.50	0.49	0.50	0.43	0.50	0.42	0.50
For Profit	0.49	0.50	0.41	0.49	0.52	0.50	0.57	0.50	0.42	0.50
Not For Profit, Private	0.36	0.48	0.45	0.50	0.33	0.47	0.24	0.43	0.44	0.50
Number of Hospitals	113		150		92		37		145	
ASCs' Characteristics										
With Accreditation	0.35	0.48	0.41	0.50	0.43	0.50	0.35	0.48	0.33	0.47
Number of ASCs	110		56		82		55		67	

Notes: The data for hospitals' characteristics come from American Hospital Association's Annual Survey (AHA), 2006 and 2008. The data for ASCs' characteristics come from the Provider of Services File (PSF), 2006 and 2008.

2.2.4 Medicare Reimbursement Rate

I obtain payment data from the Medicaid Services Medicare Provider Utilization and Payment Data: Outpatient. The CMS updates national average facility payments annually. The actual payment for each facility is further adjusted by the local wage index annually. In each surgery category, there is more than one procedures. Some of the procedures under the same surgery category were paid differently. For example, both treatment of retinal lesion (CPT code: 67228) and laser treatment of retina (CPT code: 67039) are under the retina surgery category. In 2008, the Medicare reimbursement rates for ASCs were $251 and $1,131, respectively. I create a weighted price for each surgery in each year, which is the weighted sum of all procedures' reimbursement rates within the surgery category in a year. I use the number of surgeries by CPT code as the weight.[12]

Table 5 lists the weighted reimbursement rates for the relevant procedures for hospitals and ASCs in 2006 and 2008.[13] Hospital reimbursement rates experienced steady increases. In my sample, the only surgery that experienced a decrease in the Medicare reimbursement rate was retinal surgery. From 2006 to 2008, the Medicare reimbursement rate for a retina surgery decreased by about 10 percent. On average, in 2006 and 2008, the national reimbursement rates across surgeries increased by 6.8 percent. For ASCs, reimbursement rates increased for all surgeries in my sample. The magnitude of the change varied by surgeries. The national reimbursement rate for retina surgeries increased by about 46 percent, while the national reimbursement rate for breast lesion removal increased by 14 percent.

The ratio of the reimbursement rate of ASCs and the median cost of hospitals reflects the profitability of performing the surgery in ASCs. The profitability across surgeries changed differently during this period. Compared with 2006, tonsil and adenoid removal surgeries performed in ASCs became less profitable in 2008. The profitability of performing hernia repair surgeries became stable in two years. Knee arthroscopy and breast lesion removal surgeries became slightly

[12] I construct the weight for each procedure by pooling all patients' discharge records in 2006 and 2008 together. The weight of a procedure is the same across facilities and years.

[13] In this table, the weighted reimbursement rates are calculated based on the Medicare reimbursement rate without adjusting for local cost factors.

more profitable, while retina surgeries experienced a huge increase in profitability in 2008.

Table 5: Reimbursement Rates and Profitability across Surgeries, 2006 and 2008

	Year 2006		
	ASC Reimbursement	Hospital Reimbursement	ASC payment to Hospital Cost Ratio
Surgery			
Knee Arthroscopy	611.6	1754.4	0.33
Breast Lesion Removal	429.0	1228.5	0.35
Tonsil and Adenoid Removal	588.5	1301.9	0.53
Retina Surgery	400.3	1300.6	0.30
Hernia Repair	750.2	1704.6	0.45
	Year 2008		
	ASC Reimbursement	Hospital Reimbursement	ASC payment to Hospital Cost Ratio
Surgery			
Knee Arthroscopy	773.0	1929.1	0.37
Breast Lesion Removal	553.2	1314.8	0.39
Tonsil and Adenoid Removal	671.8	1417.6	0.47
Retina Surgery	587.6	1175.0	0.42
Hernia Repair	880.1	1954.1	0.46

Note: The weighted price is calculated base on procedure's national average reimbursement rate without adjusting for local cost.

3 Model

In this section, I develop a model to show how each patient chooses a facility for surgery, how each hospital selects a surgery quality level, and how each ASC makes an entry decision. I define a market as a category of surgeries in a year.[14]

On the demand side, I consider a patient and her surgeon as an agent. After observing each ASC's entry decision and each facility's surgery quality level, each agent decides whether to have a surgery and, if so, in which facility to have surgery, based on traveling distances, facilities' quality levels, facilities' observed and unobserved characteristics, and the characteristics of the agent.[15]

[14]For simplicity, I use a surgery and a category of surgeries interchangeably.

[15]Modeling the process of seeking a surgeon is beyond the scope of this paper. I assume that a patient has decided on her surgeon before searching for a facility. A patient's choice set might be restricted by her surgeon's admitting privileges, which cannot be observed from my dataset. I do not limit a patient's choice based on her

On the supply side, I focus on competition in the outpatient surgery market along the dimension of surgery quality levels. I model competition among hospitals and ASCs as a two-stage game. In the first stage, at the beginning of the year, each hospital chooses its surgery quality levels simultaneously for each market. In the second stage, at the beginning of the year, after observing surgery quality levels of the hospitals, each ASC makes entry decisions simultaneously for each market.

In theory, facilities may also compete along the dimension of prices. However, using lower prices to attract more patients might not be effective in the health care market due to the two major reasons. First, a single hospital has little power in choosing prices for a large portion of its patients. Around 50 percent of the patients in my sample who receive surgeries are covered by Medicare or Medicaid. The prices paid by these patients are determined by the Centers for Medicare and Medicaid Services (CMS). Second, patients who are covered by private insurance pay the facilities through their insurance companies and become less sensitive to prices. Insensitivity to price may lead facilities to focus on non-price competition (Feldstein, 1971; Fournier and Mitchell, 1992; Robinson and Luft, 1987). In my model, instead of modeling each facility's pricing decision, I model the average payment received by each facility as a function of the predetermined Medicare reimbursement rate, the local demographics, and the number of hospitals and ASCs in the area. [16]

At the beginning of the year, each hospital chooses its surgery level to maximize its profit with the understanding that its quality choice affects ASCs' entry probabilities. Given other hospitals' choice of quality levels, each hospital forms a correct expectation about the ASCs' entry probabilities and the hospital's average markup for each surgery as a function of its own quality choice. A high surgery quality level in a hospital increases the hospital's profit through

choice of surgeon. An alternative method is to model a patient's choice set as all the facilities in which her surgeon has performed surgeries. This method allows a patient's choice set to vary by her choice of surgeon. Without modeling the process of seeking a surgeon, the choice set created by this method suffers from omitted-variable bias. It is possible that a patient takes the surgeon's admitting privileges into account when seeking a surgeon. If so, the choice set is not independent of the patient's preferences for the facilities conditional on the explanatory variables of the models. I obtain biased estimates of patient's preferences for different hospitals, and incorrect expectations of each patient's choice probabilities (Manski, 2004).

[16] Clemens and Gottlieb (2017) found that private insurers' payments for physicians' services followed the Medicare payments. The Medicare payments had stronger influences on the private payments in areas with concentrated insurers and competitive physician markets.

two channels. First, it increases each patient's utility from choosing the hospital, hence increasing demand. Second, it could potentially deter ASCs from entering the market, which would result in a higher markup for surgery and a higher demand for the hospital. I assume that each hospital pays a one-time payment each year for choosing its quality level. The marginal cost of performing surgery is not affected by the chosen quality level. The marginal cost of investing in surgery quality level depends on the hospital's observed characteristics, local conditions, and the chosen surgery quality level.

3.1 Demand

3.1.1 Utility Function

In each year t, each agent chooses a facility for surgery m within 50 miles of the patient's zip code area z.[17] The outside option is to not receive a surgery. $\mathbb{J}_{iz}^{c}$ represents the choice set for patient i who lives in zip code location z, including the outside option. I consider the choice of the surgeon as an exogenous decision made before the facility choice. For the rest of this paper, I use i to denote both the patient and the agent formed by the patient and her surgeon.

There are two types of facilities: ASC (A) and hospital (H). I denote g_j as the type of facility j, $g_j \in \{A, H\}$. The outside option is indexed as $j = 0$. Suppressing surgery m and time t for ease of exposition, I use U_{ijz} to denote the utility from receiving a surgery in facility j for patient i who lives in zip code location z. U_{ijz} is a function of the patient's observed characteristics, $\mathbf{X}_i$, the facility's observed characteristics, $\mathbf{Z}_j$, traveling cost, $\mathcal{D}_{ijz}$, utility from the facility's quality level, $\mathcal{Q}_{ij}$, and preference for receiving a surgery in an ASC, $\mathcal{V}_{iz}$. U_{ijz} is also a function of the facility's unobserved characteristics, ξ_j, and an idiosyncratic match value between patient i and facility j,

[17] In my dataset, more than 93 percent of the patients received surgeries within 50 miles of their location. Kessler and McClellan (2000) assumed that patients traveled no more than 35 miles for heart attack care. I allow longer traveling distances for outpatient surgery patients, who were facing less urgent conditions and could afford to travel further. I treat patients who decided to travel more than 50 miles for surgery as having chosen the outside option. By setting a limit for the search area, I restrict the number of facilities in a patient's choice set to a manageable number. This assumption allows me to ignore direct competition among facilities that are far away from each other. Each facility's entry decision and its quality level only have direct impact on surgery volumes of facilities nearby. As a result, by limiting the search area, I guarantee enough exogenous variations in my model, which allows me to obtain consistent estimates for the parameters. Limiting the search area also reduces the computational complexity of my model.

ϵ_{ijz}. The utility of receiving a surgery at facility j for patient i is

$$U_{ijz} = \mathbf{X}_i\boldsymbol{\beta}_1 + \mathbf{Z}_j\boldsymbol{\beta}_2 + \mathcal{D}_{ijz} + \mathcal{Q}_{ij} + \mathbb{1}\{g_j = A\}\mathcal{V}_{iz} + \xi_j + \epsilon_{ijz}, \qquad \forall j \in \mathbb{J}^c_{iz}. \tag{3.1}$$

The vector of the patient's characteristics, $\mathbf{X}_i$, includes the patient's sex, age category and insurance coverage. $\boldsymbol{\beta}_1$ captures the effects of the patient's characteristics on the utility of receiving an outpatient surgery. I assume the utility from not receiving a surgery equals the unobserved patient-specific preference: $U_{i0z} = \epsilon_{i0z}$. Patients choose the facility with the highest utility or to not receive any surgery. A similar form of utility function is adopted by previous literature that highlights the trade off between the quality of care and traveling distance for consumers in the healthcare market (Kessler and McClellan (2000); Tay (2003)).

I assume the facilities' unobserved characteristics, $\{\xi_j, j = 1, ...J\}$, are independent across facilities, surgeries, and years. The distribution of ξ_j is

$$\xi_j \sim iidN(0, \mathbb{1}\{g_j = A\}(\sigma^A_\xi)^2 + \mathbb{1}\{g_j = H\}(\sigma^H_\xi)^2). \tag{3.2}$$

The standard deviations of both types of facilities, σ^A_ξ and σ^H_ξ, vary by years and by surgeries.[18] The distribution of the unobserved agent-facility-specific match value, ϵ_{ijz} is discussed later in section (3.1.2).

The remainder of this section describes the structure of traveling cost, utility from the surgery quality level, and preference for receiving a surgery in an ASC in more detail.

[18] One caveat of this model is that a facility's quality choice could be correlated with its unobserved characteristics. Berry, Levinsohn and Pakes (1995) discussed the problem caused by the endogenous price. The observed price for each product is correlated with the unobserved quality of the product. Ignoring the endogeneity problem leads to biased estimates, particularly for the coefficient of price. In extreme cases, researchers estimated positive correlations between the consumer's utility and the product's price due to ignoring the endogeneity problem. My model suffers from a similar problem. If the facility's unobserved characteristics, which do not affect the patient's surgery outcome, are positively correlated to the facility's surgery quality, I overestimate the effect of quality on patient's utility. Berry, Levinsohn and Pakes (1995) solved this problem by introducing an instrument for the price. Adopting a similar method greatly increases the computational burden of the model.

3.1.1.1 Traveling Cost

Previous studies have found that distance is an important predictor of health care facility choice ((Gowrisankaran and Town, 2003; Tay, 2003)). To capture the idea that patients may prefer to receive a surgery from a nearby facility over facilities that are farther away, I allow the patient's utility to depend on the patient's traveling cost, $\mathcal{D}_{ijz}$, which is a function of the distance, d_{ijz}, and the patient's characteristics, X_i.[19] The traveling cost is

$$\mathcal{D}_{ijz} = \beta_1^d d_{ijz} + \beta_2^d d_{ijz}^2 + \beta_3^d d_{ijz}^3 + d_{ijz}\mathbf{X}_i\boldsymbol{\beta}_4^d. \tag{3.3}$$

Allowing traveling distance to affect the patient's utility creates spatial competition among facilities (Davis (2006); Thomadsen (2005)). Hospitals with fewer close competitors have more market power and less incentive to invest in their surgery quality levels, holding other things constant.

3.1.1.2 Surgery Quality

I construct a surgery quality measurement for each facility by focusing on patients' health outcomes associated with outpatient surgeries. If a patient is hospitalized or treated in an emergency room within 14 days after the surgery, I assume this patient suffers from a complication associated with the surgery.[20] A facility with a higher surgery quality level reduces the probability of surgery complications.

I use vector $\mathbf{c}_i = \{c_{i1}...c_{iJ}\}$ to denote patient i's facility choice. The j^{th} element of the vector,

[19] The traveling distance, d_{ijz}, is constructed using a program that extracts actual driving distances from Google maps between the patient's zip code centroid and the facility.

[20] The Centers for Medicare and Medicaid Services (CMS) has recognized subsequent hospitalizations as an important quality measure for outpatient surgery and includes this measure in the Hospital Outpatient Quality Reporting Program. Readmission rates are also common measures for surgery outcomes in previous literature. Munnich and Parente (2014) used readmission rate within 7 days after the surgery as the measurement for surgery quality level. In my sample, lower than 2 percent of the patients are readmitted into inpatient hospitals or emergency rooms within 7 days which would not allow me to precisely estimate hospital-specific surgery quality levels, especially for hospitals that perform only a small number of surgeries in a year. Other reasonable measures include readmission rates within 14 days and 30 days, 5.4 percent and 7.8 percent respectively in my sample. Since I can observe only readmission but not the reason for readmission, it is possible that the cause of the observed readmission is irrelevant to the outpatient surgery the patient received earlier. To minimize such concerns, I choose the shorter window.

To summarize, I choose the 14-day readmission rate as my surgery quality measure because it affords enough power to produce precise estimates for hospital surgery quality while minimizing potential measurement errors.

c_{ij}, equals 1 iff patient i chooses facility j.[21] The surgery outcome for a patient is a function of a vector of the patient's characteristics, $\mathbf{X}_i$, the patient's facility choice, $\mathbf{c}_i$, and an unobserved patient-specific shock, μ_i, which can be considered as the unobserved severity of illness of patient i. I denote $O_i = 1$ iff patient i suffers from a complication. The patient's surgery outcome is affected by the surgery level of the chosen facility. I use a linear probability model to characterize the occurrence of surgery complication.[22] In this model, $\{q_j, j = 1, ...J\}$ is a vector of parameters to be estimated. The outcome function is

$$O_i = \mathbf{X}_i \boldsymbol{\lambda} - \sum_{j=1}^{J} c_{ij} q_j + \mu_i. \tag{3.4}$$

Patient i's utility from facility j, U_{ijz}, depends on $\mathcal{Q}_{ij}$, which is a function of the surgery quality level, q_j, and the patient's characteristics, $\mathbf{X}_i$. The utility from surgery quality, $\mathcal{Q}_{ij}$, is

$$\mathcal{Q}_{ij} = \beta_1^q q_j + q_j \mathbf{X}_i \boldsymbol{\beta}_2^q. \tag{3.5}$$

3.1.1.3 Utility from Receiving a Surgery in an ASC

Agents may have different preferences for receiving surgeries from nontraditional health care providers such as ASCs. For example, one surgeon might prefer ASCs over hospitals because she can control her schedule in ASCs without worrying about unforeseen emergency room demands. Another surgeon might prefer to schedule her operations, both inpatient and outpatient surgeries, in the same hospital. I allow the patient's and her surgeon's characteristics, $\mathbf{X}_i$ and $\mathbf{G}_i$ respectively, to affect the agent's utility from having a surgery in an ASC. The vector of the surgeon's characteristics, $\mathbf{G}_i$, includes the number of patients treated by the surgeon in a year and the percentage of the patients treated in ASCs by the surgeon.[23]

[21] $c_{ij} = 0$ if facility j is not within patient i's choice set.

[22] An alternative method is to use the Probit model. In this paper, I choose the linear probability model because it reduces the computational complexity of the model.

[23] The percentage of the patients treated in ASCs by the surgeon could be an endogenous variable, especially when the surgeon treats a small number of patients. Each agent-facility-specific shock, ϵ_{ijz}, affects the choice of facility. If agent i receives a large ϵ_{ijz} from ASC j, the agent is more likely to choose the ASC over other facilities, holding other things constant. At the same time, it also results in an increase in the percentage of the patients treated in ASCs by the surgeon. If a surgeon treats only a small number of patients, the impact of the facility choice of one patient has a significant impact on the percentage of the patient treated in ASCs by the surgeon. However,

I also allow the agent's utility from receiving a surgery in an ASC to be affected by some local conditions, such as the local income level and the number of primary physicians per resident. Ideally, I should allow the patient's socioeconomic status to affect her preference for receiving a surgery in an ASC directly. However, such information is not available. I use the local level income measurements as proxies for individual socioeconomic status. Moreover, a place with better health care resources can provide more information to the public and help the agent choose a facility type that suits the patient's needs. I consider the local conditions at the county level. For a patient who lives in zip code area z, I use the population center of the zip code area to determine to which county the patient belongs.[24] The vector of county's characteristics, $\mathbf{W}_z$, includes poverty rate, median household income, and the number of primary physicians per 100,000 residents in the county. The number of primary physicians per resident can be considered as a measurement for the accessibility of local health care resource. In the utility function (equation (3.1)), the patient i's general preference of receiving a surgery in an ASC is

$$\mathcal{V}_{iz} = \boldsymbol{\beta}_0^v + \mathbf{X}_i\boldsymbol{\beta}_1^v + \mathbf{G}_i\boldsymbol{\beta}_2^v + \mathbf{W}_z\boldsymbol{\beta}_3^v. \tag{3.6}$$

3.1.2 Error Structure: Unobserved Severity of Illness and Agent-specific Choice Error

In the previous subsections, I have introduced the equation that determines the agent's utility from each of her facility options (equation (3.1)) and the equation that determines the patient's outcome (equation (3.4)). The patient's utility function (equation (3.1)) includes an idiosyncratic agent-facility-specific error, ϵ_{ijz}. The patient's outcome function (equation (3.4)) includes a patient-specific unobserved severity of illness, μ_i. It is usually the case that the severity of illness would

when the number of patients treated by each surgeon increases, the impact of one patient's choice is very small. In my sample, on average, a surgeon performs 187 surgeries in a year. The endogeneity is negligible. One way to account for the surgeon's preference for ASCs is to include a surgeon fixed-effect in the utility function. However, in each year, there are more than 800 surgeons for each surgery. Using a fixed-effect model greatly increases the number of parameters in the model. The other way is to include a physician random-effect in equation (3.6), which requires extra assumptions on the distribution of the physician's preference for ASCs.

[24] Some zip code areas span multiple counties. Using population center of the zip code area to assign county level characteristics to each patient could cause measurement errors for patients who live in zip code areas that span multiple counties. However, less than 3 percent of the population in Florida lives in a zip code area that spans multiple counties. The impact of the measurement error is very small.

affect both the agent's choice of facility and the patient's surgery outcome. In order to incorporate this feature into my model, I allow μ_i and ϵ_{ijz} to be correlated. The assumptions I impose on the correlation are discussed in this subsection.

As is customary in the discrete choice model (McFadden (1980); Train (2009)), the utility of the outside option is normalized to zero. $\mathbb{J}^c_{iz/0}$ denotes the realized choice set for patient i who lives in zip code area z, excluding the outside option. Given ASCs' entry decisions, the number of facility choices for patients who live in zip code area z is N^c_{zJ}. Accordingly, I redefine the agent-facility-specific shock as $\tilde{\epsilon}_{ijz} = \epsilon_{ijz} - \epsilon_{i0z}$ and use $\tilde{\boldsymbol{\epsilon}}_{\boldsymbol{iz}}$ to denote the vector of agent-facility-specific errors for patient i from zip code area z, $\tilde{\boldsymbol{\epsilon}}_{\boldsymbol{iz}} = \{\tilde{\epsilon}_{ijz}, j \in \mathbb{J}^c_{iz/0}\}$.

The correlation between μ_i and $\tilde{\epsilon}_{ijz}$ is ρ_{ij}, $\rho_{ij} = \rho_j \mathbb{1}\{j \in \mathbb{J}^c_{iz/0}\}$. A larger ρ_j means that a patient with a high unobserved severity of illness, μ_i, is more likely to choose facility j. I use $\tilde{\Sigma}_{iz\epsilon}$, a $N^c_{zJ} * N^c_{zJ}$ matrix, to denote the covariance matrix of vector $\tilde{\boldsymbol{\epsilon}}_{\boldsymbol{iz}}$ and use σ^2_μ to denote the variance of μ_i. The covariance matrix of the joint error term is

$$cov(\mu_i, \tilde{\boldsymbol{\epsilon}}_{\boldsymbol{iz}}) = \begin{bmatrix} \sigma^2_\mu & \boldsymbol{\pi}'_{iz} \\ \boldsymbol{\pi}_{iz} & \tilde{\Sigma}_{iz\epsilon} \end{bmatrix}, \tag{3.7}$$

where $\boldsymbol{\pi}_{iz}$ is a $N^c_{zJ} * 1$ vector, and the j^{th} element of vector $\boldsymbol{\pi}_{iz}$ is π_{ijz}, $\boldsymbol{\pi}_{ijz} = \rho_j \sigma_\mu (\tilde{\Sigma}_{iz\epsilon})^{1/2}_{jj}$. In theory, the only other restriction I need for identification is that $cov(\mu_i, \tilde{\boldsymbol{\epsilon}}_{\boldsymbol{iz}})$ should always be positive definite. In order to simplify the model, I impose two assumptions on the error covariance matrix, following Geweke et al. (2003). Firstly, I assume that the patient's unobserved severity of illness is a linear function of the agent-facility-specific shock, $\tilde{\epsilon}_{ijz}$,

$$\mu_i = \sum_{j \in \mathbb{J}^c_{iz/0}} \tilde{\epsilon}_{ijz} \delta_j + \eta_i; \qquad cov(\eta_i, \tilde{\epsilon}_{ijz}) = 0, \tag{3.8}$$
$$\eta_i \sim iidN(0, \sigma^2_\eta).$$

The number of free parameters in $\tilde{\Sigma}_{iz\epsilon}$ is $N^c_{zJ} * (N^c_{zJ} + 1)/2$. Considering all the possible combinations in a choice set, there are around 4,000 parameters to be estimated. In order to make this model computationally feasible, I make the second simplification by assuming $\epsilon_{ijz} \sim$

$iidN(0,1)$. After subtracting ϵ_{i0z} from each agent-facility-specific shock, the covariance matrix is $\tilde{\Sigma}_{iz\epsilon} = I_{N^c_{zJ}} + w_{N^c_{zJ}} w'_{N^c_{zJ}}$, where $I_{N^c_{zJ}}$ is an $N^c_{zJ} * N^c_{zJ}$ identity matrix and $w_{N^c_{zJ}}$ is a $N^c_{zJ} * 1$ vector of units.

3.1.3 Demand for Surgery for Each Facility

Each agent chooses the facility from her choice set that gives the agent the highest utility. The j^{th} element of the agent i's decision indicator vector, $c_{ij} \in \mathbf{c}_i$, is

$$\begin{aligned} c_{ij} &= 1, \qquad if \;\; j \in \mathbb{J}^c_{iz/0} \;\; and \;\; (\tilde{U}_{ijz} \geq \tilde{U}_{ij'z} \cap \tilde{U}_{ijz} \geq 0), \forall j' \in \mathbb{J}^c_{iz/0} \\ c_{ij} &= 0, \qquad otherwise. \end{aligned} \tag{3.9}$$

The demand faced by each facility is the sum of individual demands from all zip code areas within 50 miles of the facility. I use V_{jz} to denote the surgery demanded from zip code area z for facility j, $\Pr(i_z \rightarrow j)$ to denote the probability of patient i in zip code location z choosing facility j, and I_z to denote the set of patients who live in zip code area z. $\mathbb{Z}_j$ denotes a set of zip code areas within 50 miles of facility j. I refer to $\mathbb{Z}_j$ as the service area for facility j. The demand for the facility j is

$$V_j = \sum_{z \in \mathbb{Z}_j} V_{jz} = \sum_{z \in \mathbb{Z}_j} \sum_{i \in I_z} \Pr(i_z \rightarrow j). \tag{3.10}$$

3.2 Supply

Hospitals and ASCs engage in a two-stage static game. I assume that each hospital chooses its surgery quality level to maximize its annual profit, and each ASC makes its entry decision based on its expected annual profit. However, in reality, an ASC can spread the one-time entry expenses over a longer period of time. Ignoring the dynamic nature of the entry decision leads to underestimating the one-time entry costs and underestimating the cost associated with investing in the hospital's surgery quality level in order to deter ASCs from entering the market.

In the first stage, each hospital chooses its surgery quality level for each surgery simultaneously by making a lump sum investment.[25] In the second stage, after observing hospitals' surgery quality

[25] It is possible that a hospital needs to pay a higher marginal cost to achieve better surgery outcome. If this is

levels, each ASC makes its entry decision simultaneously for each surgery. I assume that each ASC does not choose its surgery quality level. All ASCs with the same accreditation status have the same quality levels for surgery m at year t. When making its entry decision, each ASC knows all potential ASC entrants' quality levels.

This assumption simplifies my model in two ways. First, the quality measurement is constructed based on the patients' 14-day readmission rates after the surgery. For ASCs that do not enter the market, there is no information regarding their patients' readmission rates which makes it impossible to estimate facility-market-specific quality levels for these ASCs without further assumptions about the distribution of the surgery quality level. Under the assumption that all ASCs with the same accreditation status share the same surgery quality level, I can determine surgery quality levels for all potential ASC entrants based on the readmission rates for the ASCs in the market.[26] Second, compared with hospitals, ASCs are smaller in their operation scales. The number of surgeries operated in an ASC is much smaller than the number of surgeries operated in a standard hospital. Pooling ASCs with the same accreditation status together allows me to obtain more accurate estimates for the average surgery quality levels for ASCs.[27]

3.2.1 ASC's Entry Decision

An ASC enters surgery market m at year t by providing surgery equipments and services for surgery m at year t. There are two types of potential ASC entrants. The first type includes all ASCs with physical locations last year. The second type includes potential newly built ASCs. I assume there are two potential newly built ASC entrants in each county, one with accreditation,

the case, I am underestimate the marginal increase in patient volume due to investing in the surgery quality level.

[26] One of the concerns for employing such an assumption is that I ignore the selection of entry along the dimension of surgery quality level. ASCs that enter the market are more likely to have higher surgery quality levels than ASCs that do not enter the market. A way to improve the current assumption is employing a random effect model. I can assume that ASCs with the same accreditation status draw their surgery quality levels from a common distribution. Each ASC knows its own surgery quality level, the common distribution of the surgery quality level for ASCs and hospitals' surgery quality levels before entering the market. Under this more flexible assumption, an ASC that draws a higher surgery quality level is more likely to enter the market than an ASC with a lower draw. However, employing the more flexible assumption means that I allow the selection for entry along two different dimensions, the surgery quality level and the unobserved characteristics of the ASCs, which greatly increases the complicity of the model.

[27] If in the reality, the ASCs with better quality levels are selected into the market, employing this assumption leads to overestimating the average quality level of ASCs.

and one without accreditation. [28] Each hospital that has established a physical location in the last year remains at the same location. For each potential newly built ASC entrant in county l, since it does not have a physical location in the last year, I assume it is located at the population center of county l.

At the beginning of each year, each potential ASC entrant makes entry decisions for each market. An ASC knows all facilities' observed characteristics and unobserved characteristics, $\{\xi_{jmt}, j = 1, .., J\}$, and surgery quality levels, $\{q_{jmt}, j = 1, .., J\}$. Each ASC holds correct common beliefs about other ASCs' entry probabilities. It also receives a private shock associated with its fixed entry cost. I denote ASC j's entry decision at time t for market m as a_{jmt}. I define $a_{jmt} = 1$ iff ASC j enters market m at time t. $\sigma(a_{jmt})$ denotes the probability that ASC j chooses entry decision a_{jmt}.

An ASC located in county l enters market m at time t if its expected profit is positive in year t. The ASC's expected profit equals its operating profit minus its entry cost. The ASC's expected operating profit equals its average markup, $\mathcal{M}^A_{jlmt}$, multiplied by its expected volume, EV_{jmt}. The entry cost equals a fixed entry cost, $\mathcal{F}_{jlmt}$, minus an idiosyncratic private entry cost shock, e_{jlmt}. The expected profit for ASC j is

$$E\Pi^A_{jlmt} = \mathcal{M}^A_{lmt} EV_{jmt} - \mathcal{F}_{jlmt} + e_{jlmt}. \tag{3.11}$$

With the assumption that $e_{jlmt} \sim iidN(0, 1)$, the ASC j's entry probability is

$$\sigma(a_{jmt} = 1) = \Phi(\mathcal{M}^A_{lmt} EV_{jmt} - \mathcal{F}_{jlmt}). \tag{3.12}$$

The remainder of this section describes the structure of the average markup, expected surgery volume, and fixed entry cost in more detail.

[28] For any surgery, there is no county that has more than one newly built ASC with the same accreditation status within a year. The set of potential ASC entrants defined by the model includes all the ASC entrants observed from the dataset.

3.2.1.1 Average Markup

I assume there is no capacity constraint for ASCs, and the average cost for performing a surgery is constant for a facility. The average markup for the ASC, $\mathcal{M}^A_{lmt}$, is a function of the Medicare reimbursement rate, P^A_{lmt}, a vector of local demographics, $\mathbf{K}_{ct}$, the number of hospitals and the expected number of ASCs per 100,000 residents in the county, N^H_{lmt} and EN^A_{lmt} respectively, and the average cost of performing the surgery in the U.S., c_{mt}. The markup is

$$\mathcal{M}^A_{lmt} = \underbrace{(\boldsymbol{\gamma}^A_0 + \mathbf{K}_{lt}\boldsymbol{\gamma}^A_1 + \gamma^A_2 N^H_{lmt} + \gamma^A_3 EN^A_{lmt}) * P^A_{lmt}}_{\text{Average payment}} - \underbrace{\gamma^A_4 * C_{mt}}_{\text{Average operating cost}} . \tag{3.13}$$

In year t, an ASC located in county l gets P^A_{lmt} for surgery m for treating a patient covered by Medicare, which is provided by the CMS and observed by the econometricians. For treating a patient covered by private insurance, her payment cannot be directly observed. The actual payment received by the ASC is guided by P^A_{lmt} and determined by a bargaining process between the ASC and private insurance companies.

The first part of the right hand side of the equation represents the average payment for each surgery. It is the Medicare reimbursement adjusted by the local conditions. I consider the local conditions at the county level. The vector of the local level characteristics for county l in year t, $\mathbf{K}_{lt}$, includes the percentages of residents who have private insurance, Medicare or Medicaid, and the number of the Medicare Advantage providers per 100,000 residents in the county. Insurance coverages in a county affect the correlation between the average markup and the Medicare payment. The Medicare payments might have stronger influences on the average payments in counties where higher percentages of the residents are covered by Medicare. The number of Medicare Advantage providers per resident represents the level of concentration of insurers. The number of hospitals and the expected numbers of the ASCs per resident represent the competitiveness of the local health care market. In the county with high insurer concentration and low health care market competition, each ASC would be able to negotiate higher reimbursement prices for surgeries.

The second term on the right hand side is the average cost of operating the surgery. C_{mt} is the average cost of performing surgery m at time t published by the CMS using data from hospital visits. I assume that the cost of performing a surgery in an ASC is proportional to the cost of performing the same surgery in a hospital.[29] γ_4^A represents the average ratio of the surgery cost between an ASC and a hospital.

3.2.1.2 Expected Surgery Volume

Each ASC makes its entry decision simultaneously with correct beliefs about other ASCs' entry probabilities. Each ASC's patients come from all zip code areas within 50 miles of the ASC's location. In each zip code area, each ASC competes with all other facilities within 50 miles of that zip code location. Each ASC's expected surgery volume in each zip code area is affected by the entry decisions and surgery quality levels of its competing facilities in that zip code area.

Suppressing surgery m and year t, I use $\mathbf{J}_z$ to denote the set of all potential ASC entrants and hospitals that are within 50 miles of zip code area z. There are N_z^A potential ASC entrants in this potential entry set. Since hospitals do not make entry decisions, i.e. $a_j = 1$ if facility j is a hospital, there are $2^{N_z^A}$ different possible realizations of the entry decision combinations. [30] I use $\{\mathbf{a}_{\mathbf{J}_z}^k, k = 1, ..., 2^{N_z^A}\}$ to denote the set of all possible entry decision combinations of the potential entry set $\mathbf{J}_z$. The entry combination, $\mathbf{a}_{\mathbf{J}_z}^k$, is realized with probability $\sigma(\mathbf{a}_{\mathbf{J}_z}^k)$. ASC j has a correct belief about the probability that the entry combination $\mathbf{a}_{\mathbf{J}_z}^k$ being realized, denoted as $\hat{\sigma}_{-j}(\mathbf{a}_{\mathbf{J}_z}^k)$, given its own entry decision.

ASC j's expected surgery volume from a zip code area z, EV_{jz}, is the weighted sum of the expected surgery volume under different entry decision combinations. I use $\Pr_{i_z \to j}(\mathbf{a}_{\mathbf{J}_z}^k, \mathbf{q}_{J_z})$ to denote the probability of patient i choosing facility j, given a certain realization of the entry combination, $\mathbf{a}_{\mathbf{J}_z}^k$, and surgery quality levels of the facilities in the relevant potential entry set,

[29] In 2006, Government Accounting Office (GAO) showed the cost ratios between surgery costs and the basic service unit cost in facilities were the same in hospitals and ASCs across different surgeries.

[30] The realizations of the entry combinations for different potential entry sets are not independent. Each ASC's entry decision affects all the potential entry set of the zip code areas within 50 miles of the facility.

denoted as $\mathbf{q}_{J_z}$. The expected surgery volume for facility j from zip code area z is

$$\begin{aligned} EV_{jz} &= \sum_k \hat{\sigma}_{-j}(\mathbf{a}^k_{\mathbf{J}_z}) \sum_{i \in \mathbf{I}_z} \Pr_{i_z \to j}(\mathbf{a}^k_{\mathbf{J}_z}, \mathbf{q}_{\mathbf{J}_z}) \\ &= \sum_k \hat{\sigma}_{-j}(\mathbf{a}^k_{\mathbf{J}_z}) \hat{V}_{jz}(\mathbf{a}^k_{\mathbf{J}_z}, \mathbf{q}_{\mathbf{J}_z}) \end{aligned} \tag{3.14}$$

The expected surgery volume for facility j, EV_j, is the sum of expected surgery volumes from all the zip code areas within 50 miles of the facility's location. The expected surgery volume is

$$EV_j = \sum_{z \in \mathbb{Z}_j} EV_{jz}. \tag{3.15}$$

3.2.1.3 Fixed Entry Cost

ASC j's profit function also depends on a fixed entry cost, $\mathcal{F}_{jlmt}$. It is a function of ASC j's characteristics, $\mathbf{Z}_{jmt}$, local housing costs, H_{lt}, whether the facility was on the market last year, L_{jmt}, a location-specific fixed entry cost, ς^1_l, a time-specific fixed cost, ς^2_t, a surgery-specific fixed entry cost, ς^3_m. The fixed entry cost is

$$\mathcal{F}_{jlmt} = \gamma^f_0 + \mathbf{Z}_{jmt}\boldsymbol{\gamma}^f_1 + \gamma^f_2 H_{lt} + \boldsymbol{\gamma}^f_3 L_{jmt} + \varsigma^1_l + \varsigma^2_t + \varsigma^3_m. \tag{3.16}$$

3.2.2 Hospital's Optimal Surgery Quality Levels

Each hospital chooses a surgery quality level for each surgery m simultaneously in the first stage of the game. At the beginning of each year, I assume each hospital knows all facilities' observed and unobserved characteristics. Given other hospitals' surgery quality levels, each hospital holds the same correct beliefs about all ASCs' entry probabilities as a function of its own surgery quality level.

The investments in surgery quality levels are surgery-specific. I assume that investing in surgery m's quality level would not affect other surgery quality levels in the same hospital.[31] Each

[31]Hospitals invest in surgery quality levels through adopting new technologies and creating closer working relationships with surgeons. These investments are less likely to have impacts on all surgeries.

hospital chooses a surgery quality level for each surgery to maximize its profit from the surgery. The investment for increasing surgery quality level is a lump sum investment. The marginal cost of operating a surgery does not vary by the quality level. Hospital j's profit from surgery m at time t, $E\Pi^H_{jlmt}$, depends on the average markup, $\mathcal{M}^H_{lmt}$, its expected surgery volume, EV_{jmt}, and a fixed cost of investing in quality level, Γ_{jlmt}. The profit function is

$$E\Pi^H_{jmt} = \mathcal{M}^H_{lmt} EV_{jmt} - \Gamma_{jlmt}. \tag{3.17}$$

The choice of surgery quality level is determined by solving the first-order condition for the profit function. Hospital j's optimal surgery quality level for surgery m at year t, q_{jmt}, satisfies the condition that

$$\frac{d\mathcal{M}^H_{lmt}}{dq_{jmt}} EV_{jmt} + \mathcal{M}^H_{lmt} \frac{dEV_{jmt}}{dq_{jmt}} = \frac{d\Gamma_{jlmt}}{dq_{jmt}}. \tag{3.18}$$

The first term in the left hand side captures the indirect impact of the hospital quality level on the average markup. The second term in the left hand side captures the impact of the hospital's quality level on the its expected volume. The right hand side is the marginal cost of investing in surgery quality level.

The remainder of this section describes the structure of marginal effect of surgery quality on the average markup, expected surgery volume, and the cost in more detail.

3.2.2.1 Marginal Return on Markup

The average markup for hospital, $\mathcal{M}^H_{lmt}$, shares the same functional form as the ASC's markup function, with different parameters,

$$\mathcal{M}^H_{lmt} = (\boldsymbol{\gamma}^H_0 + \mathbf{K}_{lt}\boldsymbol{\gamma}^H_1 + \gamma^H_2 N^H_{lmt} + \gamma^H_3 EN^A_{lmt}) * P^H_{lmt} - C_{mt}. \tag{3.19}$$

C_{mt} is the national average cost of performing surgery m at time t, which does not vary by facility-specific quality choice. The expected number of ASCs in a county is the sum of entry probabilities of the ASCs in the county. Each ASC's entry probability depends on its expected surgery volume which is a function of the surgery quality levels of its competing facilities. Since each ASC makes its entry decision after observing all hospitals' quality levels, high quality levels in hospitals could potentially deter ASCs from entering the market and allow hospitals to enjoy higher markups,

$$\frac{d\mathcal{M}^H_{lmt}}{dq_{jmt}} = \gamma^H_3 \Big(\sum_{\substack{j' \in A \\ j' \in \text{county } l}} \frac{d\sigma(a_{j'mt} = 1)}{dq_{jmt}} \Big) * P^H_{cmt}, \tag{3.20}$$

where the marginal effect of surgery quality of hospital j on ASC j's entry probability is

$$\frac{d\sigma(a_{j'mt} = 1)}{dq_{jmt}} = \mathcal{M}^A_{lmt} \phi(\mathcal{M}^A_{lmt} EV_{j'mt} - \mathcal{F}_{j'lmt}) \frac{dEV_{j'mt}}{dq_{jmt}}. \tag{3.21}$$

3.2.2.2 Marginal Return on Expected Surgery Volume

Suppressing surgery m and year t, hospital j's expected surgery volume is the sum of expected surgery volume from all the zip code areas within 50 miles of the hospital,

$$EV_j = \sum_{z \in \mathbb{Z}_j} EV_{jz}. \tag{3.22}$$

In each zip code area, hospital j's expected surgery volume is a weighted sum of the expected surgery volume under different entry decision combinations,

$$EV_{jz} = \sum_k \hat{\sigma}(\mathbf{a}^k_{\mathbf{J}_z}) \sum_{i \in \mathbf{I}_z} \hat{\Pr}_{i_z \to j}(\mathbf{a}^k_{\mathbf{J}_z}, \mathbf{q}_{J_z}). \tag{3.23}$$

The hospital's surgery quality level can change its expected surgery volume through two channels. First, it can change the probability of a certain entry decision combination being realized. Second, it can change how likely patients would choose the hospital over other facilities, given a certain realization of the entry combination and the quality choices of all the competing facilities. The marginal effect of surgery quality level on the hospital's expected volume of zip code area z is

$$\frac{dEV_{jz}}{dq_j} = \sum_k \Big(\underbrace{\frac{d\hat{\sigma}(\mathbf{a}^k_{\mathbf{J}_z})}{dq_j} \sum_{i \in \mathbf{I}_z} \hat{\Pr}_{i_z \to j}(\mathbf{a}^k_{\mathbf{J}_z}, \mathbf{q}_{J_z})}_{\text{Effect of entry deterrence}} + \underbrace{\hat{\sigma}(\mathbf{a}^k_{\mathbf{J}_z}) \sum_{i \in \mathbf{I}_z} \frac{d\hat{\Pr}_{i_z \to j}(\mathbf{a}^k_{\mathbf{J}_z}, \mathbf{q}_{J_z})}{dq_j}}_{\text{Effect of direct competition}} \Big). \tag{3.24}$$

The first part of the right hand side captures the marginal effect of quality on expected surgery volume due to the effect of entry deterrence. The second part captures the effect due to direct competition among facilities.

The effect of surgery quality level on expected volume is

$$\frac{EV_j}{dq_j} = \sum_{z \in \mathbb{Z}_j} \frac{dEV_{jz}}{dq_j}. \tag{3.25}$$

3.2.2.3 Marginal Cost

The marginal cost of investing in surgery quality level depends on the chosen surgery quality level, the hospital's observed characteristics, a location-specific fixed cost, κ_c^1, a time-specific fixed cost, κ_t^2, a surgery-specific fixed entry cost, κ_m^3, an idiosyncratic investment shock, ε_{jlmt}. The marginal cost is

$$\frac{d\Gamma_{jlmt}}{dq_{jmt}} = \omega_0 + \omega_1 q_j + \mathbf{Z}_{jmt}\boldsymbol{\omega}_2 + \kappa_l^1 + \kappa_t^2 + \kappa_m^3 + \varepsilon_{jlmt}, \tag{3.26}$$

where, $\varepsilon_{jlmt} \sim iidN(0, \sigma_\varepsilon^2)$.

3.3 Equilibrium

The equilibrium of the model is defined by two conditions.

First, in market m and year t, at the beginning of the year, each facility knows the same set of information about other potential ASC entrants. As a result, all facilities hold the same beliefs about ASCs' entry probabilities, denoted as $\{\hat{\sigma}(a_{jmt} = 1)\}_{j \in ASC}$. Each ASC's entry probability is function of its expected surgery volume (equation(3.12)). The expected surgery volume of the ASC is a function of its beliefs about other ASCs' entry probabilities and its expected surgery volume given different realizations of the entry decision combinations (equation (3.14) and equation (3.15)). At the equilibrium, given beliefs about other ASCs' entry probabilities, $\{\hat{\sigma}(a_{j'mt} = 1), j' \neq j\}$, and all facilities' surgery quality levels, $\mathbf{Q}_{mt}$, each ASC's entry probability equals the belief about its entry probability. In other words, for any ASC, at the equilibrium:

$$\sigma(a_{jmt} = 1 | \{\hat{\sigma}(a_{j'mt} = 1), j' \neq j\}_{j' \in ASC}, \mathbf{Q}_{mt}) = \hat{\sigma}(a_{jmt} = 1), \qquad \forall j \in ASC. \tag{3.27}$$

Second, in market m and time t, given other hospitals' surgery quality levels, each hospital's surgery quality level maximizes its profit. Hospital j's optimal surgery quality choice is determined by its first-order condition (equation (3.18)). Evaluating this condition involves calculating the hospital's expected surgery volume, EV_{jmt}, marginal effect of surgery quality on its own expected surgery volume, $\frac{dEV_{jmt}}{dq_{jmt}}$, and the marginal effect of the surgery quality on ASCs' entry probabilities, $\{\frac{d\sigma(a_{j'mt}=1)}{dq_{jmt}}\}_{j' \in ASC}$. All these three variables are functions of other hospitals' surgery quality levels (equation (3.21), equation (3.23) and (3.24)). At the equilibrium, for any hospital, its optimal surgery quality level solves equation (3.18), given other hospitals' optimal surgery quality levels.

4 Bayesian Estimation

I employ the Markov Chain Monte Carlo (MCMC) method for estimation. The ability to sample from the posterior distribution is essential to the practice of Bayesian statistics. However, in my model, direct sampling is impossible. In order to solve this problem, I use the Gibbs sampling method, which allows me to obtain the posterior distribution for each set of parameters sequentially. This method has several attractive feature. First, it allows me to simulate the expected surgery volume for each facility without considering all possible realizations of the market structure. As shown in equation (3.14) and equation (3.15), the expected surgery volume for each facility is the sum of expected surgery volume under different realizations of the market structure (combinations of ASCs' entry decisions), weighted by the probability of the market structure being realized. On average, each facility faces 9 potential ASC entrants, which results in $2^9 = 512$ possible combinations of ASCs' entry decisions. Evaluating the expected surgery volume under all the possible realizations of the market structure for each facility is computationally impossible. The MCMC method allows me to evaluate only one of the market realizations at a time, which greatly simplifies the estimation process. Second, it allows me to estimate each hospital's quality level by controlling the selection bias due to the unobserved match value between the sickness of the patient and the facility. As shown in equation (3.8), I allow the severity of sickness, μ_i, and the idiosyncratic agent-facility shock, $\{\epsilon_{ijmt}, j \in \mathbf{J}^c_{izmt/0}\}$, to be correlated. Instead of directly estimating a high dimensional vector of parameters by maximizing a non-linear likelihood function, the MCMC method allows me to separately estimate the utility function and the surgery outcome function easily.

In this section, I first rewrite the model using abbreviated notation that helps the discussion of the estimation process. Secondly, I construct the likelihood function based on the specified error structure. Then, I describe the estimation strategy.

4.1 Abbreviated Notation

In this section, for ease of exposition in later discussions, I rewrite the model using abbreviated notations and define three sets of variables, observed data (both endogenous and exogenous variables), the latent variables created by the data augmentation method and the parameters to be estimated.

In my model, facilities' surgery quality levels affect both the agent's facility choice and the surgery outcome of the patient. All facilities' quality levels are known to all agents but cannot be observed directly by econometricians. As introduced in section (3.2), I make different assumptions about how surgery quality levels are determined for hospitals and ASCs. Each hospital chooses its surgery quality level actively to maximize its expected profit. I treat hospitals' surgery quality levels as a part of the augmented data, denoted as $\mathbf{Q}^H_{mt} = \{q_{jmt}\}_{j \in Hospital}$. On the other hand, each ASC has a predetermined surgery quality level based on its exogenous observed characteristics, the accreditation status of the ASC. I consider the surgery quality levels of ASCs as parameters, denoted as $\mathbf{Q}^A_{mt} = \{q_{jmt}\}_{j \in ASC}$.

For the outcome equation, I use $\mathbf{O}_{mt} = \{O_{imt}\}_{i=1}^{I}$ to denote the observed readmission status for all patients who received surgery m at year t. I use $\mathbf{\Theta}^o_{mt}$ to denote the other parameters in the surgery outcome equation (equation (3.4)) for surgery m and year t, including the coefficients of the patient's observed characteristics, $\boldsymbol{\lambda}_{mt}$ and the parameters in the unobserved illness function (equation (3.8)), $\boldsymbol{\delta}_{mt}$ and $\sigma^2_{\eta mt}$.

On the demand side, $\mathbb{Y}^D_{mt}$ denotes the set of observed data for surgery m and year t, which includes agents' choice of facilities ($\mathbf{c}_{mt} = \{\mathbf{c}_{imt}\}_{i=1}^{I}$), and exogenous variables that affect the patient's utility function, denoted as $\mathbb{X}^D_{mt}$. The set of exogenous variables that affect agent i's utility from facility j for surgery m in time t, denoted as $\mathbb{X}^D_{ijzmt}$, includes agent i's characteristics ($\boldsymbol{X}_{imt}$ and $\boldsymbol{G}_{imt}$), the facility's characteristics ($\boldsymbol{Z}_{jmt}$), the patient's traveling distance (d_{izjmt}), the characteristics of the county where patient i lives ($\boldsymbol{W}_{izmt}$). Collectively, the set of exogenous variable $\mathbb{X}^D_{mt} = \{\{\mathbb{X}^D_{ijzmt}\}_{i=1}^{I}\}_{j=1}^{J}$. I use $\boldsymbol{\Theta}^D_{mt}$ to denote the set of parameters in the agent's utility function (equation (3.1), equation(3.3) and equation(3.6)), $\boldsymbol{\Theta}^D_{mt} = \{\boldsymbol{\beta}_{mt}, \boldsymbol{\beta}^d_{mt}, \boldsymbol{\beta}^q_{mt}, \boldsymbol{\beta}^v_{mt}\}$. I allow the coefficients in the patient's utility function to vary by year and by surgery.

As mentioned in the previous section (section (3.1.2)), I define $\tilde{U}_{ijzmt}$ as the utility of patient i from facility j relative to patient i's value from the outside option, $\mathbb{J}^c_{izmt/0}$ as the choice set for patient i, excluding the outside option. The utility function (equation (3.1)) could be rewritten as

$$\tilde{U}_{ijzmt} = f(q_{jmt}, \mathbb{X}^D_{ijzmt}, \boldsymbol{\Theta}^D_{mt}) + \xi_{jmt} + \tilde{\epsilon}_{ijzmt}, \qquad j \in \mathbb{J}^c_{izmt/0}, \tag{4.1}$$

where $f(q_{jmt}, \mathbb{X}^D_{ijzmt}, \boldsymbol{\Theta}^D_{mt})$ is a linear function of $\boldsymbol{\Theta}^D_{mt}$. Collectively, $\tilde{\mathbf{U}}_{izmt} = \{\tilde{U}_{ijzmt}, j \in \mathbb{J}^c_{zmt/0}\}$ is a vector of agent i's utility which determines her facility choice, and $\tilde{\mathbf{U}}_{mt} = \{\tilde{\mathbf{U}}_{izmt}\}_{i=1}^{I}$ is the set of utilities for all the patients' facility choices in market m and year t.

On the supply side, $\mathbb{Y}^A_{mt}$ denotes the set of observed data involved in each ASC's entry decision for surgery m in time t. $\mathbb{Y}^{\mathbb{A}}{}_{mt}$ includes all ASCs' entry decisions, $\mathbf{a}_{mt} = \{a_{jmt}, j \in ASC\}$, and all exogenous variables in the ASC's profit function (equation(3.11), equation (3.13) and equation (3.16)), denoted as $\mathbb{X}^A_{mt} = \{\{\mathbb{X}^A_{jlmt}, j \in ASC\}_{j=1}^{J}\}_{l=1}^{L}$. For surgery m in time t at county l, the exogenous variables that affect ASC j's expected profit, $\mathbb{X}^A_{jlmt}$, includes facility j's observed characteristic, the ASC's performing status in the last year, the Medicare reimbursement rate and a vector of county l's characteristics.

As introduced in equation (3.11), ASC j's expected profit also depends on its expected volume of the facility, EV_{jmt}, which is a function of the common beliefs about other ASCs' entry probabilities. I consider the common beliefs about ASCs' entry probabilities for surgery m in year

t, $\{\hat{\sigma}(a_{jmt}=1), j \in ASC\}$, to be a set of latent variables. The set of parameters in the ASC's markup function (equation (3.13)) and the fixed cost function (equation (3.16)) is denoted as $\mathbf{\Theta}^A$, $\mathbf{\Theta}^A = \{\boldsymbol{\gamma}^{\boldsymbol{A}}, \boldsymbol{\gamma}^{\boldsymbol{f}}, \varsigma_l^1, \varsigma_t^2, \varsigma_m^3\}$. The ASC's profit function (equation (3.11)) can be written as

$$\Pi_{jlmt}^A = g(EV_{jmt}(\{\hat{\sigma}(a_{jmt}=1), j \in ASC\}), \mathbb{X}_{jlmt}^A, \mathbf{\Theta}^A) + e_{jlmt}. \tag{4.2}$$

I use $\Pi_{mt}^A = \{\Pi_{jlmt}^A, j \in ASC\}$ to denote a vector of ASCs' profit m in year t, which is considered to be a vector of latent variables.

For the hospital j providing surgery m in time t in county l, I use $\mathbb{X}_{jlmt}^H$ to denote the set of exogenous variables that affect its optimal quality choice, including its observed characteristics, the Medicare reimbursement rate, the average cost of operating a surgery and county-level characteristics. The set of all exogenous variables that affect hospitals' quality choice for surgery m and time t is $\mathbb{X}_{mt}^H = \{\mathbb{X}_{jlmt}^H, j \in Hosp\}$. According to equation (3.17) to equation (3.21), hospital j's optimal surgery quality level for surgery m in year t also depends on its expected surgery volume (EV_{jmt}), its marginal effect of quality on expected surgery volume ($\frac{dEV_{jmt}}{dq_{jmt}}$), the marginal effect of its quality on ASCs' entry probabilities ($\frac{d\sigma(\mathbf{a}_{mt})}{dq_{jmt}} = \{\frac{d\sigma(a_{j'mt}=1)}{dq_{jmt}}\}_{j' \in ASC}$), and a set of parameters, denoted as $\mathbf{\Theta}^H$. The set of parameters includes all parameters in the hospital's average marginal benefit function (equation (3.20)), parameters in the marginal benefit function (equation (3.26)) and the variance of the marginal investment errors, $var(\varepsilon_{jcmt})$, $\mathbf{\Theta}^H = \{\boldsymbol{\gamma}^H, \boldsymbol{\omega}, \sigma_\varepsilon^2\}$. Hospital j's optimal surgery quality level is determined by solving the first-order condition of the expected profit function with respect to its surgery quality level (equation (3.18)), which can be rewritten as

$$h(EV_{jmt}, \frac{dEV_{jmt}}{dq_{jmt}}, \frac{d\sigma(\mathbf{a}_{mt})}{dq_{jmt}}, \mathbb{X}^H, q_{jmt}, \mathbf{\Theta}^H) + \varepsilon_{jcmt} = 0. \tag{4.3}$$

where $\varepsilon_{jcmt} \sim N(0, \sigma_\varepsilon)$ is an idiosyncratic shock to the marginal cost of investing in surgery quality level.

To summarize, in my model, the observed data are $\mathbb{Y} = \{\{\{\mathbb{Y}_{mt}^D, \mathbf{O}_{mt}, \mathbb{Y}_{mt}^A, \mathbb{X}_{mt}^H\}\}_{m=1}^M\}_{t=1}^T$. I use $\mathbb{X}_{mt} = \{\mathbb{X}_{mt}^D, \mathbb{X}_{mt}^A, \mathbb{X}_{mt}^H\}$ to denote the set of exogenous variables for surgery m in year t. The parameters are $\mathbf{\Theta} = \{\{\{\mathbf{\Theta}_{mt}^P\}_{m=1}^M\}_{t=1}^T, \mathbf{\Theta}^A, \mathbf{\Theta}^H\}\}$, where $\mathbf{\Theta}_{mt}^P = \{\mathbf{\Theta}_{mt}^O, \mathbf{\Theta}_{mt}^D, \boldsymbol{Q}_{mt}^A\}$. In order to estimate the model using a Markov Chain Monte Carlo method, I use the data augmentation method (Tanner and Wong (1987); Wei and Tanner (1990)) to create latent variables, including ASCs' entry probabilities, hospitals' surgery quality levels, patients' utilities and ASCs' profits, denoted as $\mathbb{R} = \{\{\{\{\hat{\sigma}(a_{jmt} = 1)\}_{j \in ASC}, \mathbf{Q}^H_{mt}, \tilde{\mathbf{U}}_{mt}, \Pi^A_{mt}\}_{m=1}^M\}_{t=1}^T\}$.

4.2 Inference

4.2.1 Posterior

I employ the Bayesian Markov Chain Monte Carlo (MCMC) method to sample the parameter vector $\mathbf{\Theta}$ and the augmented data $\mathbb{R}$ from the posterior distribution, given the prior distribution of $\mathbf{\Theta}$, $\pi(\mathbf{\Theta})$, and the likelihood $\mathcal{L}(\mathbb{Y}, \mathbb{R}|\mathbf{\Theta})$. The posterior distribution is

$$\mathcal{P}(\mathbf{\Theta}, \mathbb{R}|\mathbb{Y}) \propto \mathcal{L}(\mathbb{Y}, \mathbb{R}|\mathbf{\Theta})\pi(\mathbf{\Theta}). \tag{4.4}$$

4.2.2 Likelihood Function

From the demand side, for each surgery m in year t, I observe two outcomes from each patient: the choice of facility, $\{\mathbf{c}_{imt}\}_{i=1}^I$, and the surgery outcome, $\{O_{imt}\}_{i=1}^I$. Conditional on all observed exogenous variables, $\mathbb{X}_{mt}$, a full set of parameters, $\mathbf{\Theta}$, and a vector of unobserved characteristics of facilities, $\boldsymbol{\xi}_{mt}$, the joint density of the observed data and augmented data for patient i for surgery m in time t is

$$\begin{aligned}\mathcal{L}^d_{imt}(\tilde{\mathbf{U}}_{izmt}, \mathbf{c}_{imt}, O_{imt}|\mathbb{X}_{mt}, \mathbf{\Theta}, \boldsymbol{\xi}_{mt}, \mathbf{Q}^H_{mt}) = {} & \Pr(\tilde{\mathbf{U}}_{izmt}|\mathbb{X}_{mt}, \mathbf{\Theta}^P_{mt}, \mathbf{Q}^H_{mt}, \boldsymbol{\xi}_{mt}) \\ & * \Pr(\mathbf{c}_{izmt}|\tilde{\mathbf{U}}_{izmt}, \mathbb{X}_{mt}, \mathbf{\Theta}^P_{mt}, \mathbf{Q}^H_{mt}, \boldsymbol{\xi}_{mt}) \\ & * \Pr(O_{imt}|\mathbf{c}_{izmt}, \tilde{\mathbf{U}}_{izmt}, \mathbb{X}_{mt}, \mathbf{\Theta}^P_{mt}, \mathbf{Q}^H_{mt}, \boldsymbol{\xi}_{mt})\end{aligned} \tag{4.5}$$

which is determined by the products of three conditional density functions, each denoted as Pr.

Given the unobserved characteristics of facility j, ξ_{jmt}, the only error in the agent's utility function (equation 4.1) is the idiosyncratic match value between the facility and the agent, $\tilde{\epsilon}_{ijz}$.

The conditional density of $\tilde{\mathbf{U}}_{izmt}$ is

$$\begin{aligned}\Pr(\tilde{\mathbf{U}}_{izmt}|\mathbb{X}_{mt}, \mathbf{\Theta}_{mt}, \mathbf{Q}^{H}_{mt}, \boldsymbol{\xi}_{mt}) =& \Pr(\tilde{\mathbf{U}}_{izmt}|\mathbb{X}^{D}_{mt}, \mathbf{\Theta}^{D}_{mt}, \mathbf{Q}^{H}_{mt}, \mathbf{Q}^{A}_{mt}, \boldsymbol{\xi}_{mt}) \\ =&(2\pi^{N^c_{zmtJ}}|\tilde{\Sigma}_{iz\epsilon}|)^{-\frac{1}{2}} e^{-0.5\tilde{\boldsymbol{\epsilon}}'_{izmt}\tilde{\Sigma}^{-1}_{izmt\epsilon}\tilde{\boldsymbol{\epsilon}}_{izmt}},\end{aligned} \tag{4.6}$$

where $\tilde{\boldsymbol{\epsilon}}_{izmt}$ is the agent-facility-specific idiosyncratic shock determined by equation (4.1).

Conditional on $\tilde{\mathbf{U}}_{izmt}$, the choice of the facility for agent i, $\mathbf{c}_{izmt}$, is deterministic,

$$\begin{aligned}&\Pr(\mathbf{c}_{izmt}|\tilde{\mathbf{U}}_{izmt}, \mathbb{X}_{mt}, \mathbf{\Theta}_{mt}, \mathbf{Q}^{H}_{mt}, \boldsymbol{\xi}_{mt}) = \Pr(\mathbf{c}_{izmt}|\tilde{\mathbf{U}}_{izmt}) \\ =& \sum_{j\in\mathbb{J}^c_{izmt/0}} c_{ijzmt}(\mathbb{1}\{\tilde{U}_{ijzmt} \geq \tilde{U}_{ij'zmt}, \forall j' \in \mathbb{J}^c_{izmt/0}\} * \mathbb{1}\{\tilde{U}_{ijzmt} > 0\}).\end{aligned} \tag{4.7}$$

Conditional on the utility vector, $\tilde{\mathbf{U}}_{izmt}$, the choice vector, $\mathbf{c}_{izmt}$, the patient's observed characteristics, $\mathbf{X}_{imt}$, surgery quality levels, $\mathbf{Q}_{mt}$, and parameters in the surgery outcome function, $\mathbf{\Theta}^{O}_{mt}$, the true random variable that determines the patient's surgery outcome is $\eta_i \sim iidN(0, \sigma^2_{\eta_{mt}})$ (equation (3.4) and equation (3.8)). The conditional density of patient i's surgery outcome, O_{imt}, is

$$\begin{aligned}&\Pr(O_{imt}|\mathbf{c}_{izmt}, \mathbf{U}_{izmt}, \mathbb{X}_{mt}, \mathbf{\Theta}_{mt}, \mathbf{Q}^{H}_{mt}, \boldsymbol{\xi}_{mt}) \\ =&\Pr(O_{imt}|\mathbf{c}_{izmt}, \mathbf{U}_{izmt}, \mathbf{X}_{imt}, \boldsymbol{\lambda}_{mt}, \boldsymbol{\delta}_{mt}, \mathbf{Q}^{H}_{mt}, \mathbf{Q}^{A}_{mt}) \\ =&\frac{1}{\sqrt{2\pi}\sigma_{\eta_{mt}}} e^{\frac{-1}{2\sigma_{\eta_{mt}}}(O_{imt} - \sum\limits_{j\in\mathbb{J}^c_{iz/0}} c_{ijzmt}q_{jmt} - \sum\limits_{j\in\mathbb{J}^c_{iz/0}} \tilde{e}_{ijz}\delta_{jmt} - \mathbf{X}_{imt}\boldsymbol{\lambda}_{mt})}.\end{aligned} \tag{4.8}$$

On the supply side, the vector of hospitals' surgery quality levels, $\boldsymbol{Q}^{H}_{mt}$, is created as a part of the augmented data and determined by equation (4.3). For hospital j, given other hospitals' surgery quality levels $\{q_{j'mt}, j' \neq j\}_{j'\in Hospital}$, a set of parameters, $\{\mathbf{\Theta}^{D}_{mt}, \mathbf{Q}^{A}_{mt}, \mathbf{\Theta}^{A}, \mathbf{\Theta}^{H}\}$, a full set of observed data, $\mathbb{X}_{mt}$, and a vector of unobserved characteristics, $\boldsymbol{\xi}_{mt}$, for each surgery quality level, q_{jmt}, the hospital can calculate (1) its expected surgery level (EV_{jmt} based on equation 3.14 and equation (3.15)), (2) the marginal impact of surgery quality on its expected surgery volume ($\frac{dEV_{jmt}}{dq_{jmt}}$ based on equation (3.24)) and (3) the marginal effect of surgery quality level on ASC's entry decisions ($\frac{d\sigma(\mathbf{a}_{mt})}{dq_{jmt}}$ based on equation (3.21)). I detail the process of calculating these variables in the later section. for ease of exposition, I consider the three sets of variables, $\{EV_{jmt}, \frac{dEV_{jmt}}{dq_{jmt}}, \frac{dEV_{jmt}}{dq_{jmt}}\}_{j\in Hospital}$ as functions of $\mathbf{Q}^H_{mt}$. The random variable that determines the optimal surgery quality level for hospital j is $\varepsilon_{jmt} \sim iidN(0, \sigma^2_\varepsilon)$ (equation (4.3)). The joint density of hospitals' quality levels, $\mathbf{Q}^H_{mt}$, for surgery m in year t is

$$
\begin{aligned}
&\mathcal{L}^H_{mt}(\mathbf{Q}^H_{mt}|\mathbb{X}_{mt}, \mathbf{\Theta}, \boldsymbol{\xi}_{mt}, \mathbf{Q}^A_{mt}) \qquad (4.9)\\
&= \prod_{j\in Hospital} \frac{1}{\sqrt{2\pi}\sigma_\varepsilon} e^{-\frac{1}{2\sigma_\varepsilon}(h(EV_{jmt}(\mathbf{Q}^H_{mt}), \frac{dEV_{jmt}}{dq_{jmt}}|_{\mathbf{Q}^H_{mt}}, \frac{d\sigma(\mathbf{a}_{mt})}{dq_{jmt}}|_{(\mathbf{Q}^H_{mt})}, \mathbb{X}^H_{mt}, q_{jmt}, \mathbf{\Theta}^H))^2}.
\end{aligned}
$$

For potential ASC entrants, I observed a vector of entry decisions, $\mathbf{a}_{mt} = \{a_{jmt}\}_{j\in ASC}$. There are other two sets of latent variables, ASCs' profits, $\Pi^A_{mt} = \{\Pi^A_{jmt}\}^J_{j=1}$, and the common beliefs about ASCs' entry probabilities, $\{\hat{\sigma}(a_{jmt} = 1)\}_{j\in ASC}$, obtained from the data augmentation method. Given full sets of exogenous variables, X_{mt}, parameters, $\boldsymbol{\theta}$, hospitals' quality levels, $\mathbf{Q}^H_{mt}$ and the facilities' unobserved characteristics, $\boldsymbol{\xi}_{mt}$, the joint density of observed entry decisions and the augmented data for surgery m in year t is

$$
\begin{aligned}
&\mathcal{L}^A_{mt}(\{a_{jmt}, \Pi^A_{jmt}, \hat{\sigma}(a_{jmt} = 1)\}_{j\in ASC}|\mathbb{X}_{mt}, \mathbf{\Theta}, \boldsymbol{\xi}_{mt}, \mathbf{Q}^H_{mt})\\
&= \Pr(\{\Pi^A_{jmt}, \hat{\sigma}(a_{jmt} = 1)\}_{j\in ASC}|\mathbb{X}_{mt}, \mathbf{\Theta}, \boldsymbol{\xi}_{mt}, \mathbf{Q}^H_{mt}) \qquad (4.10)\\
&* \Big(\prod_{j\in ASC} \Pr(a_{jmt}|\Pi^A_{jmt}, \mathbf{\Theta}, \boldsymbol{\xi}_{mt}, \mathbf{Q}^H_{mt})\Big).
\end{aligned}
$$

ASC j's expected profit, Π^A_{jmt}, depends on its expected volume (equation (4.2)) and so does for its entry probability (equation (3.12)). According to the equilibrium that I defined in section (3.3), without knowing the facility-specific entry shock, the entry probability of facility j equals the common beliefs about its entry probability. In other words, the common belief about the ASC's entry probability is also determined by equation (3.12). As discussed in section (3.2.1.2), ASC j's expected surgery volume can be calculated as a function of other ASCs' entry probabilities, $\{\hat{\sigma}(a_{j'mt} = 1)\}_{j'\in ASC, j'\neq j}$, parameters in the patient's utility function, $\mathbf{\Theta}^D_{mt}$ and $\mathbf{Q}^A_{mt}$, all exogenous variables in the patient's utility function, $\mathbb{X}^D_{mt}$, hospitals' surgery quality levels, $\mathbf{Q}^H_{mt}$, and unobserved characteristics for all facilities, $\boldsymbol{\xi}_{mt}$. I discuss how to calculate the expected volume later in detail. The true random variable that determines both the belief about ASC j's entry probability and ASC j's profit is $e_{jcmt} \sim N(0,1)$ (equation (4.2)). The conditional density of $\{\Pi^A_{jmt}, \hat{\sigma}(a_{jmt}=1)\}_{j\in ASC}$ is

$$\begin{aligned} &\Pr(\{\Pi^A_{jmt}, \hat{\sigma}(a_{jmt}=1)\}_{j\in ASC} | \mathbb{X}_{mt}, \boldsymbol{\Theta}, \boldsymbol{\xi}_{mt}, \mathbf{Q}^H_{mt}) \\ &= \prod_{j\in ASC} \big(\phi(e_{jlmt}) * \Phi(e_{jlmt})\big), \end{aligned} \tag{4.11}$$

where

$$e_{jlmt} = \Pi^A_{jmt} - g(EV_{jmt}, \mathbb{X}^A_{jlmt}, \boldsymbol{\Theta}^A). \tag{4.12}$$

Conditional on the expected profit, Π^A_{jmt}, whether ASC j enters the market is deterministic,

$$\begin{aligned} \Pr(a_{jmt} | \Pi^A_{jmt}, \mathbb{X}_{mt}, \boldsymbol{\Theta}, \boldsymbol{\xi}_{mt}) &= \Pr(a_{jmt} | \Pi^A_{jmt}) \\ &= \mathbb{1}\{a_{jmt}=1\}\mathbb{1}\{\Pi^A_{jmt} \geq 0\} + \mathbb{1}\{a_{jmt}=0\}\mathbb{1}\{\Pi^A_{jmt} < 0\}. \end{aligned} \tag{4.13}$$

The join likelihood function is

$$\begin{aligned} \mathcal{L}(\mathbb{Y}, \mathbb{R} | \boldsymbol{\Theta}) = \prod_{m=1}^{M} \prod_{t=1}^{T} \int_{\boldsymbol{\xi}_{mt}} (\prod_{i=1}^{I} & \mathcal{L}^d_{imt}(\mathbf{U}_{izmt}, \mathbf{c}_{imt}, O_{imt} | \mathbb{X}_{mt}, \boldsymbol{\Theta}, \boldsymbol{\xi}_{mt}, \mathbf{Q}^H_{mt}) \\ & * \mathcal{L}^A_{mt}(\{a_{jmt}, \Pi^A_{jmt}, \hat{\sigma}(a_{jmt}=1)\}_{j\in ASC} | \mathbb{X}_{mt}, \boldsymbol{\Theta}, \boldsymbol{\xi}_{mt}, \mathbf{Q}^H_{mt}) \\ & * \mathcal{L}^H_{mt}(\mathbf{Q}^H_{mt} | \mathbb{X}_{mt}, \boldsymbol{\Theta}, \boldsymbol{\xi}_{mt}) d\mathcal{G}(\boldsymbol{\xi}_{mt}), \end{aligned} \tag{4.14}$$

where $\mathcal{G}(\boldsymbol{\xi}_{mt})$ is the joint distribution of the facilities' unobserved characteristics, $\boldsymbol{\xi}_{mt}$.

4.3 Algorithm

The posterior distribution in equation (4.4) is a high-dimensional and complex function of the parameters and the augmented data. It is known that, instead of drawing the entire parameter vector at once, it is often simpler to partition it into blocks and draw the parameters of each block separately given the other parameters and augmented data (Damlen et al., 1999; Gilks et al., 1995;

Gilks and Wild, 1992). Based on the model, I partition all parameters and latent variables in to eight blocks.

Block 1: The parameters in the agent's utility function, $\{\{\mathbf{\Theta}^D_{mt} = \{\boldsymbol{\beta}_{mt}, \boldsymbol{\beta}^d_{mt}, \boldsymbol{\beta}^q_{mt}, \boldsymbol{\beta}^v_{mt}\}\}^M_{m=1}\}^T_{t=1}$.

Block 2: Unobserved facility characteristics, $\{\{\boldsymbol{\xi}_{mt}\}^M_{m=1}\}^T_{t=1}$, and the variances for hospitals and ASCs, $\{\{(\sigma^H_{\xi_{mt}})^2\}^M_{m=1}\}^T_{t=1}$ and $\{\{(\sigma^A_{\xi_{mt}})^2\}^M_{m=1}\}^T_{t=1}$.

Block 3: Parameters in the patient's outcome function, $\{\{\mathbf{\Theta}^o_{mt}\}^M_{m=1}\}^T_{t=1}$, and facilities surgery quality levels, $\{\{\mathbf{Q}^A_{mt}, \mathbf{Q}^H_{mt}\}^M_{m=1}\}^T_{t=1}$.

Block 4: Each agent's utility, $\{\{\tilde{\mathbf{U}}_{mt}\}^M_{m=1}\}^T_{t=1}$.

Block 5: Parameters in the ASC's profit function, $\mathbf{\Theta}^A = \{\boldsymbol{\gamma}^{\boldsymbol{A}}, \boldsymbol{\gamma}^{\boldsymbol{f}}, \varsigma^1_l, \varsigma^2_t, \varsigma^3_m\}$.

Block 6: Each ASC's profit, $\{\{\Pi^A_{jmt}, \forall j \in ASC\}\}^M_{m=1}\}^T_{t=1}$.

Block 7: Beliefs about ASCs' entry probabilities, $\{\{\{\hat{\sigma}(a_{jmt} = 1), j \in ASC\}^M_{m=1}\}^T_{t=1}$.

Block 8: Parameters in hospitals' optimal choice equation, $\mathbf{\Theta}^H = \{\boldsymbol{\gamma}^H, \boldsymbol{\omega}, \sigma^2_\varepsilon\}$.

I update each block sequentially. The detail of the updating process is documented in the Appendix A. In general, given parameters and the augmented data generated in other blocks, parameters in block 1, 3, 5 and 8 are parameters in linear functions. I assume that the prior distributions of these sets of parameters are normal distributions. In each iteration, a new draw for each set of parameters is obtained from the corresponding updated posterior distribution, which also follows a normal distribution. The standard procedure of obtaining a posterior distribution for parameters in a linear function is discussed in Box and Tiao (2011). Block 2 includes the unobserved characteristics of each ASC and each hospital. Since the posterior distributions for the unobserved characteristics are difficult to obtain, a Metropolis-Hasting (MH) step (Chib and Greenberg (1995)) is employed to update the unobserved characteristics. The second block also contains the variance for the unobserved characteristics of each type of facility. I assume the prior distributions for the variances are inverted gamma distributions. The posterior distributions for the variances are updated in each iteration based on the newly updated $\boldsymbol{\xi}_{mt}$. The augmented data in block 4 is a set of latent variables in a multinomial probit model, and the augmented data in block 6 is a set of latent variables in a probit model. I follow McCulloch and Rossi (1994) to obtain new sets of latent variables in each iteration. Block 7 includes facilities' beliefs about each

ASC's entry probability. Because in the equilibrium, facilities hold correct beliefs about other ASCs' entry probability. Given parameters in other blocks and ASC j's expected surgery volume, other facilities beliefs about ASC j's entry probability can be updated based on equation (3.12).

Many updating steps involve calculating the expected volume of the surgery quality levels ($\{EV_{jmt}\}_{j=1}^{J}$), the marginal effect of increasing the hospital's surgery quality level on its expected volume ($\{\frac{dEV_{jmt}}{dq_{jmt}}\}_{j\in Hospital}$) and the marginal effect of increasing the hospital's surgery quality level on ASCs' entry probabilities ($\{\{\frac{d\sigma(a_{j'mt=1})}{dq_{jmt}}\}_{j'\in ASC}\}_{j\in Hospital}$). The detail of the simulation steps can be found in Appendix A.

5 Results

The results section reports statistics of posterior distributions. I draw 20,000 samples from the posterior distribution and use the last 5,000 samples to compute the posterior means and standard deviations.[32]

5.1 Patient Surgery Outcome and Facility Choice

Parameters in the surgery outcome function and the patient's utility function are surgery-year-specific. There are 10 sets of estimates in total.

5.1.1 Patient Surgery Outcome

The surgery outcome equation has two groups of covariates: demographics and facilities' quality levels, i.e., a set of $\boldsymbol{\lambda}$ and $\{q_j, j = 1, 2, ..., J\}$ in equation (3.4) for each surgery m and year t. The full set of covariates for demographic variables are presented in Appendix B.1. For most surgeries, females, African-Americans, older patients and patients with more diagnoses related to the surgery are slightly more likely to suffer from surgery complications than their counterparts.[33]

[32] The posterior standard deviation presented in this section is the standard deviation of the posterior density, which is a random variable in the Bayesian paradigm. Posterior standard deviations characterize the dispersion of the parameters in the model.

[33] One notable exception is that older patients who receive tonsil and adenoid removal surgeries are less likely to be readmitted. The result is intuitive, since the tonsil and adenoid removal surgeries are common among very young children, and the surgery for an older child is less risky than surgery for an younger child, holding other

The estimates also show that, compared with patients without insurance, the readmission rates are higher for patients with insurance. One possible explanation is that patients without insurance may avoid hospitalization due to potential high out-of-pocket medical expenditure.

The second set of the parameters in the outcome function is the facilities' surgery quality levels. I consider the mean of the posterior means of the facility's quality level as the estimated surgery quality level for the facility. Table 6 presents the means and the standard deviations of the estimated hospitals' quality levels for each surgery in each year. From 2006 to 2008, the average surgery quality level for breast lesion removal surgery increases significantly. Compared with 2006, averaged across hospitals, the readmission rate for a patient who receives a breast lesion removal surgery in a hospital decreases by about 28 percentage points in 2008. One possible explanation for this large increase in the estimated surgery quality level is that hospitals become more efficient in diagnosing breast cancer. It becomes less likely for a hospital to discover more severe symptoms, which could result in hospitalization, during a breast lesion removal surgery. For retina surgery and hernia repair, averaged across hospitals, the estimated quality levels increase. Holding all other variables constant, the readmission rate for a patient who receives a retina surgery decreases by 4.5 percentage points, and the readmission rate for a patient who receives a hernia repair surgery decreases by 1.7 percentage points.

Table 6: Means and Standard Deviations,
Estimated Hospitals' Surgery Quality Levels

Year	2006		2008	
Surgery	Mean	Std	Mean	Std
Knee Arthroscopy	-0.135	0.148	-0.183	0.162
Breast Lesion Removal	-0.334	0.395	-0.054	0.355
Tonsil and Adenoid Removal	-0.604	0.418	-0.768	0.435
Retina Surgery	-0.099	0.170	-0.051	0.149
Hernia Repair	-0.220	0.227	-0.202	0.219

The average estimated hospital surgery quality levels decrease for both knee arthroscopy, and tonsil and adenoid removal. Compared with 2006, it becomes less profitable for ASCs to perform

variables constant.

tonsil and adenoid removal in 2008.[34] As a result, fewer ASCs are interested in entering the market. Hospitals face less competition in the tonsil and adenoid removal surgery market and decrease their investment in surgery quality levels in 2008. However, the explanation of why hospitals decrease their surgery quality levels for knee arthroscopy in 2008 is less clear. The distributions of the surgery quality levels for hospitals and ASCs are presented in Appendix B.2.

5.1.2 Patient's Facility Choice

Each agent chooses whether to have a surgery and where to have a surgery after observing each facility's surgery quality level. Each agent chooses the option that provides her the highest utility. The utility function (equation (3.1)) of an agent has five sets of parameters for each year t and surgery m: preference for receiving a surgery ($\boldsymbol{\beta}_{1mt}$ in equation (3.1)), preference for a facility's characteristics ($\boldsymbol{\beta}_{2mt}$ in equation (3.1)), preference for traveling distance ($\boldsymbol{\beta}^d_{mt}$ in equation (3.3)), preference for quality level ($\boldsymbol{\beta}^q_{mt}$ in equation (3.5)) and individual-specific and location-specific preferences for receiving surgery in an ASC ($\boldsymbol{\beta}^v_{mt}$ in equation (3.6)).

In this section, I discuss three sets of parameters in detail, $\boldsymbol{\beta}_{1mt}$, $\boldsymbol{\beta}^d_{mt}$ and $\boldsymbol{\beta}^q_{mt}$. As suggested in previous literature, traveling distance and surgery quality levels are two of the most important factors that determine a patient's choice of facility. Quantifying the trade-off between quality and distance faced by agents is essential for understanding hospitals' investment decisions in their surgery quality levels (Kessler and Geppert, 2005; Tay, 2003). The estimates for other parameters are presented and discussed in Appendix B.3

Table 7a and Table 7b present the posterior means of the parameters that affect the patient's preference for having a surgery, $\boldsymbol{\beta}_{1mt}$. A positive coefficient means that increasing the corresponding variable would result in a higher utility from receiving a surgery for the patient. For all surgeries, compared with patients without insurance, patients who are covered by Medicare, private insurance or other types of insurance are more likely to receive outpatient surgeries (row 9, row 11 and row 12 in Table 7a and Table 7b), there are two possible explanations for the positive correlation between the patient's health insurance coverage and the probability of

[34] As shown in Table 5, the ratio between the ASC payment and the median cost of performing a tonsil and adenoid removal decreased from 0.53 in 2006 to 0.47 in 2008.

Table 7a: Posterior Means,
Preference for Surgery, 2006

Surgery	Knee Arthroscopy	Breast Lesion Removal	Tonsils and Adenoids Removal	Retina Surgery	Hernia Repair
Variables	Mean	Mean	Mean	Mean	Mean
Constant	-3.2800	-3.1240	-2.9430	-3.5732	-3.4420
Patient's Characteristics					
Female	-0.0153	–	0.0299	0.0084	–
Age Group 2	0.0003	-0.0149	0.0225	0.0129	-0.0187
Age Group 3	0.0252	0.0008	0.0342	0.0410	0.0095
Age Group 4	0.0034	0.0645	-0.1412	0.0104	0.0563
Age Group 5	0.0249	-0.0336	-0.1124	-0.0031	-0.0339
African-American	-0.0221	-0.0171	-0.0585	-0.0228	-0.0281
Other Races	-0.0105	0.0297	-0.0665	0.0898	-0.0581
Medicare	0.0272	0.0858	0.1512	0.0287	0.0639
Medicaid	0.0180	0.0176	-0.0016	-0.0123	-0.0322
Private Insurance	0.0023	0.0447	0.0327	0.0028	0.0097
Other Types of Insurance	0.3317	0.1366	0.1775	0.1558	0.0427
Surgeon's Characteristics					
Number of Surgeries Performed	0.0288	0.0399	0.0094	0.0185	0.0056
Surgeries Performed in ASCs (%)	-0.0488	-0.0658	0.0124	0.0032	-0.0256
Local Characteristics					
Poverty Rate	-0.0569	-1.0826	-0.0275	-1.0694	-1.0359
Median Household Income ($100,000)	1.0251	1.0258	0.9177	2.0258	0.0222

Note that for tonsils and adenoids removal surgery, age group 2 represent people of age 4-7, group 3 represents people of age 7-12, age group 4 represents age 13-18 and age group 5 represents age > 18. The omitted age category is the youngest age group, people of age 0-3. For other surgery categories, age group 2, 3, 4, 5 represent people of age 45-54, 55-64, 65-75 and >75, The unit for the number of surgeries performed by the surgeon is 100 cases.

Table 7b: Posterior Mean,
Preference for Surgery, 2008

Surgery	Knee Arthroscopy	Breast Lesion Removal	Tonsils and Adenoids Removal	Retina Surgery	Hernia Repair
Variables	Mean	Mean	Mean	Mean	Mean
Constant	-3.2805	-3.0653	-2.9886	-3.5782	-3.4405
Patient's Characteristics					
Female	0.0014	–	-0.0269	0.0001	–
Age group 2	0.0974	0.0315	0.0094	-0.0110	0.0295
Age Group 3	0.1105	0.0737	0.0358	-0.0115	0.0176
Age Group 4	0.1287	-0.0332	0.0226	-0.0411	0.0798
Age Group 5	0.1029	-0.0233	-0.0184	-0.0073	0.0890
African-American	-0.1132	-0.0506	-0.0016	-0.0180	-0.0494
Other Races	-0.0420	-0.0632	0.0163	0.0192	-0.0122
Medicare	-0.0236	0.0312	-0.0301	-0.0594	-0.0218
Medicaid	0.1262	0.0647	0.0116	-0.1003	0.0086
Private Insurance	0.0557	-0.0066	-0.0178	-0.0282	-0.0224
Other Types of Insurance	-0.0630	-0.0559	0.1015	0.0392	0.1655
Surgeon's Characteristics					
Number of Surgeries Performed	0.0316	0.0279	0.0123	0.0592	0.0102
Surgeries Performed in ASCs (%)	0.0432	-0.0532	0.0335	0.0152	-0.098
Local Characteristics					
Poverty Rate	-0.0313	-2.1253	-0.9237	-2.1312	-1.0356
Median Income ($100,000)	1.5313	1.123	1.0315	2.0315	1.1553

Note that for tonsils and adenoids removal surgery, age group 2 represent people of age 4-7, group 3 represents people of age 7-12, age group 4 represents age 13-18 and age group 5 represents age > 18. The omitted age category is the youngest age group, people of age 0-3. For other surgery categories, age group 2, 3, 4, 5 represent people of age 45-54, 55-64, 65-75 and >75, The unit for the number of surgeries performed by the surgeon is 100 cases.

receiving an outpatient surgery. First, as suggested in the previous literature, health insurance eligibility increases the use of health care services (Card et al., 2008; Finkelstein et al., 2012). Second, each individual chooses her health insurance coverage based on her private information about her health status. As a result, we observe adverse selection in the health insurance market. An individual with higher health risk is more likely to enroll in a health insurance plan. If an individual's health insurance coverage is affected by how likely she has an outpatient surgery, my model suffers from an endogeneity problem. However, Cardon and Hendel (2001) shows information asymmetric does not explain the correlation between higher demand for health insurance and higher level of health care. Moreover, the surgeries studied in this paper are not treatments for chronic disease, and patients are less likely to have private information about whether and when they need surgeries. The endogeneity problem is less a concern for my model. The effects of having Medicaid on receiving surgery are not consistent across different surgeries. Although previous literature suggests that Medicaid eligibility can increase health care service utilization, including primary and preventive care as well as hospitalizations (Finkelstein et al., 2012), the effect of Medicare eligibility on the probability of having an outpatient surgery is unclear. One possible explanation is that low-income individuals who are eligibles for Medicaid may not have proper primary care resources to help them diagnose the disease and to give them suggestions about treatment plans.

Table 8a: Posterior Means,
Utility Function, Distance Covariates, 2006

Surgery	Knee Arthroscopy	Breast Lesion Removal	Tonsils and Adenoids Removal	Retina Surgery	Hernia Repair
Variables	Mean	Mean	Mean	Mean	Mean
Distance	-8.3259	-9.4107	-12.0029	-7.7269	-10.0457
Distance^2	6.3087	7.5116	9.4084	7.4696	8.9850
Cross terms: Distance *					
Female	0.0455	–	-0.0948	0.1513	–
Age Group 2	-0.4469	-0.2707	1.1656	-0.9621	-0.4596
Age Group 3	-0.5941	-0.2839	1.2223	-1.0582	-0.6015
Age Group 4	-0.5822	-0.0150	1.4562	-1.7892	-0.6256
Age Group 5	-0.4814	-0.0646	1.1956	-1.7459	-0.5209
African-American	0.5300	-0.0886	0.1456	-1.0357	0.0929
Other Races	0.6706	0.3249	0.1333	-0.5187	0.0893
Medicare	-1.8190	-1.4330	-1.5224	0.0028	-1.4894
Medicaid	-0.9352	-0.6375	-1.1524	0.0000	-0.7765
Private Insurance	-1.3980	-1.0069	-1.5058	-0.2907	-1.2413
Other Types of Insurance	-1.4182	-1.4499	-1.9614	-0.9179	-1.3726

Note that for tonsils and adenoids removal surgery, age group 2 represent people of age 4-7, group 3 represents people of age 7-12, age group 4 represents people of age 13-18 and age group 5 represents people of age > 18. The omitted age category is the youngest age group, age 0-3. For other surgery categories, age group 2, 3, 4, 5 represent people of age 45-54, 55-64, 65-75 and >75. The distance is measured in 100 miles.

Table 8a and Table 8b present the posterior means of the parameters for distance covariates in the utility function ($\boldsymbol{\beta}^d_{mt}$ in equation (3.3)). Estimates are similar for the same surgery in two years.

Table 8b: Posterior Means,
Utility Function, Distance Covariates, 2008

Surgery	Knee Arthroscopy	Breast Lesion Removal	Tonsils and Adenoids Removal	Retina Surgery	Hernia Repair
Variables	Mean	Mean	Mean	Mean	Mean
Distance	-8.9623	-9.4655	-11.0988	-7.3920	-10.8166
Distance^2	6.3223	7.1731	9.4897	7.4697	8.3030
Cross Terms: Distance *					
Female	-0.0063	–	-0.1945	-0.0081	–
Age Group 2	-0.3010	-0.4248	1.2559	-1.0086	-0.4897
Age Group 3	-0.4756	-0.4000	1.5252	-1.0577	-0.6935
Age Group 4	-0.8573	-0.3669	1.5477	-1.3371	-0.8640
Age Group 5	-0.4423	-0.2453	2.2782	-1.5760	-0.6558
African-American	0.5727	0.0401	0.5601	0.2667	0.1771
Other Races	-0.1147	0.1648	-0.5459	1.0518	0.0193
Medicare	-1.6911	-1.3852	-1.5445	-0.6290	-1.2081
Medicaid	-1.2642	-1.0279	-1.4384	-0.0111	-0.5896
Private Insurance	-1.3542	-1.0546	-1.9456	-0.3219	-0.9503
Other Types of Insurance	-1.3090	-1.3950	-2.2894	0.4672	-1.1475

Note that for tonsils and adenoids removal surgery, age group 2 represent people of age 4-7, group 3 represents people of age 7-12, age group 4 represents people of age 13-18 and age group 5 represents people of age > 18. The omitted age category is the youngest age group, age 0-3. For other surgery categories, age group 2, 3, 4, 5 represent people of age 45-54, 55-64, 65-75 and >75. The distance is measured in 100 miles.

However, the estimates vary greatly for different types of surgeries. Interactions between distance and age groups have negative coefficients, except for tonsil and adenoid removal. Compared with patients under 45, older patients have higher traveling costs, except for tonsil and adenoid removal patients (row 6 to row 9 in Table 8a and Table 8b).[35]

Interactions between distance and different types of insurance coverage have negative coefficients, which means that the traveling costs for patients without insurance coverage are smaller, holding other variables constant (row 11 to row 14 in Table 8a and Table 8b). One possible explanation is that, when a patient does not have health insurance to help her to cover the cost of a surgery, she might want to travel a longer distance in order to find a facility with a lower price.

Table 9 shows the average marginal effect of distance on a patient's choice probability (av-

[35]For patients who receive tonsil and adenoid removal surgery, the omitted age group is age 0-6. The positive sign for the interactions between traveling distance and age group means that older children have lower traveling costs.

Table 9: Average Marginal Effect of Distance on Facility Choice Probability (%)

	Patients Who Have Surgery		Patients Who Have No Surgery	
Surgery	Year 2006	Year 2008	Year 2006	Year 2008
Knee Arthroscopy	-0.321	-0.306	-0.011	-0.029
	(0.025)	(0.010)	(0.010)	(0.020)
Breast Lesion Removal	-0.346	-0.249	-0.0141	-0.009
	(0.035)	(0.015)	(0.004)	(0.020)
Tonsil and Adenoid Removal	-0.497	-0.427	-0.007	-0.007
	(0.010)	(0.013)	(0.009)	(0.007)
Retina Surgery	-0.320	-0.309	-0.030	-0.045
	(0.027)	(0.015)	(0.010)	(0.098)
Hernia Repair	-0.378	-0.396	-0.040	-0.034
	(0.027)	(0.031)	(0.011)	(0.011)

Standard deviations in parentheses.

eraged across individual and facility). The numbers in the table represent the average change in the patient's choice probability if the facility moves one mile away from the patient's location.[36] I show the means and the standard deviations for the marginal effects of distance on facility choice probabilities for patients who receive surgeries in column 1 and column 2, and the marginal effects of distance on facility choice probabilities for patients who do not receive surgeries in column 3 and column 4. The standard deviations of the elasticities are calculated based on the means of the posterior standard deviations of the parameters.

For patients who do have surgeries, the marginal effects of traveling distance on facility choice probabilities range from -0.2493 to -0.4966. For example, averaged across individuals and facilities, for a patient who receives a knee arthroscopy, an increase of traveling distance by one mile decreases the probability of choosing that facility by 0.32 percentage points. My estimates for the marginal effects of distance on facility choice probabilities for patients who have surgery are similar to those found in previous literature.[37] For patients who do not have surgeries, their choice probabilities for

[36]When calculating the marginal effect of distance on patient's choice probability for each patient and each facility in her choice set, I keep the distance between the patient and other facilities unchanged. In other words, I change the traveling distance for each patient one option at a time.

[37]Weber (2014) estimates a multinomial logit model of consumer demand for healthcare facilities in the outpatient surgery markets. Using the universal data of outpatient procedures performed in Florida in 2007, the paper estimates that, for four categories of surgeries, the marginal effects of increasing traveling time by one minute on the facility choice probability range from -0.0897 to -0.1539.

Table 10: Average Elasticities,
Choice Probabilities with Respect to Distance

	Patients Who Have Surgery		Patients Who Have No Surgery	
Surgery	Year 2006	Year 2008	Year 2006	Year 2008
Knee Arthroscopy	-0.374	-0.346	-0.068	-0.089
	(0.016)	(0.022)	(0.010)	(0.010)
Breast Lesion Removal	-0.603	-0.751	-0.016	-0.057
	(0.023)	(0.073)	(0.010)	(0.018)
Tonsil and Adenoid Removal	-0.318	-0.162	-0.012	-0.023
	(0.023)	(0.019)	(0.009)	(0.011)
Retina Surgery	-0.630	-0.721	-0.031	-0.047
	(0.043)	(0.033)	(0.017)	(0.010)
Hernia Repair	-0.513	-0.498	-0.037	-0.039
	(0.041)	(0.074)	(0.018)	(0.062)

Standard deviations in parentheses

facilities are largely unaffected by traveling distance. This is because the observed characteristics of patients who do not receive surgeries are very different from the characteristics of those patients who receive surgeries. By including the interactions between the patient's traveling distance and the patient's observed characteristics, I allow patients' traveling costs to vary by their observed characteristics. The estimates suggest that a patient with certain observed characteristics is less likely to receive a surgery, and her choice of facility is also less likely to be affected by traveling distance.

Table 10 presents the elasticities of choice probabilities with respect to distance (averaged across individuals and facilities). For patients who have surgeries, the elasticities in different markets range from -0.951 to -0.162. For example, averaged across individuals and facilities, for a patient who receives knee arthroscopy, a one percent increase in traveling distance to the facility leads to a 0.374 percent decrease in the choice probability for that facility. The elasticities of choice probabilities with respect to distance are very small for patients who do not have surgeries.

Table 11a and Table 11b present the posterior means of the parameters for quality covariates in the utility function. The posterior means for quality levels are positive for all the markets. Compared with patients without insurance, patients with private insurance or with Medicare value quality more (row 8 and row 10 in Table 11a and Table 11b). Exceptions include Medicare patients who receive hernia repair or receive tonsil and adenoid removal in 2006. Compared with patients without insurance, patients with Medicaid or other types of insurance coverage value facility quality levels differently for different surgeries (row 9 and row 11 in Table 11a and Table 11b). For example, compared with patients without health insurance, Medicaid patients care less about surgery quality levels for knee arthroscopy and retina surgery, but they care more about surgery quality levels for the other three surgery categories. It is very difficult to know the reason behind Medicaid patients' different attitudes toward quality levels for different surgeries. One possible explanation is that the technology and equipments for performing outpatient knee arthroscopy and retina surgeries changed rapidly in the 2000s. Medicaid patients may be less informed about the new development in technology and fail to choose facilities based on facilities' true quality levels.

Table 11a: Posterior Means,
Utility Function, Quality Covariates, 2006

Surgery	Knee Arthroscopy	Breast Lesion Removal	Tonsils and Adenoids Removal	Retina Surgery	Hernia Repair
Variables	Mean	Mean	Mean	Mean	Mean
Quality	0.2169	0.0266	0.0759	0.3799	0.0085
Cross terms: Quality *					
Female	0.0070	–	-0.0184	0.0266	–
Age Group 2	-0.0092	-0.0012	-0.0508	0.0623	-0.0544
Age Group 3	-0.0158	0.0066	-0.0701	0.0964	-0.0479
Age Group 4	0.0127	-0.0310	-0.0591	0.1173	-0.0312
Age Group 5	0.0479	-0.0873	-0.0283	0.1397	-0.0359
African-American	0.0081	-0.1338	0.0748	0.0404	-0.0391
Other Races	0.0831	-0.1431	0.0338	-0.0665	-0.0146
Medicare	-0.0640	0.0666	-0.0100	0.0129	-0.0734
Medicaid	-0.0555	0.0379	0.0016	-0.0862	0.0805
Private Insurance	-0.0100	0.0208	0.0489	0.1096	-0.0036
Other Types of Insurance	-0.0365	0.0692	0.0429	-0.2307	-0.0505

Note that for tonsils and adenoids removal surgery, age group 2 represent people of age 4-7, group 3 represents people of age 7-12, age group 4 represents people of age 13-18 and age group 5 represents people of age > 18. The omitted age category is the youngest age group, age 0-3. For other surgery categories, age group 2, 3, 4, 5 represent people of age 45-54, 55-64, 65-75 and >75.

Table 11b: Posterior Means,
Utility Function, Quality Covariates, 2008

Surgery	Knee Arthroscopy	Breast Lesion Removal	Tonsils and Adenoids Removal	Retina Surgery	Hernia Repair
Quality	0.0463	0.0875	0.1826	0.0757	0.0822
Cross terms: Quality *					
Female	-0.0047	–	-0.0157	0.0448	–
Age Group 2	0.0106	-0.0132	-0.0116	0.0270	-0.0456
Age Group 3	0.0250	-0.0076	-0.0330	0.0487	-0.0275
Age Group 4	0.0191	-0.0108	-0.0074	0.0923	-0.0319
Age Group 5	0.0199	-0.0207	-0.0334	0.0025	-0.0288
African-American	0.0372	-0.0645	0.1199	0.1749	0.0050
Other Races	0.0346	-0.0265	-0.0402	-0.1761	0.0346
Medicare	-0.0836	-0.0026	0.0057	0.1061	0.0021
Medicaid	-0.0700	-0.0287	0.0271	-0.0005	0.0258
Private Insurance	0.0690	0.0010	0.0599	0.0406	-0.0032
Other Types of Insurance	0.1059	-0.0409	0.1835	-0.2513	-0.0040

Note that for tonsils and adenoids removal surgery, age group 2 represent people of age 4-7, group 3 represents people of age 7-12, age group 4 represents people of age 13-18 and age group 5 represents people of age > 18. The omitted age category is the youngest age group, age 0-3. For other surgery categories, age group 2, 3, 4, 5 represent people of age 45-54, 55-64, 65-75 and >75.

Table 12 shows the elasticities of the choice probabilities with respect to surgery quality (averaged across individuals and facilities). I report the elasticities of the choice probabilities with respect to surgery quality for patients who receive surgeries in the first two columns, and the elasticities of the choice probabilities with respect to surgery quality for patients who do not receive surgeries in the last two columns.

Table 12: Average Elasticities,
Choice Probabilities with Respect to Surgery Quality

	Patients Who Have Surgery		Patients Who Have No Surgery	
Surgery	Year 2006	Year 2008	Year 2006	Year 2008
Knee Arthroscopy	0.353	0.316	0.003	0.006
	(0.022)	(0.010)	(0.010)	(0.003)
Breast Lesion Removal	0.316	0.301	0.014	0.011
	(0.018)	(0.026)	(0.013)	(0.009)
Tonsil and Adenoid Removal	0.222	0.2009	0.010	0.011
	(0.012)	(0.034)	(0.012)	(0.008)
Retina Surgery	0.614	0.429	0.016	0.013
	(0.052)	(0.046)	(0.009)	(0.010)
Hernia Repair	0.154	0.115	0.007	0.010
	(0.011)	(0.026)	(0.007)	(0.01)

Standard deviations in parentheses.

For patients who have surgeries, the elasticities of the choice probabilities with respect to surgery quality in different markets range from 0.115 to 0.614. Patients who seek a facility for retina surgery are very sensitive to facilities' surgery quality levels. Averaged across patients and facilities, in 2006, a one percent increase in the facility's quality level in retina surgery increases the patient's probability of choosing that facility by 0.61 percent. Meanwhile, patients who seek facilities for hernia repair surgeries are much less sensitive to facilities' surgery quality levels. Averaged across patients and facilities, in 2006, a one percent increase in the facility's quality level in hernia repair increases the patient's probability of choosing that facility by 0.12 percent. For patients who do not have surgeries, the elasticities of the choice probabilities with respect to surgery quality are very small. The reason behind this is similar to the reason for the small marginal effects of traveling distance on facility choice probabilities for patients who do not receive surgeries. A patient's observed characteristics can affect both the patient's probability of receiving a surgery and how much her facility choice is affected by surgery quality levels. The estimates suggest that, when a facility increases its surgery quality level, the increase in surgery volume is largely caused by attracting patients from other facilities.

5.2 ASC's Entry Decision

Table 13 presents posterior means of the parameters in ASC's profit function. A positive sign for the parameter in the fixed cost function means that, on average, when the corresponding variable increases, an ASC spends more money as its fixed entry cost. Each ASC's performing status in the last year (whether the ASC was in the market last year, or not) is the strongest predictor for the ASC's entry decision in the current year (the last row in Table 13). Averaged across ASCs for all surgeries in all years, changing the performance status in the last year from not performing to performing increases an ASC's entry probability from 3.75 percent to 89.9 percent, holding other variables constant.

In my model, I consider the payment schedule change for ASCs in 2008 provides exogenous variations in ASCs' incentives of entering surgery markets over time and across procedures. Figure 2 presents the distribution of the effects of a one-standard-deviation increase in the Medicare reimbursement on ASCs' entry probabilities.

Averaged across ASCs for all surgeries in all years, a one-standard-deviation ($18.17) increase in the Medicare reimbursement rate for ASCs from the current price increases an ASC's entry probability by 2.01 percentage points. Given the average entry probability of 16.04 percent, a one-standard-deviation increase in the Medicare reimbursement rate results in a 12.5 percent increase in the entry probability from the mean. On average, the elasticity of the entry probability with respect to the Medicare reimbursement rate is 0.26.

Table 13: Posterior Means and Standard Deviations,
ASC's Profit Function

	Mean	Std. Dev
Parameters in the markup function		
Medicare Reimbursement Rate	6.123	0.081
Cross terms: Medicare Reimbursement Rate *		
Private Insured%	2.041	0.952
Medicare%	1.322	0.510
Medicaid%	0.235	0.122
Number of Medicare Advantage Plans (per 100,000 residents)	1.121	0.002
Number of Hospitals (per 100,000 residents)	-1.019	0.114
Number of ASCs (per 100,000 residents)	-0.017	0.023
Cost	-0.341	0.003
Parameters in the fixed cost function		
Constant	2.994	0.004
Accreditation Status	0.023	0.019
Housing Price	-0.028	0.033
Last Year Performing	-3.523	0.001

Note that the model controls for surgery-fixed effects, year-fixed effects and core-based statistical area-fixed effects. All the demongraphics characteristics, including the number of hosptials and ASCs per 100,000 residents are measured at the county level. The Medicare reimbursement rate is measured in units of $1,000. Expected surgery volume is measured in units of 1,000 patients.

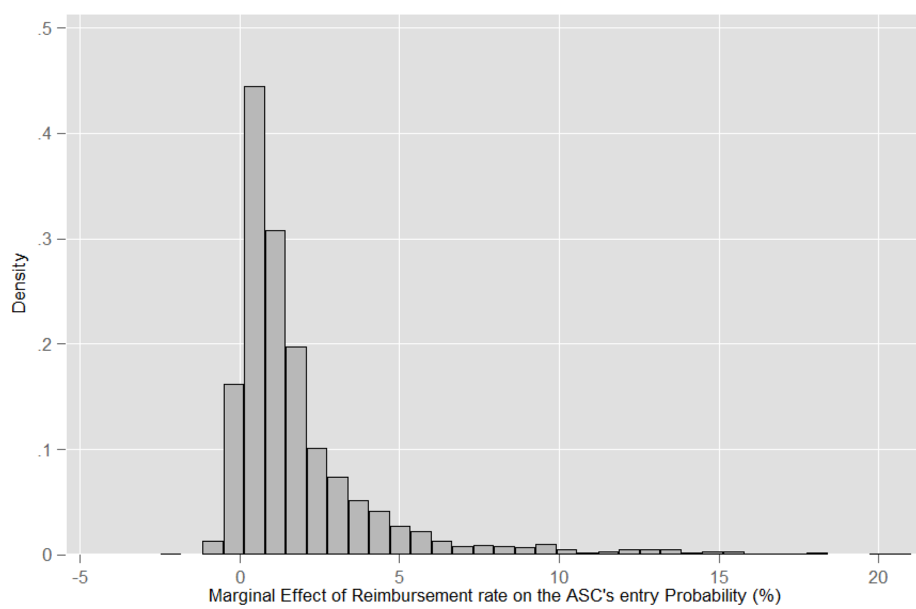


Figure 2: Distribution of the Marginal Effect of Reimbursement Rate on Entry Probability

The parameters for interactions between the Medicare reimbursement rate and the percentage of residents covered by different insurance types are positive (row 3 to row 5 in Table 13). This means that, when the Medicare reimbursement rate increases, the markup increases more in areas with higher insurance coverage (Medicare and private insurance) rates. As a result, ASCs are more likely to enter the market in counties with higher insurance coverage rates.

As expected, the parameters for the interactions between the number of facilities (hospitals and ASCs) in the county and the Medicare reimbursement rate are negative (row 7 and row 8 in Table 13). This means that, when there are more hospitals in an area, each ASC has less bargaining power against insurance companies, and the surgery markup for the ASC decreases. However, the parameters for the interaction between the Medicare reimbursement and the number of Medicare Advantage plans per 100,000 residents is negative (row 6 in Table 13), which contradicts my assumption.

The estimates also show that it costs more for an ASC with accreditation status to enter the market than an ASC without accreditation. The entry costs are actually lower in areas with higher housing prices. One possible explanation is that the housing price in an area is an indicator of the local wealth level. A richer area may have better services to support small businesses and reduce ASCs' entry costs. Given the estimates from the model, averaged across ASCs for all surgeries in all years, the average markup for performing a surgery in an ASC is \$67.2, and the average fixed cost of entering the market is \$153,792.

5.3 Hospital's Optimal Surgery Quality Level

Table 14 presents posterior means and standard deviations of the parameters in the hospital's markup function (equation (3.19)) and the hospital's marginal cost function (equation (3.26)). A positive parameter in the hospital's marginal cost function means that, when the corresponding variable increases, the hospital spends more money on increasing its quality level.

A higher Medicare reimbursement rate leads to a higher markup for the hospital. The coefficients for the interactions between the Medicare reimbursement rate and the percentage of patients covered by different types of insurance are positive (row 3 to row 5 in Table 14). This means that

Table 14: Posterior Means and Standard Deviations
Hospital's Markup and Marginal Cost

	Mean	Std. Dev
Parameters in the markup function		
Medicare Reimbursement Rate	1.135	0.039
Cross Term: Medicare Reimbursement Rate*		
Private Insured%	1.836	0.023
Medicare%	1.142	0.005
Medicaid%	0.624	0.004
Number of Medicare Advantage Plans (per 100,000 residents)	0.011	0.002
Number of Hospitals (per 100,000 residents)	0.015	0.002
Number of ASCs (per 100,000 residents)	-0.032	0.001
Parameters in the marginal cost function		
Constant	1.314	0.021
Quality	0.640	0.030
Number of Outpatient Visits per Year (10,000)	-0.108	0.014
Teaching Status	1.784	0.041
Within Network	-0.801	0.026
For Profit	-0.502	0.025
Not For Profit, Private	-0.471	0.026
Breast Lesion Removal	-0.563	0.028
Tonsil and Adenoid Removal	0.965	0.033
Retina Surgery	8.032	0.040
Hernia Repair	5.906	0.029
Year 2008	-0.213	0.025

Note that the model controls for surgery-fixed effects, year-fixed effects and core-based statistical area-fixed effects. All the demongraphics characteristics, including the number of hosptials and ASC per 100,000 residents are measured at the county level. The Medicare reimbursement rate is measured in units of $1,000. Expected surgery volume is measured in units of 100 patients.

a hospital's markup is higher in areas with better health care coverage rate. As discussed earlier, I find a similar impact of the county-level insurance coverage rates on ASCs' markup.

The coefficient for the interaction between the Medicare reimbursement rate and the number of Advantage plans in a county per 100,000 residents is positive (row 6 in Table 14). This means that, in an area with a higher level of competition among insurance companies, each hospital has more bargaining power against the insurance companies and gains a higher markup for each surgery. The coefficients of the interactions between the Medicare reimbursement rate and both the number of hospitals and the number of ASCs per 100,000 residents are negative (row 7 and row 8 in Table 14). This means that each hospital can negotiate a better price with insurance companies when there are fewer health care providers in the county.

When the hospital increases its surgery quality level, it reduces the expected number of ASCs in the same county and results in a higher markup. At the equilibrium, averaged across hospitals, the average markup for performing a surgery is \$197.7. Averaged across hospitals, a one-tenth-standard-deviation increase in surgery quality level from the current level leads to a 0.013 percent decrease in the number of expected ASCs per 100,000 capita in the county and a 0.006 percent (\$1.08) increase in the markup.[38] The effect of increasing quality on the mark-up is very small.

A higher surgery quality level can attract more patients to choose the hospital over other facilities. Averaged across hospitals for all surgeries in all years, a one-tenth-standard-deviation increase in surgery quality level from the current level leads to around 5 more patients per hospital for a particular surgery in a year. Given that the average number of patients treated in a hospital is around 205 per year, a one-tenth-standard-deviation increase in surgery quality level from the current level results in a 2.4 percent increase in the expected surgery volume. The effect of entry deterrence explains 47 percent of the increase, while the effect of direct competition explains 53 percent of the increase.

Using parameters in the marginal cost function, I estimate the cost associated with investing in surgery quality level. Averaged across hospitals, a one-tenth-standard -deviation increase in

[38]As shown in Table 6, the means and the standard deviations for the surgery quality levels are of similar magnitude. Since the model should only be used to evaluate the impact of a local change, I choose to consider the impact of a one-tenth-standard-deviation change in hospitals' surgery quality level on ASCs' entry probabilities.

the surgery quality level costs \$1,315 per year. The marginal costs of investing in quality vary by surgeries. It is more costly to invest in retina surgery and hernia repair than other surgeries. The estimates also show that it is less expensive for a hospital within a hospital network to improve its surgery quality level, while it is more expensive for a teaching hospital to improve its quality level.

Combining the estimates from the ASCs' profit function and hospitals' optimal quality choice, I can estimate the marginal effect of increasing ASCs' Medicare reimbursement rate by taking the total derivative of equation (3.18),

$$\begin{aligned}
&[\frac{d^2\mathcal{M}^H_{lmt}}{dq^2_{jmt}}EV_{jmt} + 2\mathcal{M}^H_{lmt}\frac{d^2EV_{jmt}}{dq^2_{jmt}} + \frac{d\mathcal{M}^H_{lmt}}{dq_{jmt}}\frac{dEV_{jmt}}{dq_{jmt}}]dq_{jmt} \\
&+[\frac{d^2\mathcal{M}^H_{lmt}}{dq_{jmt}dP^A_{jmt}}EV_{jmt} + \frac{d^2\mathcal{M}^H_{lmt}}{dq_{jmt}dP^A_{jmt}}\frac{dEV_{jmt}}{dP^A_{jmt}} + \frac{d\mathcal{M}^H_{lmt}}{dP^A_{jmt}}\frac{dEV_{jmt}}{dq_{jmt}} + \mathcal{M}^H_{lmt}\frac{d^2EV_{jmt}}{dq_{jmt}dP^A_{jmt}}]dP^A_{jmt} \\
&=\frac{d^2\Gamma_{jlmt}}{dq^2_{jmt}}dq_{jmt}.
\end{aligned} \tag{5.1}$$

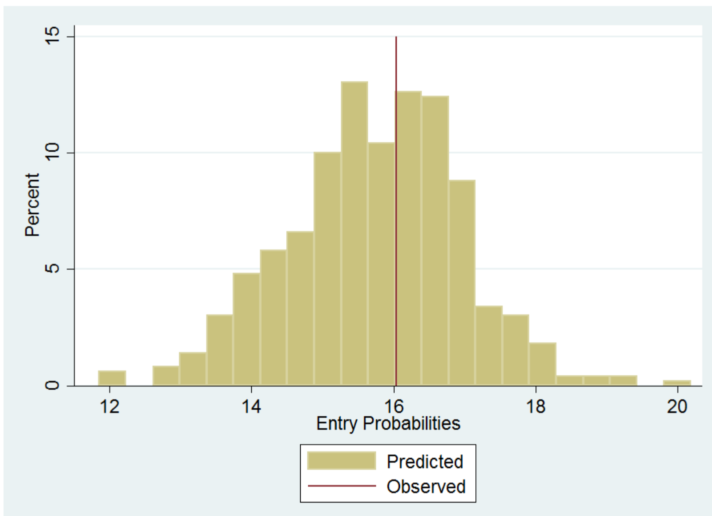
The ASCs' reimbursements affect hospital's quality levels by changing the ASCs' entry probabilities. A higher ASC entry probability decreases the expected volume of the hospitals, and increases the expected number of ASCs in an area. By solving equation (5.1). I found that a one-standard-deviation increase in ASCs' Medicare reimbursement (\$18.17) increases hospital's quality level by 0.17 standard deviation, or equivalently \$2,251 more investment on surgery quality level.

Meanwhile, patients' welfare are also affected by increasing the Medicare reimbursement rate. The patient enjoys more facility choices for having a surgery and can receive a higher quality of care from hospital. Averaged across all patients, if there is a one-standard-deviation increase in the Medicare reimbursement rate for ASCs, the average surgery quality level received increases by 1.9 percent, and the average utility level increases by 0.87 percent, which is equivalent to reducing travel distance by about three miles.

5.4 Fit of Model

To consider the fit of the model, I follow Gelman et al. (2013) to examine whether the replicated data generated under the model looks similar to the observed data. The basic idea is to draw several sets of parameters from the posterior distributions, simulate relevant predictors from the model and compare the distributions of the predictors to the observed data. In this section, I focus on two sets of the most important predicted results from the model, ASCs' predicted entry probabilities and hospitals' predicted optimal surgery quality levels. To simulate a distribution for each of the predicted results, I draw 500 samples of the parameters from the posterior distribution.[39]

Figure 3: Distributions of the Average Predicted Entry Probability



First, I examine whether the predicted entry probabilities for ASCs are similar to the observed entry probabilities. Given the k^{th} draw of parameters from the posterior distribution, for ASC j in year t and market m, I use equation (3.12) to predict its entry probability, $\hat{\sigma}_{jmt,k}$, which is a function of the facility's expected surgery volume. Each ASC's expected surgery volume depends on other ASCs' entry probabilities. As discussed in Section 4.3 and Appendix A.1, even if I know each ASC's entry probability at the equilibrium, it is still impossible to calculate directly the expected surgery volume. To solve this problem, in each iteration, I simulate an entry decision for each ASC. The expected surgery volume is the average surgery volume calculated based on the last 5,000 samples of the simulated ASCs' entry decisions. For each draw from the posterior

[39]The parameters are drawn from the last 5,000 samples of the posterior distributions with replacement.

distribution, I calculated an average entry probability across all ASCs. The average observed entry probability is 16.04, and the average predicted entry probabilities, $\{\hat{\sigma}_k, k = 1, ..., 500, \}$, range from 11.9 percent to 20.2 percent, with the mean equals 16.02. Figure 3 displays a histogram of the predicted average entry probabilities, which are calculated based on the 500 samples of parameters from the posterior distribution, and the observed average entry probability, which is shown by the solid vertical line. As shown in Figure 3, most of the predicted average entry probabilities are close to the observed average entry probability.

Table 15: The Observed and the Predicted Average Readmission Rates

	Year 2006			
	Observed	Predicted		
	Mean	Mean	25th percentile	75th percentile
Knee Arthroscopy	3.17	3.20	2.85	3.52
Breast Lesion Removal	5.21	5.10	4.92	5.37
Tonsils and Adeniods Removal	6.49	6.32	5.98	6.60
Retina Surgery	4.92	4.80	4.55	5.18
Hernia Repaire	4.41	4.32	4.11	4.70
	Year 2008			
	Observed	Predicted		
	Mean	Mean	25th percentile	75th percentile
Knee Arthroscopy	3.42	3.40	3.09	3.72
Breast Lesion Removal	5.63	5.73	5.33	6.01
Tonsils and Adeniods Removal	6.57	6.42	6.21	6.67
Retina Surgery	4.42	4.39	4.20	4.64
Hernia Repaire	4.88	4.90	4.62	5.07

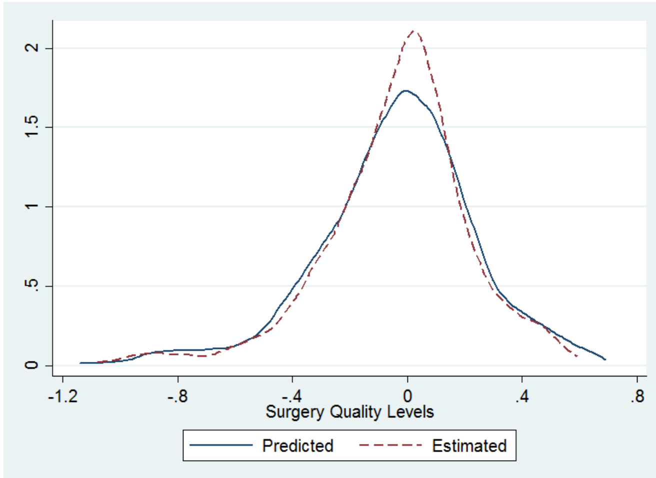
Samples of the 500 readmission rates averaged across patients for each surgery in each year are calculated base on 500 sets of parameters drawn from the posterior distributions. The mean, the 25th percentile and the 75th percentile are calculated based on the distributions of the average readmission rates.

Second, I want to examine whether hospitals' predicted optimal surgery quality levels are similar to the observed surgery quality levels. However, the true surgery quality levels are unobserved for econometricians. I separate the task into two parts. First, I use the hospitals' estimated quality levels to predict each patient's probability of readmission based on equation (3.4) and compare it to the observed readmission for the patient. If the predicted readmission rates are very close to the observed readmission rates, I can conclude that the estimated surgery quality levels reflect the true surgery quality levels. Second, I calculate the predicted surgery quality level for each hospital in each surgery market based on equation (3.18), where each hospital chooses an optimal surgery quality level to maximize its profit while taking other hospitals' estimated surgery quality levels as the true surgery quality levels at the equilibrium. By comparing each hospital's predicted surgery quality level with the estimated surgery quality level, I evaluate whether the model can successfully predict the optimal quality choices for hospitals.

Using each draw of the parameters from the posterior distribution, I predict an average readmission rate across all patients for each surgery each year. The average predicted readmission rates calculated from the 500 draws of parameters constitute a distribution of predicted readmission rates. Table 15 shows the average observed readmission rates and moments from the distributions of the average predicted readmission rates (mean, the 25th percentile and the 75th percentile). Table 15 suggests that the means of the distributions of the predicted average readmission rates are similar to the observed average readmission rates, and the 25th and the 27th percentiles are not far away from the means. When controlling for surgery quality levels, my model does a successful job in predicting patients' readmission rates. In the rest of the section, for each hospital, I take the average estimated surgery quality level from the last 5,000 draws of the posterior distribution and treat it as the point estimate for its surgery quality level.

Then I compare the estimated surgery quality levels and the predicted optimal surgery quality levels. For each draw of parameters from the posterior distribution, I calculate an optimal surgery quality level for each hospital, taking other hospitals' estimated surgery quality levels as given. The average predicted optimal surgery quality level for each hospital is the average of the optimal predicted surgery quality levels calculated based on 500 draws of parameters. Figure 4 shows two kernel density plots. The dotted line represents the density of the estimated surgery quality levels, while the solid line represents the density of the average predicted surgery quality levels. Figure 4 indicates that the proposed model can generate surgery quality levels with similar density to the estimated surgery quality levels. Overall, compared with the distribution of the estimated surgery quality levels, the distribution of the predicted surgery quality levels has a very similar mean and a larger standard deviation.

Figure 4: Kernel Density Plots
the Estimated and the Predicted Surgery Quality Levels



6 Policy Simulation

In this section, I consider one policy change, reducing the hospital Medicare reimbursement by 10 percent from the actual payment in 2018. For the policy change, I simulate the potential impact it has on ASCs' entry decisions, hospitals' quality choices and patients' utilities.

I evaluate this policy change by considering two different scenarios. In the first scenario, I assume that the market structure is not affected by the change in the Medicare reimbursement rate. In other words, each hospital chooses its optimal surgery quality level knowing that ASCs' entry decisions will not be affected, and has no incentive to invest in surgery quality level to deter ASCs from entering the market. In the second scenario, I allow each ASC to make its entry decision based on hospitals' chosen quality levels. Hospitals have the incentive to invest to deter ASCs from entering the market.

6.1 Without Entry Deterrence

Conditional on the current market structure, a decrease in the hospital reimbursement rate decreases the expected markup for each hospital. Considering a small change in the Medicare reimbursement rate, I obtain the marginal effect of the price change on the hospital's quality level by taking the total derivative of equation (3.18). With the assumption that ASCs' entry decisions are not affected by hospitals quality levels, equation (3.20) shows that the hospital's markup is not affected by its quality level, $\frac{d\mathcal{M}_{lmt}^H}{dq_{jmt}} = 0$. The marginal effect of the reimbursement rate change on the hospital's quality level is

$$\mathcal{M}_{lmt}^H \frac{d^2 EV_{jmt}}{dq_{jmt}^2} dq_{jmt} + \frac{d\mathcal{M}_{lmt}^H}{dP_{jmt}^H} \frac{dEV_{jmt}}{dq_{jmt}} dP_{jmt}^H = \frac{d^2 \Gamma_{jlmt}}{dq_{jmt}^2} dq_{jmt}, \tag{6.1}$$

or equivalently,

$$\frac{dq_{jmt}}{dP_{jmt}^H} = \frac{\frac{d\mathcal{M}_{lmt}^H}{dP_{jmt}^H} \frac{dEV_{jmt}}{dq_{jmt}}}{\omega_1 - \mathcal{M}_{lmt}^H \frac{d^2 EV_{jmt}}{dq_{jmt}^2}}, \tag{6.2}$$

where ω_1 represents the increase in marginal cost for investing in surgery quality (see equation (3.26)).

Averaged across all the hospitals, without considering the effect of entry deterrence, a 10% decrease in the hospital reimbursement decreases the hospital's optimal quality level by 0.23 standard deviations or by 3.1 percent from the previous level. The decrease in the hospital's surgery quality corresponds to about a $3,024 decrease in the hospital's quality investment. The decrease in hospitals' surgery quality levels also affect patients' choices of facilities as well as their total welfare. After the policy change, because hospitals choose to invest less in their surgery quality levels, patients are more likely to choose ASCs, holding all other variables constant. Averaged across patients, the average patient utility decreases by 0.93 percent and the average quality level received by patients decreases by 2.4 percent.

6.2 With Entry Deterrence

When ASCs' entry decisions can be affected by hospitals' quality levels, the marginal effect of the reimbursement change on the hospital's quality level is also calculated by taking the total derivative of equation (3.18), which is

$$
\begin{aligned}
&[\frac{d^2\mathcal{M}^H_{lmt}}{d^2q_{jmt}}EV_{jmt} + 2\frac{d\mathcal{M}^H_{lmt}}{dq_{jmt}}\frac{dEV_{jmt}}{dq_{jmt}} + \mathcal{M}^H_{lmt}\frac{d^2EV_{jmt}}{dq^2_{jmt}}]dq_{jmt} \\
&+[\frac{d^2\mathcal{M}^H_{lmt}}{dq_{jmt}dP_{jmt}}EV_{jmt} + \frac{d\mathcal{M}^H_{lmt}}{dq_{jmt}}\frac{dEV_{jmt}}{dP_{jmt}} + \frac{d\mathcal{M}^H_{lmt}}{dP_{jmt}}\frac{dEV_{jmt}}{dq_{jmt}} + \mathcal{M}^H_{lmt}\frac{d^2EV_{jmt}}{dq_{jmt}dP_{jmt}}]dP_{jmt} \\
&=\frac{d^2\Gamma_{jlmt}}{dq^2_{jmt}}dq_{jmt}.
\end{aligned}
\tag{6.3}
$$

The marginal effect is different from equation (6.2) in two ways. First, because ASCs' entry probabilities are affected by the hospital's quality level, according to equation (3.20), $\frac{d\mathcal{M}^H_{lmt}}{dq_{jmt}}$ and $\frac{d^2\mathcal{M}^H_{lmt}}{d^2q_{jmt}}EV_{jmt}$ are not zero. According to the estimates I obtain, $\frac{d\mathcal{M}^H_{lmt}}{dq_{jmt}} < 0$. Second, the marginal effect of the quality change on its own expected surgery volume, $\frac{dEV_{jmt}}{dq_{jmt}}$, is calculated differently. When taking the effect of entry deterrence into account, reducing the hospital's quality level results in a larger change in its expected surgery volume. As a result, averaged across hospitals, a 10% decrease in the hospital's reimbursement decreases its optimal quality level by 0.31 standard deviations or by about 4.18 percent from its previous level. The decrease in the quality level corresponds to a \$4,076 decrease in the hospital's quality investment. Averaged across ASCs, the entry probability increases by 0.16 percentage points, or by 1.3 percents from the mean.

In theory, the patients' welfare change from the policy is ambiguous. On the one hand, hospitals' quality levels decrease, and patients' utility levels decrease. On the other hand, more ASCs entering the market gives patients more choices. According to my estimates, the negative effect of decreasing quality level dominates the positive effect of the increasing number of choices. Averaged across patients, the average patient utility decreases by 1.21 percent and the average surgery quality level received by patients decrease by 3.2 percent.

There are several caveats for my current policy analysis. I do not consider the cost-saving associated with decreasing the Medicare reimbursement and do not measure the monetary value of consumers' welfare change. A complete welfare analysis should take cost-saving, the consumer's welfare change, the hospital's profit decrease and the ASC's profit increase into account.

7 Conclusion

The impact of competition on health care quality has been the subject of considerable theoretical and empirical debate. Most of the previous literature focused on the competition among hospitals in the inpatient care market. However, scarce evidence exists on the fast-growing outpatient surgery market. In this paper, I investigate the impact of competition on the hospital's surgery quality levels.

In the outpatient surgery market, the hospital faces competition from other traditional hospital outpatient departments and ambulatory surgery centers. This paper evaluates the impact of competition on the hospitals' outpatient surgery quality levels by investigating the market structure change induced by a payment schedule change for ASCs in 2008. The payment change results in substantial variations in ASCs' profitability across different procedures. When the surgery becomes more profitable, more ASCs want to enter this surgery market and hospitals face increasing surgery market competition. Hospitals could respond to the emerging competition from ASCs by investing in their surgery quality levels.

Both the demand side and the supply side of the market are taken into account while evaluating the impact of competition in outpatient surgery market. On the demand side, a patient and her surgeon jointly decide in which facility she should have a surgery. On the supply side, hospitals move first as incumbents in the market. Each hospital chooses a surgery quality level based on other hospitals' optimal surgery quality levels. After observing hospitals' surgery quality levels, ASCs make entry decisions simultaneously.

My paper adds to the existing literature by explicitly modeling the strategic investment decisions made by hospitals. A high surgery quality level can attract more patients, given a certain market structure. A high surgery quality level can also deter ASCs from entering the market by reducing its expected surgery volume, thus reducing the competition the hospital would face in the outpatient surgery market. Using universal outpatient discharge data from Florida, I estimate my model using a Bayesian Markov Chain Monte Carlo method. I find that a higher Medicare reimbursement rate for ASCs can encourage ASCs to enter the market. On average, a one standard deviation increase in the reimbursement rate leads to a 11.6 percent increase in the ASC's entry probability. Hospitals invest in surgery quality levels to compete with ASCs. The effect of entry deterrence explains 47 percent of the increase, while the effect of direct competition explains 53 percent of the increase.

The results emphasize the essential role of competition in encouraging hospitals to improve their surgery quality levels, and the importance of taking the motive of entry deterrence into account when evaluating the impact of a policy that aims at enhancing competition in the outpatient surgery market.

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Appendices

A Computation Algorithm

A.1 Simulated Expected Volume

Calculating the expected volume involves evaluating all possible realizations of the market structures (equation (3.14) and equation (3.15)), which is infeasible for computation. However, under the MCMC frame work, I can simplify the problem by considering a particular realization of the entry decision combinations as a part of the augmented data and calculating the expected volume based on this particular realization of the market.

In each iteration, I first create one particular realization of the market structure, $\{\hat{a}^r_{jmt} = 1\}_{j \in ASC}$, based on the previously updated beliefs about ASCs' entry probabilities, $\{\hat{\sigma}^{r-1}(a_{jmt} = 1)\}_{j \in ASC}$. Then, I calculate the expected surgery volume based on this particular realization of the market structure, parameters in the patient's utility function, $\mathbf{\Theta}^D_{mt}$, exogenous variables that affect patients' utilities, $\mathbb{X}^D_{mt}$, facilities surgery quality levels, $\mathbf{Q}_{mt}$, and a vector of facilities' unobserved characteristics, $\boldsymbol{\xi}_{mt}$.[40]

In iteration r, given a vector of previously updated beliefs about ASCs' entry probabilities, $\{\hat{\sigma}^{r-1}(a_{jmt} = 1)\}_{j \in ASC}$, I draw a set of random variables from a uniform distribution, denoted as $\{u^r_{jmt}\}_{j \in ASC}$. For ASC j, the simulated entry decision is

$$
\begin{aligned}
&\hat{a}^r_{jmt=1} = 1, \qquad && if \quad u^r_{jmt} < \hat{\sigma}^{r-1}(a_{jmt} = 1); \\
&\hat{a}^r_{jmt=1} = 0, \qquad && otherwise.
\end{aligned}
\tag{A.1}
$$

Since hospitals do not make entry decisions, the simulated entry decisions equal 1 for all hospi-

[40]Within one iteration, I need to calculate the expected surgery volume in different blocks. Because I update the parameters and the augmented data sequentially, different parameters and augmented data are available in different blocks for simulating the expected surgery volume. I always use the most recently update parameters and augmented data when I simulate the expected surgery volume. In this section, I give a general description about how to simulate the expected volume given a full set of parameters and augmented data, without specifying whether the set of parameters and augmented data are generated in iteration r or in iteration $r-1$. In appendix A, I specify the process of updating parameters and augmented data for each block and discuss what is the latest parameters and augmented data available for calculating expected profit.

tals. For facility j, its post-entry surgery volume is simulated based on ASCs' simulated entry decisions.[41] The simulated surgery volume is the sum of the simulated surgery volume from all zip code areas within 50 miles (equation(3.10)). For patient i who lives in zip code area z, her simulated choice set, $\hat{\mathbb{J}}^c_{zmt}(\hat{\mathbf{a}}^r_{jm})$, includes all hospitals and ASCs within 50 miles of the patient's zip code location and with $\hat{a}^r_{jmt=1} = 1$ and an outside option. Given the simulated choice set, patient i's probability of choosing facility j is

$$\hat{\Pr}_{i_z \to j}(\hat{\mathbf{a}}^r_{mt}, \mathbf{Q}_{mt}) = \Pr(U_{ijzmt} \geq U_{ij'zmt}, j' \in \hat{\mathbb{J}}^c_z(\hat{\mathbf{a}}^r_{jm})). \tag{A.2}$$

The simulated surgery volume is

$$\hat{EV}_{jmt} = \sum_{z \in \mathbb{Z}_j} \sum_{i \in \mathbf{I}_z} \hat{\Pr}_{i_z \to j}(\hat{\mathbf{a}}^r_{mt}, \mathbf{Q}_{mt}). \tag{A.3}$$

A.2 Simulated Marginal Effect of Quality on ASCs' Entry Probabilities

Each hospital's surgery quality level affects ASCs' entry probability (equation (3.21)). The marginal effect of facility j's surgery quality level on ASC j''s entry probability, $\frac{d\sigma(a_{j'mt}=1)}{dq_{jmt}}$, is a function of the ASC j''s expected surgery volume, $EV_{j'mt}$, and the marginal effect of facility j's surgery quality level on ASC j''s surgery volume, $\frac{dEV_{j'mt}}{q_{jmt}}$. In each iteration, I simulate these two variables based on the simulated market structure, $\{\hat{\mathbf{a}}^r_{mt}\}$.

The process of simulating $EV_{j'mt}$ has been discussed in section (A.1). Since there is no closed form expression for $\frac{dEV_{j'mt}}{dq_{jmt}}$, I evaluate this variable using the numerical method,

$$\frac{dEV_{j'mt}(\mathbf{Q}^r_{mt})}{dq_{jmt}} = \frac{1}{\Delta q}(EV_{j'mt}(\{q^r_{lmt}\}_{l \neq j}, q^r_{jmt} + \Delta q) - EV_{j'mt}(\mathbf{Q}^r_{mt})). \tag{A.4}$$

[41] If facility j is an ASC, the expected volume is simulated based on other ASCs' simulated entry decisions

A.3 Simulated Marginal Effect of Surgery Quality Level on Expected Volume

The marginal effect of a hospital's surgery quality level on its own expected volume, $\{\frac{dEV_{jmt}}{dq_{jmt}}\}_{j\in Hospital}$, can be calculated based on equation (3.24). The process of evaluating this marginal effect involves calculating the marginal effect of increasing surgery quality on the probability of different entry decision combinations being realized,$\{\{\frac{d\hat{\sigma}(\mathbf{a}^k_{\mathbf{J}_z mt})}{dq_{jmt}}\}^Z_{z=1}\}^{K_j}_{k=1}$, where k is the indicator for different realizations of entry decision combinations. Because each ASC receives an independent entry cost shock, the marginal effect of increasing surgery quality, q_{jmt}, on the probability of entry combination $\mathbf{a}^k_{mt}$ being realized is

$$\begin{aligned}\frac{d\hat{\sigma}(\mathbf{a}^k_{\mathbf{J}_z mt})}{dq_{jmt}} &= \prod_{j'} \frac{d(\hat{\sigma}(\mathbf{a}^k_{j'mt}|j' \in ASC \cap j' \in \hat{\mathbb{J}}^c_{zjmt}(\hat{\mathbf{a}}^r_{jm})))}{dq_{jmt}} \\ &= \prod_{j'} \hat{\sigma}(\mathbf{a}^k_{j'mt}|j' \in ASC \cap j' \in \hat{\mathbb{J}}^c_{zjmt}(\hat{\mathbf{a}}^r_{jm}))) \\ &* \big(\sum_{j'} (\hat{\sigma}(\mathbf{a}^k_{j'mt}|j' \in ASC \cap j' \in \hat{\mathbb{J}}^c_{zjmt}(\hat{\mathbf{a}}^r_{jm})))^{-1} * \frac{d\hat{\sigma}(\mathbf{a}^k_{j'mt}|j' \in ASC \cap j' \in \hat{\mathbb{J}}^c_{zjmt}(\hat{\mathbf{a}}^r_{jm}))}{dq_{jmt}}\big) \\ &= \hat{\sigma}(\mathbf{a}^k_{\mathbf{J}_z mt})\big(\sum_{\substack{j' \in ASC \\ j' \in \hat{\mathbb{J}}^c_{zjmt}(\mathbf{a}^r_{jm})}} (\frac{1}{\hat{\sigma}(\mathbf{a}^k_{j'mt})} * \frac{d\hat{\sigma}(\mathbf{a}^k_{j'mt})}{q_{jmt}})\big).\end{aligned} \tag{A.5}$$

In each iteration, I evaluate $\{\frac{dEV_{jmt}}{dq_{jmt}}\}_{j\in Hospital}$ conditional on the simulated market structure, $\{\hat{\mathbf{a}}^r_{mt}\}$. Given a particular realization of the market structure, $\{\hat{\mathbf{a}}^r_{mt}\}$, I have discussed how to calculate the last term of the equation (A.5), $\{\frac{d\hat{\sigma}(\mathbf{a}^k_{j'mt})}{q_{jmt}}\}_{j' \in ASC \cap j' \in \hat{\mathbb{J}}^c_{zjmt}(\mathbf{a}^r_{jm})}$, in section (A.2). The simulated marginal effect of hospital j's surgery quality level on its own expected volume is

$$\frac{\widehat{dEV_{jmt}}}{dq_{jmt}} = \sum_{z \in \mathbb{Z}_{jmt}} \big((\sum_{\substack{j' \in ASC \\ j' \in \hat{\mathbb{J}}^c_{zjmt}(\mathbf{a}^r_{jm})}} (\frac{1}{\hat{\sigma}(\mathbf{a}^k_{j'mt})} * \frac{d\hat{\sigma}(\mathbf{a}^k_{j'mt})}{q_{jmt}})\hat{\Pr}_{i\to j}(\mathbf{a}^k_{\mathbf{J}_z}, \mathbf{Q}_{mt}) + \sum_{i \in \mathbf{I}_z} \frac{d\hat{\Pr}_{i\to j}(\mathbf{a}^k_{\mathbf{J}_z}, \mathbf{Q}_{mt})}{dq_{jmt}}\big). \tag{A.6}$$

A.4 Block 1: Parameters in the Agent's Utility Function

The first block includes parameters in the agent's utility function, $\mathbf{\Theta}^D_{mt}$, for each surgery m and year t. I assume it follows a normal distribution,$\mathbf{\Theta}^D_{mt} \sim N(\bar{\mathbf{\Theta}}^D_{mt}, V^D_{mt})$, and the prior distribution for $\mathbf{\Theta}^D_{mt}$ is $\mathbf{\Theta}^D_{mt} \sim N(\bar{\mathbf{\Theta}}^{D,0}_{mt}, V^{D,0}_{mt})$.

As mentioned earlier, $\tilde{\mathbf{U}}_{ijzmt}$ is a linear function of the set of parameters, $\mathbf{\Theta}^D_{mt}$. Conditional on $\boldsymbol{\xi}^{r-1}_{mt}$, $\{\{\tilde{\mathbf{U}}^{r-1}_{imt}\}^M_{m=1}\}^T_{t=1}$ and $\mathbf{Q}^{r-1}_{mt}$, the process of updating $\mathbf{\Theta}^D_{mt}$ is a process of obtaining the posterior distribution for parameters in a linear function and drawing a set of random variables from this posterior distribution.[42]

In this linear model, $\{\{\tilde{U}^{r-1}_{ijzmt} - \xi^{r-1}_{jmt}\}_{j \in \mathbb{J}^c_{izmt/0}}\}^I_{i=1}$ are the dependent variables, denoted as y_{mt}. The explanatory variables, x_{mt}, include facilities' surgery quality levels and all exogenous variables in equation (3.1). The process of updating the first block is equivalent to updating parameters in a standard linear function:

$$y_{mt} = x_{mt}\mathbf{\Theta}^D_{mt} + \tilde{\epsilon}_{mt}. \tag{A.7}$$

As discussed in section (3.1.2), $\tilde{\boldsymbol{\epsilon}}_{mt} \sim N(0, \tilde{\Sigma}_{\epsilon mt})$, where $\tilde{\Sigma}_{\epsilon mt}$ is a positive-definite matrix. I use $\tilde{G}'_{\epsilon mt}$ to denote the upper triangular matrix from the Cholesky decomposition, $\tilde{\Sigma}_{\epsilon mt} = \tilde{G}'_{\epsilon mt}\tilde{G}_{\epsilon mt}$. the posterior variance and mean for $\mathbf{\Theta}^D_{mt}$ are[43]

$$V^{D,r}_{mt} = ((\tilde{G}_{\epsilon mt}x_{mt})'(\tilde{G}_{\epsilon mt}x_{mt}) + (V^{D,0}_{mt})^{-1}), \tag{A.8}$$

$$\bar{\mathbf{\Theta}}^{D,r}_{mt} = (V^{D,r}_{mt})^{-1}((\tilde{G}_{\epsilon mt}x_{mt})'(\tilde{G}_{\epsilon mt}x_{mt})^{-1} + \bar{\mathbf{\Theta}}^{D,0}_{mt}). \tag{A.9}$$

The vector of the updated parameters, $\mathbf{\Theta}^{D,r}_{mt}$ is a random draw from the posterior distribution, $N(\bar{\mathbf{\Theta}}^{D,r}_{mt}, V^{D,r}_{mt})$.

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[42] Box and Tiao (2011) provide a detailed discussion on how to derive posterior distribution for parameters in a linear function.

[43] In my model, the the covariance matrix of the errors is predetermined. I assume the agent-facility specific shock is $\epsilon_{ijmt} \sim iidN(0,1)$. There is no unknown parameter for the covariance matrix of $\tilde{\epsilon}_{imt} = \{\epsilon_{ijmt} - \epsilon_{i0mt}\}$. See section (3.1.2) for specifications of the error structure.

A.5 Block 2: Unobserved Characteristics for ASCs and Hospitals

Facility j's unobserved characteristics is $\xi_{jmt} \sim N(0, \sigma^g_{\xi_{mt}})$, where $g = H, A$. The second block includes each facility's unobserved characteristics and the variances of the unobserved characteristics for hospitals and ASCs for surgery m in year t. I assume the prior of the variances follow inverted gamma distributions, $(\sigma^H_{\xi_{mt}})^2 \sim IG(\tau^{0,H}, s^{0,H})$ and $(\sigma^A_{\xi_{mt}})^2 \sim IG(\tau^{0,A}, s^{0,A})$.

I use a Metropolis-Hasting (MH) step (Chib and Greenberg (1995)) to update the vector of unobserved characteristics, $\{\{\boldsymbol{\xi}_{mt}\}_{m=1}^M\}_{t=1}^T$, and the variances for the unobserved characteristics.

In iteration r, I update the unobserved characteristics for each facility sequentially. The updating process for the unobserved characteristics, ξ^r_{jmt}, depends on other facilities' unobserved characteristics, $\boldsymbol{\xi}^r_{-jmt}$. For facility $j' \neq j$, $\hat{\xi}^r_{j'mt} = \xi^r_{j'mt}$ if $j' < j$, and $\hat{\xi}^r_{j'mt} = \xi^{r-1}_{j'mt}$ if $j' \geq j$.

The first step is to draw the candidate vector $\boldsymbol{\xi}_{mt}$ for surgery m and year t from a proposed density. I use the Random-Walk (RW) Metropolis chain as the proposal density. The proposed candidates for $\{\xi^{try}_{jmt}\}_{j\in ASC}$ and $\{\xi^{try}_{jmt}\}_{j\in Hospital}$ are

$$\begin{aligned}
\xi^{try}_{jmt} &= \xi^r_{jmt} + v\sigma^{A,r-1}_{\xi_{mt}}\eta^{rA}_{jmt}, && if \qquad j \in ASC; \\
\xi^{try}_{jmt} &= \xi^r_{jmt} + v\sigma^{H,r-1}_{\xi_{mt}}\eta^{rH}_{jmt}, && if \qquad j \in Hospital,
\end{aligned} \tag{A.10}$$

where v is a scalar determined by the researcher, $\eta^{rA}_{jmt} \sim N(0,1)$ and $\eta^{rH}_{jmt} \sim N(0,1)$.

The second step is to construct the acceptance-rejection ratio for each ASC and each hospital, $\{\mathcal{R}^{A,r}_{jmt}\}_{j\in ASC}$ and $\{\mathcal{R}^{H,r}_{jmt}\}_{j\in Hospital}$, respectively. For ASC j, the acceptance ratio is

$$\begin{aligned}
\mathcal{R}^{A,r}_{jmt} =& \frac{\prod_i \Pr(\mathbf{U}^{r-1}_{izmt}|\mathbb{X}_{mt}, \boldsymbol{\Theta}^{D,r}_{mt}, \mathbf{Q}^{r-1}_{mt}, \xi^{try}_{jmt}, \hat{\boldsymbol{\xi}}_{-jmt}) \Pr(\Pi^{A,r-1}_{jmt}|\boldsymbol{\Theta}^{D,r}_{mt}, \boldsymbol{\Theta}^{A,r-1}, \mathbf{Q}^{r-1}_{mt}, \xi^{try}_{jmt}, \hat{\boldsymbol{\xi}}_{-jmt})}{\prod_i \Pr(\mathbf{U}^{r-1}_{izmt}|\mathbb{X}_{mt}, \boldsymbol{\Theta}^{D,r}_{mt}, \mathbf{Q}^{r-1}_{mt}, \xi^{r-1}_{jmt}, \hat{\boldsymbol{\xi}}_{-jmt}) \Pr(\Pi^{A,r-1}_{jmt}|\boldsymbol{\Theta}^{D,r}_{mt}, \boldsymbol{\Theta}^{A,r-1}, \mathbf{Q}^{r-1}_{mt}, \xi^{r-1}_{jmt}, \hat{\boldsymbol{\xi}}_{-jmt})} \\
&* \frac{\phi(\xi^{try}_{jmt}|\sigma^{A,r}_{\xi mt})}{\phi(\xi^{r-1}_{jmt}|\sigma^{A,r}_{\xi mt})}.
\end{aligned} \tag{A.11}$$

For hospital j, the acceptance ratio is

$$\mathcal{R}^{A,r}_{jmt} = \frac{\prod_i \Pr(\mathbf{U}^{r-1}_{izmt}|\mathbb{X}_{mt}, \mathbf{\Theta}^{D,r}_{mt}, \mathbf{Q}^{r-1}_{mt}, \xi^{try}_{jmt}, \hat{\boldsymbol{\xi}}_{-jmt}) \Pr(\mathbf{Q}_{mt}|\mathbb{X}_{mt}, \mathbf{\Theta}, \xi^{try}_{jmt}, \hat{\boldsymbol{\xi}}_{-jmt})}{\prod_i \Pr(\mathbf{U}^{r-1}_{izmt}|\mathbb{X}_{mt}, \mathbf{\Theta}^{D,r}_{mt}, \mathbf{Q}^{r-1}_{mt}, \xi^{r-1}_{jmt}, \hat{\boldsymbol{\xi}}_{-jmt}) \Pr(\mathbf{Q}_{mt}|\mathbb{X}_{mt}, \mathbf{\Theta}, \xi^{r-1}_{jmt}, \hat{\boldsymbol{\xi}}_{-jmt})} * \frac{\phi(\xi^{try}_{jmt}|\sigma^{H,r}_{\xi mt})}{\phi(\xi^{r-1}_{jmt}|\sigma^{H,r}_{\xi mt})}. \tag{A.12}$$

Lastly, I accept the candidate ξ^{try}_{jmt} with probability $min\{\mathcal{R}^{A,r}_{jmt}, 1\}$ if facility j is an ASC, and with probability $min\{\mathcal{R}^{H,r}_{jmt}, 1\}$ if facility j is a hospital.

Given the newly updated $\boldsymbol{\xi}^r_{mt}$, the posterior distributions of the variances for the unobserved characteristics are $(\sigma^{H,r}_{\xi_{mt}})^2 \sim IG(\tau^{r,H}, s^{r,H})$ and $(\sigma^{A,r}_{\xi_{mt}})^2 \sim IG(\tau^{r,A}, s^{r,A})$. I assume there are N^H_{jm} hospitals and N^A_{jm} ASCs for surgery m in year t. The parameters in the posterior distributions are:

$$\tau^{r,g} = \tau^{0,g} + \frac{N^g_{jm}}{2}, \qquad g \in A, H; \tag{A.13}$$

$$s^{r,g} = s^{0,g} + \frac{\sum_{j\in g} \xi^r_{jmt}}{2}, \qquad g \in A, H. \tag{A.14}$$

A.6 Block 3: Parameters in the Patient's Outcome Function

The third block includes the parameters in the patient's outcome function, $\{\{\mathbf{\Theta}^o_{mt}\}^M_{m=1}\}^T_{t=1}$, and facilities surgery quality levels, $\{\{\mathbf{Q}_{mt} = \{\mathbf{Q}^A_{mt}, \mathbf{Q}^H_{mt}\}\}^M_{m=1}\}^T_{t=1}$. I assume the prior distributions for the parameters and quality levels are $\mathbf{\Theta}^o \sim N(\bar{\mathbf{\Theta}}^{o,0}_{mt}, V^{o,0}_{mt})$ and $\mathbf{Q}_{mt} \sim N(\bar{\mathbf{Q}}^{D,0}_{mt}, V^{Q,0}_{mt})$.

Given the patients' utilities from the previous iteration ($\{\{\tilde{\mathbf{U}}^{r-1}_{mt}\}^M_{m=1}\}^T_{t=1}$), the newly updated parameters in the patient's utility function ($\{\{\mathbf{\Theta}^{D,r}_{mt}\}^M_{m=1}\}^T_{t=1}$) and a set of unobserved characteristics ($\{\{\boldsymbol{\xi}^r_{mt}\}^M_{m=1}\}^T_{t=1}$), I can recover the idiosyncratic agent-facility specific shock ($\{\{\hat{\tilde{\boldsymbol{\epsilon}}}^r_{mt}\}^M_{m=1}\}^T_{t=1}$) based on equation (4.1). Since the unobserved severity of illness for patient i is a linear function of $\{\{\tilde{\epsilon}^r_{ijmt}\}^I_{i=1}\}_{j\in\mathbb{J}^c_{izmt/0}}$ (equation (3.8)), the surgery outcome function can be written as a linear function of $\mathbf{\Theta}^o_{mt}$, $\mathbf{Q}_{mt}$ and $\{\{\tilde{\epsilon}^r_{ijmt}\}^I_{i=1}\}_{j\in\mathbb{J}^c_{izmt/0}}$ (equation (3.4)). The process of updating $\mathbf{\Theta}^o_{mt}$ and $\mathbf{Q}_{mt}$ is a process of obtaining posterior distribution for parameters in a linear function and drawing a set of random variables from this posterior distribution. Detail procedure is similar to the process of updating the parameters in the first block.

A.7 Block 4: Agents' Utility

The fourth block includes the set of the agents' utilities relative to the outside option, $\{\{\tilde{\mathbf{U}}_{mt}\}_{m=1}^{M}\}_{t=1}^{T}$. I update $\mathbf{U}_{mt}$ for surgery m and year t based on parameters in the patient's utility function ($\mathbf{\Theta}_{mt}^{D,r}$), facilities' surgery quality levels ($\mathbf{Q}_{mt}^{r}$), a set of unobserved characteristics ($\boldsymbol{\xi}_{mt}^{r}$), exogenous variables in the patient's utility function ($\mathbb{X}_{mt}^{D}$) and the observed entry decision ($\{\mathbf{c}_{imt}\}_{i=1}^{I}$). The process of updating the latent variable for a multinomial probit model is discussed in detail by McCulloch and Rossi (1994). I employ the same method in this paper. For agent i, I draw $\{\hat{\epsilon}_{ijzmt}, j \in \mathbb{J}_{izmt}^{c}\}$ from truncated normal distributions sequentially. The updated latent variables $\{\mathbf{U}_{ijmt}^{r}, j \in \mathbb{J}_{izmt}^{c}\}$ are

$$U_{ijzmt}^{r} = f(q_{jmt}^{r}, \mathbb{X}_{ijzmt}^{D}, \mathbf{\Theta}_{mt}^{D,r}) + \xi_{jmt}^{r} + \hat{\epsilon}_{ijzmt}, \qquad j \in \mathbb{J}_{izmt}^{c}. \tag{A.15}$$

For agent i, U_{ijzmt}^{r} satisfies the condition that

$$\begin{aligned}
&U_{ijzmt}^{r} \geq U_{ij'zmt}^{r-1}, && \forall (j' > j) \cap (j' \in \mathbb{J}_{izmt}^{c}), && if \;\; c_{ijzmt} = 1;\\
&U_{ijzmt}^{r} \geq U_{ij'zmt}^{r}, && \forall (j' < j) \cap (j' \in \mathbb{J}_{izmt}^{c}), && if \;\; c_{ijzmt} = 1;\\
&U_{ijzmt}^{r} < U_{ij'zmt}^{r-1}, && \forall (j' > j) \cap (j' \in \mathbb{J}_{izmt}^{c}), && if \;\; c_{ijzmt} = 0;\\
&U_{ijzmt}^{r} < U_{ij'zmt}^{r}, && \forall (j' < j) \cap (j' \in \mathbb{J}_{izmt}^{c}), && if \;\; c_{ijzmt} = 0.
\end{aligned} \tag{A.16}$$

The agent i's utility from facility j relative to her outside option is

$$\tilde{U}_{ijzmt}^{r} = U_{ijzmt}^{r} - \hat{\epsilon}_{i0zmt}. \tag{A.17}$$

A.8 Block 5 and Block 6: Parameters in the ASC's Profit Function and the ASC's profit

I assume the prior distribution for the parameters in the ASC's profit fucntion is $\mathbf{\Theta}^{A} \sim N(\bar{\mathbf{\Theta}}^{A,0}, V^{A,0})$. Given simulated expected surgery volume, the ASC's entry decision is modeled as a standard Probit model (equation 3.11). The expected surgery volume for each ASC is simulated based on the augmented data and parameters obtained from the first four blocks. The simulation process is discussed in section (A.1). Again, I follow McCulloch and Rossi (1994) to update the set of parameters, $\mathbf{\Theta}^A$, and the vector of latent variables $\{\{\Pi^A_{mt}\}_{m=1}^M\}_{t=1}^T$.

First, I update the parameters in the ASC's profit function, $\mathbf{\Theta}^A$. Each ASC's profit, $\Pi^{A,r-1}_{imt}$, obtained from the previous iteration is a linear function of $\mathbf{\Theta}^A$ (equation (3.11)). The new set of parameters, $\mathbf{\Theta}^{A,r}$, is drawn from the newly updated posterior distribution.

Secondly, conditional on the newly updated $\mathbf{\Theta}^{A,r}$, for each facility $j \in ASC$, I draw a fixed-entry cost, $\hat{e}_{jlmt}$, from a truncated normal distribution and calculated the expected profit,

$$\Pi^{A,r}_{jlmt} = g(\widehat{EV}_{jmt}, \mathbb{X}^{A,r}_{jlmt}, \mathbf{\Theta}^{A,r}) + \hat{e}_{jlmt}. \tag{A.18}$$

where $\Pi^{A,r}_{jlmt}$ satisfies the condition that

$$\begin{aligned} &\Pi^{A,r}_{jlmt} \geq 0, \qquad && if \quad a_{jmt} = 1; \\ &\Pi^{A,r}_{jlmt} < 0, \qquad && if \quad a_{jmt} = 0. \end{aligned} \tag{A.19}$$

A.9 Block 7: Beliefs about ASCs' Entry Probabilities

At the equilibrium, others facilities have correct beliefs about ASC j's entry probability. Given newly updated parameters in the ASC's profit function, $\mathbf{\Theta}^A$, beliefs about ASC j's entry probability is

$$\hat{\sigma}^r(a_{jmt} = 1) = \Phi(\Pi^{A,r}_{jlmt} - g(\widehat{EV}_{jmt}, \mathbb{X}^{A}_{jlmt}, \mathbf{\Theta}^{A})). \tag{A.20}$$

A.10 Block 8: Parameters in Hospital's Marginal Cost and Marginal Revenue Function

The seventh block includes parameters that determine each hospital's optimal surgery quality level. I assume the prior distribution is $\mathbf{\Theta}^H \sim N(\bar{\mathbf{\Theta}}^{H,0}, V^{H,0})$. Each hospital chooses its optimal surgery quality level based on equation (4.3). In order to evaluate this equation, I simulate the expected surgery volume, the marginal effect of surgery quality level on ASCs' entry probabilities and the marginal effect of surgery quality on its own expected surgery volume, based on the newly updated parameters and augmented data in iteration r.

Equation (3.18) can be written as a linear function of $\boldsymbol{\Theta}^H = \{\boldsymbol{\gamma}^H, \boldsymbol{\omega}, \sigma_\varepsilon^2\}$,

$$\begin{aligned} c_{mt}\frac{dEV_{jmt}}{dq_{jmt}} =& \gamma_3^H (\sum_{\substack{j' \in A \\ j' \in \text{county l}}} \frac{d\sigma(a_{j'mt}=1)}{dq_{jmt}}) * P_{cmt}^H * EV_{jmt} \\ &+ (\boldsymbol{\gamma}_0^H + \mathbf{K}_{ct}\boldsymbol{\gamma}_1^H + \gamma_2^H N_{cmt}^H + \gamma_3^H EN_{cmt}^A) * P_{cmt}^H * \frac{dEV_{jmt}}{dq_{jmt}} \\ &- (\omega_0 + \omega_1 q_{jmt} + \mathbf{Z}_{jmt}\boldsymbol{\omega}_1 + \kappa_c^1 + \kappa_t^2 + \kappa_m^3 + \varepsilon_{jcmt}). \end{aligned} \tag{A.21}$$

Given the prior distribution for $\boldsymbol{\Theta}^H$ is a normal distribution, the posterior is $\boldsymbol{\Theta}^H \sim N(\bar{\boldsymbol{\Theta}}^{H,r}, V^{H,r})$. The process of updating the parameters in the posterior distribution, $\bar{\boldsymbol{\Theta}}^{H,r}$ and $V^{H,r}$, is similar to the process I discussed for block 1.

B Additional Estimates

B.1 Patient Surgery Outcomes

Table 16a and Table 16b present the average posterior means of the demographic covariates. A positive coefficient means that increasing the corresponding variable would result in a higher readmission rate for the patient.

Compared with males, females are slightly more likely to suffer from surgery complications (row 1 in Table 16a and Table 16b). The exceptions include patients who receive retina surgeries in 2006 and 2008. Holding all other variables constant, the readmission rate for a female is 0.34 percentage points lower than for a male who receives a retina surgery in 2006 and 0.36 percentage points lower in 2008. Compared with patients under 45, patients older than 65 are more likely to experience complications (row 4 and row 5 in Table 16a and Table 16b). For patients who receive tonsil and adenoid removal surgeries, the readmission rate is lower for older children.

On average, African-Americans have higher readmission rates than whites across different

Table 16a: Posterior Means,
Surgery Outcome Function, 2006

Surgery	Knee Arthroscopy	Breast Lesion Removal	Tonsils and Adenoids Removal	Retina Surgery	Hernia Repair
Female	0.0006	–	0.0037	-0.0034	–
Age Group 2	-0.0007	0.0092	-0.0335	0.0059	-0.0034
Age Group 3	-0.0020	0.0207	-0.0523	0.0775	-0.0060
Age Group 4	0.0101	0.0061	-0.0652	0.1030	-0.0038
Age Group 5	0.0068	0.0078	-0.0963	0.0609	0.0172
African-American	0.0047	-0.0034	0.0052	0.0091	0.0066
Other Races	-0.0039	-0.0137	0.0021	-0.0076	0.0007
Medicare	0.0292	0.0233	0.0094	0.0400	0.0083
Medicaid	0.0284	0.0350	0.0188	0.0496	0.0227
Private Insurance	0.0114	0.0015	0.0007	0.0147	-0.0062
Other Types of Insurance	0.0188	0.0179	0.0217	0.0178	0.0015
Numbers of Diagnoses	0.0277	0.0135	0.0405	0.0357	0.0278

Note the I have also allowed the patient's severity of illness to be correlated with the patient's facility-specific preference.for tonsils and adenoids removal surgery, age group 2 represent age 4-7, group 3 represents age 7-12, age group 4 represents age 13-18 and age group 5 represents age > 18. The omitted age category is the youngest age group, age 0-3. For other surgery categories, age group 2, 3, 4, 5 represent age 45-54, 55-64, 65-75 and >75, respectively.

surgeries in both years (row 6 in Table 16a and Table 16b). The exceptions include patients who receive breast lesion removal surgeries in 2006 and patients who receive knee arthroscopy in 2008. The readmission rates for patients of other races are roughly comparable to the readmission rates of whites (row 7 in Table 16a and Table 16b). In general, compared with patients without health insurance, the readmission rates for patients with health insurance are higher (row 8 to row 11 in Table 16a and Table 16b). Exceptions include patients who receive hernia repair surgeries in 2006 and 2008. One possible explanation for higher readmission rates among insured patients is that patients without health insurance may avoid hospitalization due to potential high medical expenditure. More diagnoses related to the surgery lead to higher readmission rates (row 12 in Table 16a and Table 16b). For example, the readmission of a patient who receives a retina surgery in 2006 increases by 0.36 percentage points if she has one more diagnosis related to this surgery.

Table 16b: Posterior Means,
Surgery Outcome Function, 2008

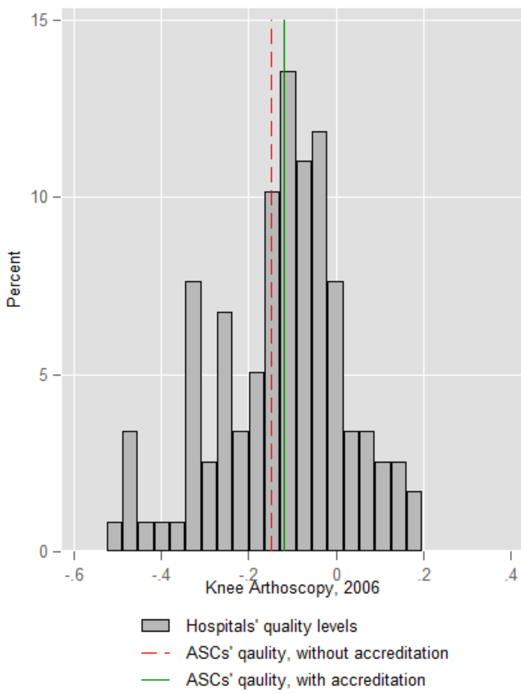
Surgery	Knee Arthroscopy	Breast Lesion Removal	Tonsils and Adenoids Removal	Retina Surgery	Hernia Repair
Variables	Mean	Mean	Mean	Mean	Mean
Female	0.0040	–	0.0066	-0.0036	–
Age Group 2	0.0092	0.0084	-0.0152	-0.0114	0.0002
Age Group 3	0.0207	0.0093	-0.0351	-0.0179	0.0025
Age Group 4	0.0061	0.0045	-0.0262	-0.0252	-0.0065
Age Group 5	0.0078	0.0045	-0.0832	-0.0240	0.0096
African-American	-0.0034	0.0105	0.0032	0.0181	0.0143
Other Races	-0.0137	-0.0097	-0.0044	-0.0051	0.0017
Medicare	0.0233	0.0299	0.0513	0.0448	0.0109
Medicaid	0.0350	0.0366	0.0142	0.0507	0.0076
Private Insurance	0.0015	0.0126	-0.0149	0.0243	-0.0102
Other Types of Insurance	0.0179	0.0206	0.0015	0.0293	0.0009
Numbers of Diagnoses	0.0135	0.0171	0.0069	0.0304	0.0099

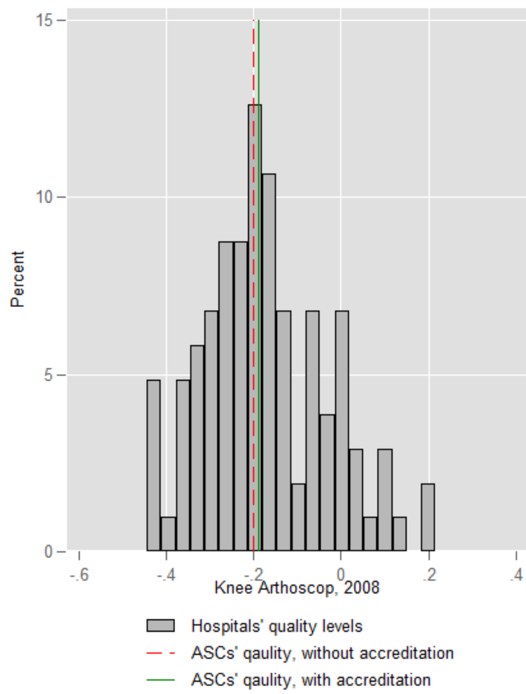
Note the I have also allowed the patient's severity of illness to be correlated with the patient's facility-specific preference.for tonsils and adenoids removal surgery, age group 2 represent age 4-7, group 3 represents age 7-12, age group 4 represents age 13-18 and age group 5 represents age $>$ 18. The omitted age category is the youngest age group, age 0-3. For other surgery categories, age group 2, 3, 4, 5 represent age 45-54, 55-64, 65-75 and >75, respectively.

B.2 The Estimated Distributions for Quality Levels

For each surgery in each year, I present the distribution of the estimated hospitals' surgery quality levels using gray bars (from figure 5a to figure 5e). The distributions vary by surgeries. For example, in 2008, the distribution of hospitals' surgery quality levels for lesion removal surgery is similar to a normal distribution but with a fatter left tail. Meanwhile, the distribution of hospitals' surgery quality levels for retina surgery in 2006 is closer to a uniform distribution but with two spikes.

Figure 5a: Distributions of Surgery Quality Levels
Knee Arthroscopy





In each graph, the dashed line represents the surgery quality level of the ASCs without accreditation status, and the solid green line represents the surgery quality level of the ASCs with accreditation. The estimated surgery quality levels for the ASCs with accreditation are higher than the ASCs without accreditation for all surgeries in all years. This means that, controlling for the patients' observed characteristics and unobserved severity of illness, an ASC with accreditation has a lower patient readmission rate than an ASC without accreditation. Compared with the

Figure 5b: Distributions of Surgery Quality Levels
Breast Lesion Removal

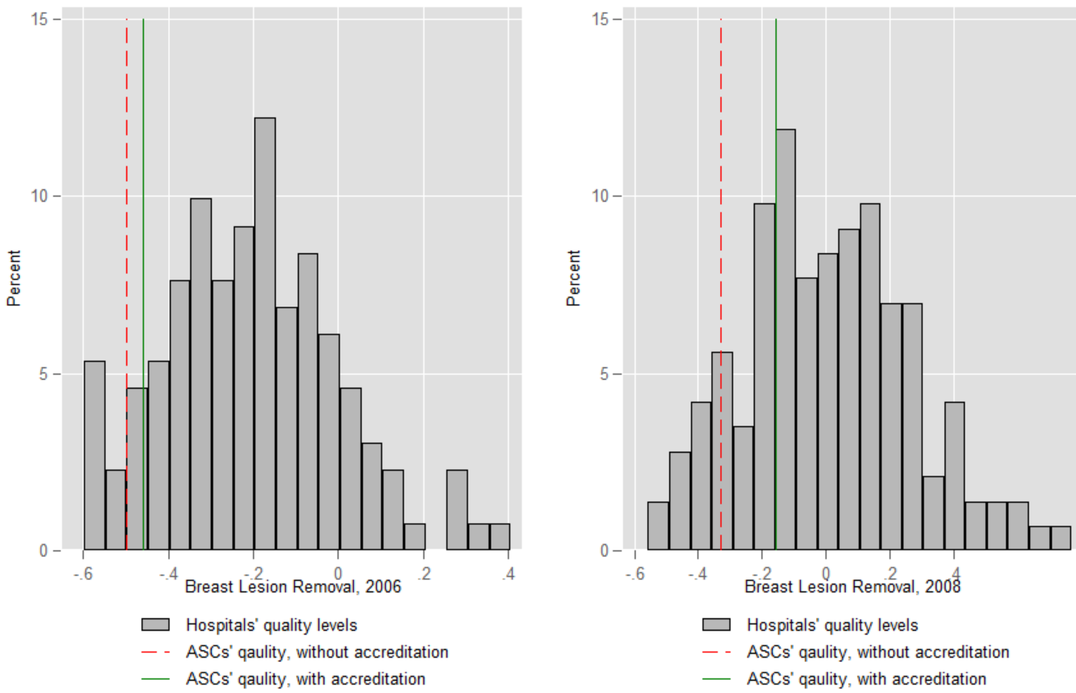


Figure 5c: Distributions of Surgery Quality Levels
Tonsil and Adenoid Removal

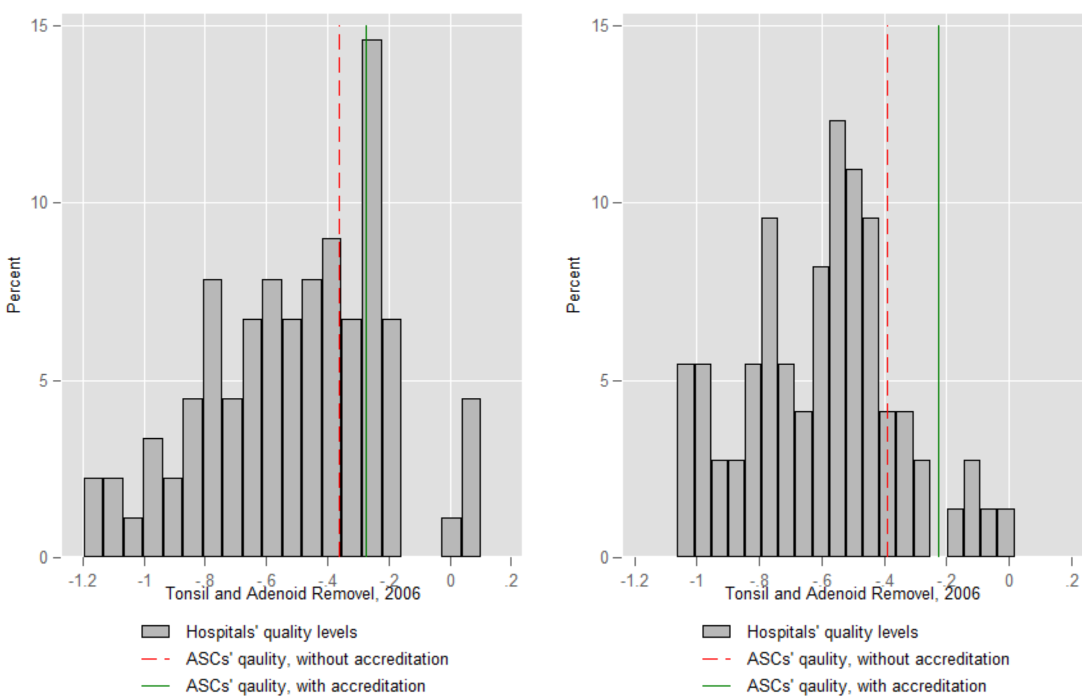


Figure 5d: Distributions of Surgery Quality Levels
Retinal Surgery

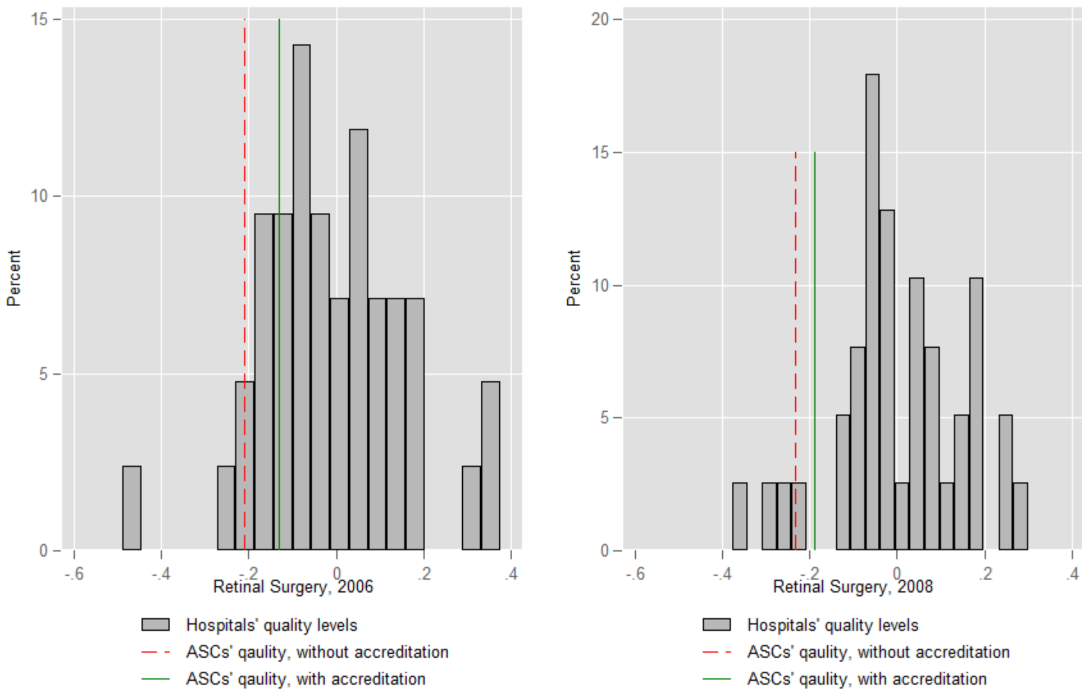
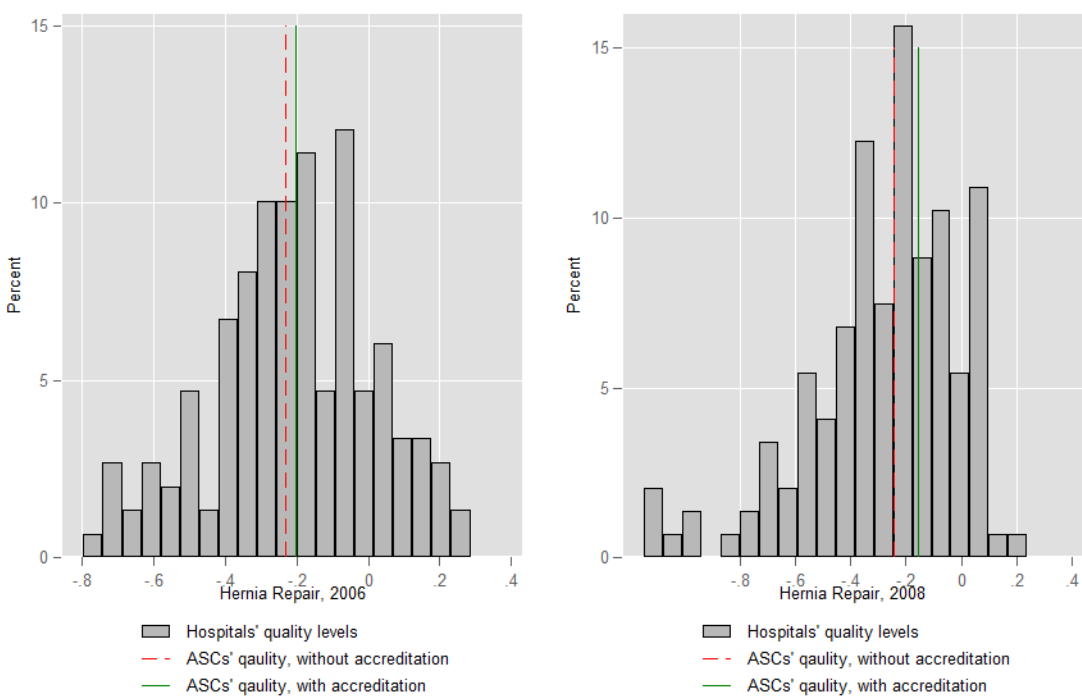


Figure 5e: Distributions of Surgery Quality Levels
Hernia Repair



average quality levels in hospitals, ASCs' quality levels are lower for breast lesion removal surgery and retinal surgery. For knee arthroscopy and hernia repair, the average quality levels for hospitals and ASCs are similar. For tonsil and adenoid removal, ASCs have higher surgery quality levels than the average hospitals in 2006 and 2008. This means that, compared with hospitals, ASCs provide better care for tonsil and adenoid removal. One possible explanation is that infection is one of the most common reasons for readmission after an outpatient surgery. More than 70 percent of the patients for tonsil and adenoid removal surgery are children younger than age 15 and are more vulnerable to hospital-acquired infections. ASCs usually are smaller than hospitals, focus on a few specialties and do not include divisions of infectious diseases, which can result in lower infection rates than hospitals.

B.3 The Estimated Parameters in the Utility Function

Table 17a and Table 17b present the posterior means of the parameters that reflect patients' preferences for facilities' characteristics, $\boldsymbol{\beta}_{2mt}$. Holding other variables constant, including the facility's surgery quality level, an ASC with accreditation attracts more patients than an ASC without accreditation (row 2 in Table 17a and Table 17b). Exceptions include breast lesion removal in both years and retina surgery in 2008. If a hospital is within a hospital network, it tends to attract more patients. The only exception is that whether a hospital is within a network does not affect the facility choice of breast lesion removal patients. In general, patients prefer private hospitals (both for profit and not for profit) over public hospitals for the surgery markets I studied.

Table 18a and Table 18b present the posterior means of the parameters of covariates in the utility function that affect patients' preferences for having a surgery in an ASC. The utility function includes a constant for each patient. The covariates for the indicator of choosing an ASC reflect the patient's preference for having a surgery in an ASC versus in a hospital. For the surgeries in my sample, on average, patients prefer hospitals to ASCs. The covariates for the interactions between the number of surgeries performed by the surgeon and the ASC indicator are positive (row 14 in Table 7a and Table 7b)). This means that high volume surgeons are more likely to

Table 17a: Posterior Means,
Preferences for Facility's Characteristics, 2006

Surgery	Knee Arthroscopy	Breast Lesion Removal	Tonsils and Adenoids Removal	Retina Surgery	Hernia Repair
Variables	Mean	Mean	Mean	Mean	Mean
ASCs' Characteristics					
accreditation	0.0458	-0.0134	0.0243	0.1831	0.0495
Hospitals' Characteristics					
Number of Total Outpatient Visit per Year	0.1165	0.0033	0.1063	0.0819	-0.0694
Teaching Hosptial	0.0262	0.0051	0.0055	-0.0619	-0.0119
Within a Hospital Network	0.0083	-0.0031	0.0289	0.0798	0.0020
For Profit	0.0482	0.0203	0.0091	0.0352	-0.0220
Not For Profit, Private	0.0495	0.0130	0.0091	0.0364	-0.0357

Note that the unit of the number of oupatient visit per year is 10,000 patients. The obmitted category of hosptial's type is public hospital

Table 17b: Posterior Means,
Preferences for Facility's Characteristics, 2008

Surgery	Knee Arthroscopy	Breast Lesion Removal	Tonsils and Adenoids Removal	Retina Surgery	Hernia Repair
Variables	Mean	Mean	Mean	Mean	Mean
ASCs' Characteristics					
accreditation	0.1141	-0.0937	-0.0222	-0.0039	0.1062
Hospitals' Characteristics					
Number of Total Outpatient Visit per Year	0.0627	0.0865	0.1055	0.1026	0.0198
Teaching Hosptial	0.0076	0.0119	-0.0089	-0.0256	0.0133
Within a Hospital Network	0.0050	0.0064	0.0304	0.0193	0.0019
For Profit	0.0795	0.0205	0.0286	-0.0229	0.0122
Not For Profit, Private	0.1205	0.0273	0.0276	-0.0084	0.0137

Note that the unit of the number of oupatient visit per year is 10,000 patients. The obmitted category of hosptial's type is public hospital perform their surgeries in ASCs, holding other variables constant.

Table 18a: Posterior Means,
Utility Function, ASC Covariates, 2006

Surgery	Knee Arthroscopy	Breast Lesion Removal	Tonsils and Adenoids Removal	Retina Surgery	Hernia Repair
Variables	Mean	Mean	Mean	Mean	Mean
ASC	-0.1285	-0.1937	-0.2264	-0.2931	-0.1290
ASC*					
Female	0.0173	–	0.0230	0.0670	–
Age Group 2	0.0871	-0.0828	-0.1342	0.0731	0.0600
Age Group 3	0.0999	-0.0766	-0.1440	0.0517	0.0870
Age Group 4	0.1404	0.0659	-0.1867	0.0731	0.2500
Age Group 5	0.0925	0.1875	-0.1815	0.1802	0.2031
African-American	0.0184	0.1311	-0.0449	0.2138	-0.0236
Other Races	0.1288	0.3524	0.2466	0.4169	0.3150
Medicare	0.2033	-0.3985	-0.0695	-0.3685	-0.2358
Medicaid	0.0172	-0.3284	-0.1236	-0.2076	-0.2730
Private Insurance	0.2735	-0.2865	-0.1708	-0.1779	-0.1071
Other Types of Insurance	0.3351	-0.2331	-0.4072	-0.1270	-0.0914
# Surgeries Performed by the Surgeon	0.4092	0.8445	0.0685	0.0142	0.8801
Surgeries% Performed in ASCs	0.6819	2.3965	1.1046	2.3677	0.1243
Poverty Rate	2.5164	-2.7811	-2.2415	-1.3348	-1.2809
Median Income ($100,000)	2.7935	1.2212	2.9224	1.5745	1.7245

Note that for tonsils and adenoids removal surgery, age group 2 represent age 4-7, group 3 represents age 7-12, age group 4 represents age 13-18 and age group 5 represents age > 18. The omitted age category is the youngest age group, age 0-3. For other surgery categories, age group 2, 3, 4, 5 represent age 45-54, 55-64, 65-75 and >75. The unit for the number of surgery performed by the surgeon is 100 cases.

The parameters for the interactions between the ASC indicator and the county level poverty rate are negative (row 16 in Table 7a and Table 7b). The only exception is the parameter for interaction between the ASC indicator and the county level poverty rate for knee arthroscopy in 2006. The parameters for the interactions between the ASC indicator and the county level median income are positive (row 17 in Table 7a and Table 7b). This means that patients who live in wealthier counties are more likely to choose ASCs over hospitals, holding other variables constant.

Table 18b: Posterior Means,
Utility Function, ASC Covariates, 2008

Surgery	Knee Arthroscopy	Breast Lesion Removal	Tonsils and Adenoids Removal	Retina Surgery	Hernia Repair
Variables	Mean	Mean	Mean	Mean	Mean
ASC	-0.27666	-0.2111	-0.1418	-0.27801	-0.10158
Cross Term: ASC*					
Female	-0.0005	–	0.0180	0.0404	–
Age Group 2	0.1302	-0.0921	-0.0485	-0.0926	0.1364
Age Group 3	0.1193	-0.0995	-0.1800	-0.1539	0.1505
Age Group 4	0.2334	0.0694	-0.1513	0.0100	0.2277
Age Group 5	0.2689	0.1751	-0.1668	0.0340	0.2843
African-American	0.0672	0.0368	0.0372	0.0634	-0.1737
Other Races	0.4574	0.2594	0.3551	-0.1314	0.2039
Medicare	-0.0260	-0.4470	0.0314	-0.2101	-0.4568
Medicaid	-0.2558	-0.2967	-0.2844	-0.1603	-0.5112
Private Insurance	0.5276	-0.2100	-0.0988	-0.0960	-0.2454
Other Types of Insurance	0.1651	-0.4179	-0.5419	-0.0737	-0.2633
# Surgeries Performed by the Surgeon	1.6183	1.0867	0.1855	0.0665	1.2129
Surgeries% Performed in ASCs	0.6964	1.9951	1.0562	2.6412	0.0927
Poverty Rate	-2.4627	-2.1522	-2.8304	-1.3554	-1.9714
Median Income	1.7040	3.2587	1.2458	1.3583	1.2257

Note that for tonsils and adenoids removal surgery, age group 2 represent age 4-7, group 3 represents age 7-12, age group 4 represents age 13-18 and age group 5 represents age $>$ 18. The omitted age category is the youngest age group, age 0-3. For other surgery categories, age group 2, 3, 4, 5 represent age 45-54, 55-64, 65-75 and $>$75. The unit for the number of surgery performed by the surgeon is 100 cases.