How do Hospitals Respond to Financial Pain?
Evidence from Hospital Markets in Texas

Lori Timmins*

Vancouver School of Economics
University of British Columbia

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Abstract

This paper studies how hospitals respond to profit shocks and the loss of profitable service lines. I use the entry of specialty hospitals, which offer a subset of procedures with high profit margins, as a supply shock for these services in a hospital market. I analyze incumbent hospital behavior in other service lines, focusing on whether hospitals adjust their procedures and, if so, whether it varies by payer type. I find that incumbent hospitals have a more sophisticated, targeted response than found in previous research. Greater specialty hospital market share causes incumbents to increase the number of surgical procedures and perform more surgeries on marginal patients. This varies with service line and payer type. The effects are concentrated in medical specialties where there are more discretionary surgeries and higher profit margins. The increase is only among private payers whose insurance reimburses hospitals more generously. Hospitals also increase the intensity of treatment among private payers, by increasing their length of stay conditional on the procedure. Additionally, hospitals cut back on unprofitable treatment by reducing emergency department admissions and uninsured elective care. My findings provide empirical evidence that hospitals cross-subsidize both across procedures and patients. This suggests that hospital spillovers are empirically important and that just looking at substitution within a service line ignores important hospital responses and subsequent welfare implications, particularly among different payer types.

*Vancouver School of Economics, University of British Columbia, 997-1873 East Mall, Vancouver, BC V6T 1Z1, Canada. E-mail: lltimmins@alumni.ubc.ca. I am grateful to Marit Rehavi and Kevin Milligan for their support and guidance. This paper also greatly benefited from discussions with Joshua Gottlieb, Nicole Fortin, Daniel Shack, and Nancy Gallini, as well as participants at the UBC Empirical Lunch and the UBC Public Finance Reading Group. Financial support from CLSRN and SSHRC is gratefully acknowledged. I thank Andrew Paget for his assistance with GIS. I also thank the Center for Health Statistics at the Texas Department of State Health Services Texas for providing the data used in this analysis and answering questions.

1 Introduction

It is widely believed that cross-subsidization is the primary means by which hospitals provide unprofitable care. Revenue from profitable procedures and patients are used to subsidize unprofitable hospital visits.[1] Implicit in this belief is that hospital departments do not operate independently from one another. Yet the bulk of empirical studies that examine changes in policies, profits, or prices within a particular hospital service line largely ignore how these changes may impact the provision of services in other areas of the hospital. Hospital spillovers may be quantitatively large. Additionally, they may be concentrated in particular service lines, types of visits, and patients. Failing to properly take into account such spillovers could result in incomplete welfare predictions.

To date, very little empirical evidence of hospital cross-subsidization exists. There is an extensive literature that shows cross-subsidization is prevalent in other industries, such as in airline, railway, and telecommunications.[2] One of the few studies to examine hospital cross-subsidization is David et al. (2011), who find that hospitals reduce the volume of admissions in unprofitable departments, particularly psychiatric, substance-abuse, and trauma care when there is a loss of profitable service lines. The focus of their study, however, is largely on the extensive margin of unprofitable department admissions. Hospitals may adjust in other ways, such as increasing the volume of profitable procedures, particularly elective procedures and procedures for which there is more clinical discretion in the course of treatment. In addition to operating on the extensive margin, hospitals can alter the intensity of treatment.[3] Importantly, hospitals may differentially target patients by insurance type, providing treatment on a case-by-case basis. In particular, they may try to augment revenue by increasing the quantity and intensity of profitable care to patients whose insurance reimburses most generously (e.g. private payers), and they may cut back on care to unprofitable patients (e.g. uninsured).

A related open question is whether hospitals can differentially target medical treatment by payer type. It has long been recognized that hospitals can differentially set fees across payer types and price discriminate (Kessel (1958)). There is also a lengthy literature on the incidence of "cost-shifting", whereby hospitals increase fees among patients with more generous reimbursement (i.e. private payers) to make up for losses from less generous insurers.[4] Many studies analyze the impact of reimbursement changes on own payer outcomes or on substitution across payers.[5] However, as McGuire and Pauly (1991) contend in their multi-product and multi-payer model of physician behavior, physicians can both substitute towards

[1] See Gruber (1994); David et al. (2011); Norton and Staiger (1994); Horwitz (2005); Banks et al. (1999).

[2] See Chevalier (2004); Kaserman and Mayo (1994); Banks et al. (1999).

[3] In this study, I define scheduled visits as "elective" and non-scheduled visits as "non-elective".

[4] See Dranove (1988); Zuckerman (1987); Wu (2010) and Frakt (2011).

[5] For example, Cutler (1995)'s study on Medicare's shift to prospective payment uses a sample of Medicare patient to examine its impact on patient outcomes. Others have used payers without a reimbursement change as a control group (e.g. Langa and Sussman (1993)). However, estimates will be biased if they are also affected.

patients with more generous reimbursement and change the mix of services they provide to specific payers.[6] Few studies explicitly test for differential medical treatment by payer type. Dor and Farley (1996) is a noticeable exception which finds some evidence that service intensity and quality differ among Medicare and Medicaid hospital patients.[7] Studies of office-based physician practices find the role of insurance is limited in treatment decisions.[8] However, hospitals have more administrative staff and greater resources to target treatment at the individual level.

This paper contributes to the existing literature by providing a more complete picture of the nature of hospital spillovers. It tests for cross-subsidization and determines where spillovers are concentrated, analyzing both the extensive and intensive margins. Like David et al. (2011), I examine changes in the volume of admissions across service lines. In addition, however, I study the intensity of treatment within particular services lines and test for heterogeneity across patient types. This paper analyzes just how sophisticated is the hospital response to profit shocks and provides a deeper understanding of hospital spillovers. While there have been many studies that have looked at cross-subsidization in other industries, the health care industry is unique. First, it is heavily regulated, where prices are administratively set. Second, patients often do not pay the full cost of their treatment because of insurance. Third, hospitals price discriminate. Fourth, there is asymmetric information whereby physicians make clinical decisions on behalf of their patients about treatment. For these reasons, the study of hospitals can add substantively to the existing literature and to understanding hospital behavior. In addition, this paper contributes to the literature on whether hospitals can differentiate treatment by payer type, treating patients on a case-by-case basis. To date, very few studies have examined this in the hospital setting.

In this study, I take advantage of a unique natural institutional feature in Texas to analyze how hospitals respond to a decline in revenue from their most profitable service lines. Specifically, I use the penetration of specialty hospitals, which concentrate on a subset of procedures with high profit margins as a supply shock for these services in Texas health care markets.[9] I measure the response of incumbent hospitals to the loss of profitable service lines, with particular attention to their behavior in other service lines. I test whether some types of visits are more affected than others, based on their overall profitability (e.g. surgical vs. non-surgical) and the nature of the visit (e.g. elective vs. non-elective). Importantly, I test

[6]There is some evidence that lower Medicaid reimbursement rates reduce service levels across all payer types in hospitals, with greatest effects among Medicaid patients (Dranove and White (1998)).

[7]While recognized as a pioneering study, its approach and estimates have been scrutinized as being driven by omitted variable bias (Danger and Frech (1997)). Dor and Farley (1996) acknowledge they face severe data limitations which led to fairly homogenous private payer type groupings and imprecise estimates. My paper does not suffer from these issues.

[8]See the findings of (Glied and Zivin (2002), Tai-Seale et al. (2007)), which are in contrast to Newhouse and Marquis (1978).

[9]The study by David et al. (2011) follows a similar approach, using the entry of specialty hospitals in Arizona and Colorado to study how hospitals adjust admissions to unprofitable departments.

whether the response varies by payer type. There has been a surge in specialty hospitals in Texas over the last decade, which has been met with strong opposition. Many policy debates center on their impact on general hospitals' ability to provide less profitable care. This study sheds light on how general hospitals are affected.

Specialty hospital entry into a market is not random, nor is the market share it captures. To address these issues, I estimate the predicted demand for specialty hospitals in a market using a patient-level hospital choice model in combination with instrumental variables. I build on the two-step approach of Kessler and McClellan (2000), by first modelling patient demand for specialty services to estimate the predicted market share of specialty hospitals, and then estimating the impact of predicted specialty hospital market share on non-specialty services at incumbent hospitals. Following previous studies, I use patients' geographic location of residence relative to specialty hospitals as an instrument for hospital choice.[10] Unlike previous studies, however, I look at medical treatment for a different set of individuals than those used to predict the specialty hospital market share. As such, the identifying assumption only requires that distances to specialty hospitals for patients obtaining specialty care do not directly affect medical treatment outcomes for patients seeking non-specialty care at incumbent hospitals (except through specialty hospital market share). I also use a rich set of patient, hospital, and market characteristics, with hospital market fixed effects and time trends to account for any unobserved factors that may be correlated with both specialty hospital market entry and non-specialty medical treatment.

This paper provides strong evidence that hospital spillovers are empirically important. I find specialty hospitals steal patients in a market. In turn, incumbent hospitals employ a sophisticated, targeted response in their non-specialty service lines. They practice both revenue augmenting and cost-cutting behavior and adjust treatment by payer type. In particular, I first find that hospitals make up for the lost volume of specialty surgeries by increasing the number of surgeries performed in other service lines. They do this by performing surgeries on patients who are healthier (i.e. marginal patients). The effects are concentrated in general surgery, a relatively high profit medical specialty where hospitals have more discretion in treatment due to clinical grey areas. Aligned with this, I find an increase in the number of elective (i.e. scheduled) general surgery admissions.

Secondly, my results provide strong evidence that hospitals vary treatment by payer type, suggesting that they treat patients on a case-by-case basis. In particular, hospitals target private payers whose insurance reimburses hospitals more generously. Increased specialty hospital market shares leads to a greater proportion of private payers with non-specialty surgical admissions, both across and within hospital departments. Effects are concentrated in elective surgeries, with large increases in the share of private payers with a general surgery

[10] The work of Kessler and McClellan (2000), Chernew et al. (2002), Li and Dor (2013), and Swanson (2012) all use distance between hospitals and patients as an instrumental variable as part of their empirical strategy.

admission. I also find strong evidence that hospitals treat private payers more intensively, by increasing their length of stay. This effect is not entirely driven by an increase in surgical procedures amongst private payers, as the length of stay increases even when factoring in patients' medical procedures. No change in the length of stay is found for public payers. While private payers tend to reimburse hospitals for each additional hospital day (i.e. per-diem), public payers reimburse hospitals a lump sum amount per admission. Unlike the literature on office-based physician practices, my findings suggest that hospitals do target treatment by payer type.

Finally, hospitals do not only augment revenue by increasing profitable procedures among the most profitable payers, but they also cut back on unprofitable procedures in response to the profit shock. In particular, they decrease the number of non-elective (i.e. emergency) admissions, which is a highly unprofitable type of hospital visit. Additionally, hospitals cut back on care to the uninsured, with a smaller proportion of uninsured having an elective visit.

The rest of the paper proceeds as follows. In the next section, I provide background information on how hospitals are reimbursed for different procedures and payer types. I also discuss the origins and growth of specialty hospitals in Texas. In Section 3, I describe the data. In Sections 4 and 5, I present the empirical model and results. I conclude in Section 6.

2 Hospital Payments and Profitability

2.1 Payer Types

There is a substantial variation in the prices paid by insurers to hospitals for care. While Medicare payment rates are publicly available, the prices paid by other insurers are difficult to observe. Although insurers typically do not pay the full hospital list charges, it is thought that private payers reimburse at the highest rates, followed by Medicare, and then Medicaid (Morrisey (1994); Dor and Farley (1996)).[11]

Public payers (i.e. Medicare and Medicaid) set payments to the providers. Medicare is the largest health insurance program in the world, and all Americans over 65 years old are eligible for coverage. Medicare pays hospitals a lump sum per admission, with the amount depending, in part, on the patient's principal disease. The reimbursement scheme reflects expected resource use and is based on average costs, not marginal costs. Medicaid is a federal and state funded program that targets very low income families, specifically children and pregnant women near the federal poverty line. The Medicaid eligibility rules for Texas are among the most stringent in the country.[12] Texas is one of the states that has decided not

[11]Ellis (2001) provides an excellent overview of hospital reimbursement in the U.S.

[12]The current eligibility rules are: 133% of the federal poverty line for children aged 1-5; 100% of the federal poverty line for children 6-18 years old; and 185% of the federal poverty line for children under 1 year and pregnant women. Adults with children are eligible only if family income is at or below 26% of the federal

to expand Medicaid under the Affordable Care Act. Medicaid is well known for providing low reimbursement rates, often below hospitals' costs (Chernew et al. (2002)). In Texas, hospitals are reimbursed by Medicaid in a similar fashion as Medicare, with a fixed amount per inpatient episode of treatment.

In contrast to public insurers, private payers negotiate payments with providers through a bargaining process (Ho (2009); Clemens and Gottlieb (2013)). There is an array of private insurance plans. In my study, I separate private payers into Health Maintenance Organizations (HMOs) and non-HMOs. Those in the latter group include indemnity plans and Preferred Provider Organizations (PPO). These patients are considered to be the most lucrative to hospitals. Although there is some variation in payment, this group of patients are generally considered to pay fee-for-service (FFS). That is, hospitals are paid for each service they provide and/or on a per-diem basis. Some private insurers also reimburse hospitals with a lump sum payment. HMOs differ from other private insurers in how they are organized. They contract selectively with only some hospitals in a given area and exert stricter gatekeeping, requiring non-urgent hospital visits to be referred through a general practitioner and to be pre-authorized. There is variation in how HMOs reimburse hospitals. In general, however, HMOs pay hospitals similar to FFS, providing payment for each service and/or on a per-diem basis, although at more discounted rates. Some HMOs also reimburse hospitals with a lump sum payment that is fixed for each inpatient visit, similar to Medicare.[13]

Individuals without insurance either reimburse hospitals for some or all of the charges (self-pay) or are charity care (i.e. uncompensated care). Texas has the highest percentage of residents without health insurance in the country. The Census Bureau estimated 6.4 million Texans had no health coverage in 2012 (25% of its population). Self-pay patients are profitable only if hospitals are able to recoup their costs. In general, however, uninsured patients are thought to be unprofitable for hospitals to care for. In light of this, why do hospitals provide unprofitable care? It is argued that non-profit hospitals are socially motivated to do so (Frank and Salkever (1991) and Gruber (1994)). Additionally, they must provide a certain level of uncompensated care (i.e. charitable care) in order to be exempt from local, state, and federal taxes. Gray (1991) argues that for-profit hospitals provide unprofitable care as a business decision. Specifically, they supply unprofitable care to reduce the likelihood of civil liability and Medicare sanctions; to strengthen their local reputation and to avoid tangible community penalties; and to enhance relations with physicians (Banks et al. (1997)). Medicare provides funding to hospitals with a disproportionate number of uninsured and Medicaid patients under the Disproportionate Share Hospital (DSH) program. It should also be noted that under the Emergency Medical Treatment and Active Labor Act (EMTALA), hospitals are required to

poverty line.

[13]Kaiser Permanente, which is a well-known vertically integrated HMO system that has its own hospitals and physician practices, did not operate in Texas throughout my sample period. It stopped operating in Texas in 1998.

treat all patients with life-threatening medical episodes, regardless of their ability to pay. Patients cannot be discharged until they have been stabilized.[14]

2.2 Hospital Services

In addition to treating multiple types of payers, general hospitals provide a variety of medical services ranging from neurology to obstetrics to cardiology. There is significant variation in the profitability of departments and procedures, with some generating huge rents and others a loss for hospitals. One factor that contributes to this variation is the prevalence of administered pricing in the medical care industry (Newhouse (2002); Horwitz (2005)). Medicare in particular creates differential rents across specialties. Medicare provides higher reimbursements to specialists whose work is predominately hospital based (as opposed to outpatient based), such as cardiovascular surgeons or neurosurgeons. Administered prices are also notoriously sticky. When procedures are first introduced, productivity tends to be low, but over time productivity improves with learning-by-doing and the cost of technology falls, which also creates rents in some specialties (Newhouse (2002)). As mentioned above, the Medicare reimbursement scheme reflects expected resource use and is based on average costs, not marginal costs. This can create distortions by giving hospitals an incentive to expand services which have the largest difference between average and marginal costs (Kim (2011)).

A list of the most and least profitable hospital specialties is provided in Table 1. Departments performing surgical-intensive procedures, such as thoracic surgery, cardiovascular surgery, and neurosurgery are the most profitable. General surgery is also a highly profitable department, performing a range of procedures from appendectomies to mastectomies, as is Urology, carrying out a large number of urethral and prostatic surgeries. Less profitable departments perform few surgeries, such as Otolaryngology (ears, nose and throat) and Nephrology (kidneys). Emergency department and psychiatric admissions are unprofitable service lines. Hospitals are thought to use the charges from their most profitable procedures and patients to cross-subsidize unprofitable care (Gruber (1994), David et al. (2011), and Banks et al. (1999)).

2.3 Specialty Hospitals

Unlike general hospitals which provide a range of services, specialty hospitals concentrate on procedures performed in the most profitable specialties. They largely provide three types of care: cardiac, orthopedic, or surgical (cardiac and/or orthopedic is the most common type of surgery performed at surgical hospitals). Historically, specialty hospitals were primarily

[14] EMTALA was passed in 1986 by the U.S. Congress as part of the Consolidated Omnibus Budget Reconciliation Act (COBRA). All hospitals that accept Medicare payments must abide by this act or else they forgo Medicare payment. This means that in practice, the act applies to virtually all hospitals in the country.

psychiatric, children, and rehabilitation facilities. A surge in specialty hospitals occurred following the passage of the Stark law in the Omnibus Budget Reconciliation Act (OBRA) of 1993, which declared that physician owners were allowed to refer patients to their own hospitals provided they had investment interest in the whole hospital.[15] This has led to significant growth in a new type of specialty hospital, namely physician-owned hospitals providing profitable surgical procedures.[16]

Despite their growth over the last 15 years, specialty hospitals are highly controversial. Proponents argue they are focused factories (Herzlinger (1997); Skinner (1974)). By offering a limited range of services, specialty hospitals allow physicians to produce care more efficiently and with higher quality. Proponents also argue that specialty hospitals spur system-wide innovation through increased competition (Barro et al. (2006)). Critics of specialty hospitals, meanwhile, contest that they cream skim the most profitable patients and undermine community hospitals' ability to subsidize the less profitable patients and services (US Congress (2006)). Physician investors argue that the primary reason they form a hospital is for greater control in determining the course of medical treatment. Profits are said to be secondary (US Congress (2006)).

Although this controversy has led many states to ban specialty hospitals, they have flourished in the state of Texas. Figures 1 to 3 show the growth of specialty hospitals in Texas over time and space.[17] In 1999, 58% of patients lived within 50 miles of a specialty hospital in Texas. This figure rose to 84% by 2007. Between 1999 and 2007, the number of specialty hospitals more than tripled from 14 to 50, making it the state with the greatest number and proportion of specialty hospitals in the U.S.[18] Although specialty hospitals are concentrated in larger urban areas, such as Dallas and Houston, they are also prevalent in small cities such as Amarillo, Edinburg, and Odessa. Additionally, while cardiac care is amongst the most profitable, orthopedic and surgical specialty hospitals are more widespread. Among the 50 specialty hospitals that existed in 2007, 8 were cardiac, 27 were orthopedic, and 15 were surgical. Although the growth in specialty hospitals across Texas has been phenomenal, it is likely to be shortlived. The Patient Protection and Affordable Care Act (ACA) of 2010 has banned physician investment in hospitals, although existing specialty hospitals can be grandfathered

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[15]Specifically, this provision was known as the "Stark II", following "Stark I" of OBRA 1989 which banned self-referrals for clinical laboratory services. The exemption described above is known as the "whole hospital exception".

[16]In Texas, 91% of specialty hospitals are for profit, and among these, 93% are physician owned.

[17]See Appendix A for details on how specialty hospitals were defined and identified.

[18]The rate of growth of specialty hospitals slowed in the later years with a moratorium on new physician-owned specialty hospitals that were not already under development. In particular, Congress enacted the Medicare Prescription Drug, Improvement and Modernization Act (MMA) of 2003, which legislated a temporary 18 month moratorium on new specialty hospitals, beginning in November 2003. The purpose of the moratorium was to allow the secretary of Health and Human Services (HHS) and MedPAC time to study the impacts of specialty hospitals and to make recommendations to Congress. The moratorium was extended by the CMS until August 2006 when it began to accept new applications for specialty hospitals.

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2.4 Possible Hospital Responses To Specialty Hospital Entry

Hospitals may respond to the increased competition in profitable services by trying to make up lost revenue in the other service lines. In particular, they may increase the volume of remaining profitable procedures, such as surgeries. Although physicians clearly must ensure patients receive adequate medical care, there is somewhat of a clinical grey area for some of these procedures. For example, there are certain illnesses that have multiple treatment possibilities (e.g. gallstones) and there are some conditions that are discretionary (e.g. obesity procedures). Many of these procedures typically arise in general surgery, as opposed to say, neurosurgery, which has fewer clinical grey areas.[19] As such, we may expect to see hospitals admitting more patients in these areas, particularly those who are less ill. Hospitals may also seek to increase revenue by targeting the more profitable patients, such as those with more generous insurance schemes or those who are healthier. Additionally, they may increase the intensity of treatment, such as extending patients' length of stay. Finally, hospitals may cut back on unprofitable care, particularly in regards to emergency admissions and care to the uninsured.

Conversely, hospitals may reduce the quantity of care across the board due to a negative budget shock. With reduced revenue from their high profit procedures, they may no longer have the resources to provide the same amount of care in other services. For example, they may respond by reducing the number of physicians, beds, and nursing staff. This may lower the quality of care all round.

My paper focuses primarily on the first type of hospital behavior, examining if hospitals expand profitable procedures among profitable payers and cut back on less profitable care. Because of data limitations, I cannot examine changes in hospital resources in detail.

3 Data Description

The primary source of data for this analysis is the Texas Inpatient Public Use Data Files (PUDF), which contain patient-level information on all inpatient hospital stays in Texas from 1999 to 2007 (24,806,916 inpatient visits). These data are collected by the Texas Health Care Information Council (THCIC), a branch of the Texas Department of State Health Services (DSHS) Center for Health Statistics. Detailed medical information surrounding the visit is recorded, including the principal diagnosis (ICD-9-CM codes), the diagnosis-related groups (CMS-DRGs), and the major diagnostic category (CMS-MDC) codes. The data include

[19] Interestingly, David et al. (2011) finds that cardiac specialty hospital entry increases the number of neurosurgeries in a hospital market. This is somewhat surprising given the clinical guidelines for these procedures, such as craniotomies, are more stringent.

the length of stay (LOS) and the discharge status (e.g. discharged home, died, transferred to another facility). The type of admission is also recorded, and I follow the THCIC by referring to scheduled visits as "elective" and emergency/urgent admissions as "non-elective" in this study. The data also contain information about the primary and secondary payer (e.g. Medicare, Medicaid, uninsured) as well as hospital charges (total and by type of service). Patient demographics (e.g. gender, five year age group, race) and approximate location of residence (e.g. five-digit zip codes and county) are also provided. To reduce computational burden, a 25% random sample is used for the analysis.

From the 25% sample, I exclude individuals residing outside of Texas as well as those missing full five-digit zip codes in order to get precise measures of hospital-patient distances.[20] I also drop patients with limited demographic information due to confidentiality reasons stipulated by the THCIC.[21] Additionally, I exclude visits relating to pregnancy and newborns since this group is quite different than the rest of the population in terms of medical care needs. I also exclude visits to other types of specialty hospitals, such as rehabilitation and psychiatric institutes, since they are not directly applicable for the analysis. For the main analysis, I only examine non-specialty services provided in general hospitals. I refer to these as "uncontested" care because they are the services in which specialty hospitals typically do not compete with incumbent hospitals for patients. However, for specialty admissions, which I refer to as "contested" services, I analyze admissions to both general and specialty hospitals. These exclusions result in a total of 3,604,585 admissions, with 2,419,772 observations for uncontested care and 1,184,813 observations for contested services.

Each patient in the sample is grouped into one of approximately 570 Diagnoses Related Groups (DRGs). The mapping between diagnoses and DRGs is not unique. Patients with the same diagnosis may be coded into different DRGs, depending on the treatment they receive (e.g. whether or not they have surgery) and whether they have complications and/or comorbidities. DRGs were introduced in 1982 as part of Medicare's move to prospective payment and are used to determine the amount hospitals should be reimbursed based on expected resource usage. The hospital is paid a fixed amount that varies by DRG. Each DRG is assigned a payment weight which functions as a price and is based on the average resources used to treat patients in that DRG, relative to the average level of resources for all Medicare patients. The weights are intended to account for cost variations between different types of procedures. More costly conditions are assigned higher DRG weights. For example, coronary bypass is assigned a DRG weight of 6.74, obesity procedures a weight of 1.91, and urinary

[20]The last two digits of the patient's zip code are suppressed if there are fewer than thirty patients included in the zip code, while the entire zip code is suppressed if a hospital has fewer than fifty discharges in a quarter or if the main diagnosis indicates alcohol or drug use or an HIV diagnosis. Additionally, zip codes are missing for patients from states other than Texas.

[21]Demographic information is suppressed for those patients obtaining care for HIV and alcohol and drug use. While age is represented by 22 age groups for the general patient population (typically five year age groups), there are only 5 groups for patients with alcohol and drug use or an HIV diagnosis.

tract infections a weight of 0.45.[22] The DRGs are further grouped into 25 mutually exclusive Major Diagnostic Categories (MDCs), which generally correspond to a single organ system. The Texas PUDF includes DRGs and MDCs for all payer types. DRGs can also be grouped into clinical specialties, which tend to correspond to hospital departments.[23]

Hospital characteristics used in this study come from the American Hospital Association (AHA) Annual Survey Database.[24] The AHA Annual Survey collects detailed information on hospitals' organizational structure (e.g. non-profit, public, for-profit), services provided, the number of beds (total and by service line), personnel (e.g. number of physicians and nurses), and financial performance. A hospital was designated as a specialty hospital if at least 45 percent of its discharges were cardiac, orthopedic or surgical in nature, or at least 66 percent of the hospitals discharges fell into two major diagnosis-related categories (MDC), with the primary one being either cardiac or orthopedic. This definition comes from the Medicare Payment Advisory Commission (MedPAC), with further details provided in Appendix A.

For my analysis, I define admissions with MDCs of 5 (Cardiac) or 8 (Orthopedic) as "contested" services. All other admissions are labelled as "uncontested" admissions. Table 2 shows that the bulk (67.39%) of specialty hospital admissions are for contested services, whereas a much smaller proportion of general hospital admissions (21.89%) are contested.[25] This table also shows the distribution of hospital admissions across medical specialty. Most specialty hospital admissions are in cardiology (27.80%) and orthopedics (29.96%), and to a lesser extent, general surgery, thoracic surgery, and vascular surgery. For general hospitals, the distribution of admissions across specialties is more evenly distributed. Although, obstetrics and neonatology form the largest shares of admissions, cardiology and orthopedics also play substantial roles, accounting for 12.30% and 6.87% of admissions, respectively. Other medical specialties such as general surgery, pulmonary, and general medicine form considerable shares of general hospitals' admissions.

I briefly explore how medical treatment in uncontested services vary by payer type in the sample. Table 3 shows that Medicare patients form the largest proportion of the sample at 44.62%, followed by FFS patients (23.40%), HMO patients (8.41%), Medicaid (11.22%), and the uninsured (8.99%). Although Medicare patients have a lower proportion of uncontested surgeries (18.7%), they have greater illness severity as seen by a higher average DRG weight, longer lengths of stay (6.414 days on average), and a higher death rate (4.6%). These results likely reflect, in part, that Medicare patients are older than the rest of the population. An important observation is that HMO and FFS patients look strikingly similar across all dimen-

[22] To obtain the DRG weights in this analysis, I use the 2007 mapping provided by Centers for Medicare & Medicaid Services (CMS).

[23] I used data from the Massachusetts Health Data Consortium to map DRGs into clinical specialties.

[24] These data were generously provided by the Texas Health Care Information Council (THCIC).

[25] These statistics were derived using all patients in the 25% sample, except for those without five-digit Texan zip codes.

sions of care. They have similar rates of uncontested surgeries (approximately 40%), lengths of stay (roughly 4.25 days), DRG weights, and rates of death. Among all payers, they have the greatest rates of surgery and elective visits. Another important observation from Table 3 is that uninsured patients have the lowest rates of elective care. This is unsurprising given they must pay out-of-pocket for treatment if hospitals don't absorb the costs.

4 Empirical Approach

4.1 Overview

The primary relationship of interest is the extent to which hospital profits in contested services affect medical treatment in uncontested services:

$$Y_{ikjt} = \gamma \pi_{jt} + \omega_{ikjt} \tag{1}$$

where Y_{ijkt} is the medical treatment of individual i from market k seeking uncontested care at hospital j and time t (e.g. procedure, mortality, length of stay); π_{jt} are profits of hospital j at time t in contested services. The residual is given by ω_{ikjt}. In this study, the parameter of interest is the coefficient on hospitals' profits in contested services, γ. Hospital profits are not directly observed in the data. Additionally, there may be unobserved factors correlated with both π_{jt} and Y_{ikjt}, and ordinary least squares estimation of Equation (1) may lead to biased estimates. As such, I use the market share of specialty hospitals as a shock to incumbent hospitals' most profitable services to test whether hospitals adjust the medical treatment in uncontested care. In particular, in its most basic form, the relationship between specialty hospital market share and uncontested outcomes is as follows:

$$Y_{ikjt} = \gamma SMKS_{kt} + u_{ikjt}$$

where $SMKS_{kt}$ is the specialty hospital market share for contested services in market k at time t and u_{ikjt} is an error term.

There may be unobserved factors in the error term u_{ikjt} that are correlated with both $SMKS_{kt}$ and uncontested medical treatment Y_{ikjt}, making the specialty hospital market share endogenous. Both the entry of specialty hospitals into a market (location and timing) and the market share of specialty hospitals in contested services (i.e. the volume of patients) are unlikely to be random. In particular, there may be unobserved hospital market characteristics (both fixed and time-varying), unobserved patient characteristics (health and preferences), and unobserved general hospital characteristics that impact both specialty hospital market share and uncontested outcomes. I decompose the error term into these separate factors as follows:

$$u_{ikjt} = \delta_{it} + \delta_k + \delta_t + \delta_{kt} + \delta_{jt} + \omega_{ikjt}$$

where δ_{it} represents characteristics of patient i at time t; δ_k represents characteristics of hospital market k; δ_t represents factors common to all patients (from all markets) at time t; δ_{kt} represents characteristics of market k at time t; and δ_{jt} represents characteristics of hospital j at time t. The true error term is given by ω_{ikjt}.

In terms of the location of specialty hospital entry, it is likely that specialty hospitals only consider the potential demand and revenue in the market for contested services, not the uncontested. It is nonetheless possible that the demand for contested and uncontested services in a market are correlated. For example, if specialty hospitals locate in areas where patients are generally healthier and health is correlated across the dimensions of contested and uncontested illnesses, then this would lead to biased estimates. Similarly, if the overarching administration at incumbent hospitals was poor and specialists decided to leave and start their own specialty hospital, this could also lead to biased estimates of how incumbent hospitals respond. As such, I employ market fixed effects in all my analyses and market time trends, which alleviates some of these concerns. Additionally, I include year effects to capture shocks that are common to all patients in a given year. The impact of specialty hospital penetration is identified off deviations from trends within a market region. Li and Dor (2013) use this approach to estimate the impact of the repeal of Certificate of Need (CON) regulations on coronary procedures, while Finkelstein (2007) uses a similar model to analyze the introduction of Medicare.

It is likely that specialty hospitals choose their location with the intention of serving the demand of patients from all across that market. It is nonetheless possible that within a hospital market, they locate in areas where patients are healthier and wealthier. To capture this possibility, I control for observed patient characteristics. In particular, I control for patient demographic characteristics (age, gender, race, ethnicity, urban) as well as patient zip code characteristics (per capita income and population 65 years and older).[26] There may also be unobserved individual heterogeneity, which I address below. I also include hospital characteristics (total beds, for profit, and teaching hospital) to capture any factors that are correlated with uncontested outcomes at incumbent hospitals and the specialty hospital market share. To summarize, I account for factors that may be correlated with specialty hospital market

[26]The zip code data come from the U.S. Census, years 2000 and 2010. Zip code data are not released every year, so I only include these two years of data for all patients.

share and uncontested medical treatment as follows:

$$\begin{aligned}
\delta_{it} &= \boldsymbol{X_{it}}\beta + v_{it} \\
\delta_k &= \alpha_k I(k) \\
\delta_t &= \alpha_t I(Year_t) \\
\delta_{kt} &= \theta_k [I(k) \cdot t] \\
\delta_{jt} &= \boldsymbol{Z_{jt}}\eta
\end{aligned}$$

where $\boldsymbol{X_{it}}$ are observed characteristics of individual i at time t (including zip code characteristics); v_{it} are unobserved preferences of individual i; θ_k is the linear time trend of market k; and $\boldsymbol{Z_{jt}}$ are characteristics of hospital j at time t.

Thus, my main equation of interest becomes:

$$Y_{ikjt} = \alpha_k I(k) + \alpha_t I(Year_t) + \theta_k [I(k) \cdot t] + \gamma SMKS_{kt} + \boldsymbol{X_{it}}\beta + \boldsymbol{Z_{jt}}\eta + \epsilon_{ikjt} \tag{2}$$

where the variables are specified as above and $\epsilon_{ikjt} = v_{it} + \omega_{ikjt}$.

As discussed, there may still be unobserved heterogeneity that affects the volume of patients admitted to specialty hospitals for contested care (and consequently the specialty hospital market share) which is correlated with uncontested medical treatment. In particular, unobserved deviations from trend in individual preferences and health may be correlated across contested and uncontested services. In Equation 2, this is v_{it}. To address this possibility, I extend the two step estimator developed by Kessler and McClellan (2000). I first construct predicted specialty hospital market shares using a multinomial choice model for contested services. The probability that a patient attends a given hospital for contested care is a function of observed hospital and patient characteristics, as well as the distance between the patient's residence and the hospital location. In the next step, I estimate the impact of specialty hospital market share on uncontested services at incumbent hospitals using the specialty hospital market shares derived in the first step.

The approach is in the same spirit as previous studies that use distances to hospitals in a patient's geographic region as instrumental variables.[27] The identifying assumption is that unobserved deviations from market trends affecting uncontested medical treatment are uncorrelated with the distance between hospitals and patients seeking care for contested services. That is, conditional on observed patient and hospital characteristics, as well as market characteristics and time trends, the distance between hospitals and patients obtaining contested care has no direct impact on uncontested outcomes, except through specialty hospital market shares of contested services. The exclusion restriction is arguably less demanding in this

[27] See for example Kessler and McClellan (2000); Chernew et al. (2002); Li and Dor (2013) and Swanson (2012).

study than previous work since I focus on the medical treatment of uncontested patients, a different set of individuals than those used to obtain predicted market shares.[28] Essentially, the distances between hospitals and patients seeking care for contested services are being used to forecast the predicted specialty hospital market share for uncontested patients in an area.[29] Previous studies have found distance to be a primary determinant of hospital choice (Burns and Wholey (1992); Luft et al. (1990)). The estimates are also robust to endogenous hospital choice because I assign specialty hospital shares to where a patient lives, not to the hospital to which she is admitted for uncontested care. This is important because hospital choice may be endogenous if changes in specialty hospital market shares cause patients to alter where they seek care for uncontested services, or if market shares are correlated with unobserved hospital quality.[30] The details of the estimation strategy are described below.

4.2 Specialty Hospital Market Shares

I first estimate the market share of specialty hospitals in contested services. The market area used for analysis is defined as the Hospital Service Area (HSA), with 208 HSAs in Texas.[31] The specialty hospital market share is defined as the proportion of patients residing in the HSA that are admitted to specialty hospitals. I specify a patient-level hospital choice model for patients seeking contested care (i.e. those obtaining cardiac or orthopedic care). I model the hospital choice decision for contested care as a function of hospital and patient characteristics which are arguably orthogonal to uncontested patient outcomes.

In particular, individual i's indirect utility from choosing hospital j is given by:

$$U_{ij} = V(\boldsymbol{D_{ij}}; \boldsymbol{Z_j}) + W(\boldsymbol{X_i}; \boldsymbol{Z_j}) + \xi_{ij} \tag{3}$$

where $\boldsymbol{D_{ij}}$ is non-parametric function of the distance from individual i to hospital j; $\boldsymbol{Z_j}$ are characteristics of hospital j; $\boldsymbol{X_i}$ are characteristics of individual i. The choice set for each individual is comprised of all hospitals within a 50 mile radius of her residence, or 100 mile radius for teaching hospitals, with patient location being approximated by the centroid of her zip code.[32] Euclidean distances between patients' residences and hospitals were calculated

[28] Formally, the exclusion restriction is that cov($\boldsymbol{D}$,ϵ_{ikjt})=0, where $\boldsymbol{D}$ is the distance between hospitals and patients seeking contested care.

[29] It should be noted that the approach I take does not explicitly depend on the choice decision between any two hospitals being independent of irrelevant alternatives (IIA), which imposes strong substitution patterns between hospitals.

[30] For example, this would occur if patients observe a decline in contested services at incumbent hospitals and believe that this provides information about its quality so obtain care elsewhere. Similarly, if patients seeking high quality, cutting edge care are likely to travel further to urban areas which have more specialty hospitals, then this would lead to biased estimates.

[31] A map of HSAs in Texas is provided in the Appendix. HSAs are local health care markets for hospital care. An HSA is a collection of zip codes whose residents receive most of their hospitalizations from the hospitals in that area. It is produced by the Dartmouth Atlas of Health Care.

[32] Nearly 95% of patients chose a hospital within 50 miles. Within the 50 mile radius, the median patient

using GIS. Further details are provided in the Appendix.

For every $i - j$ pair, V(.) is a nonparametric function of distance and hospital characteristics $h = 1, ..., H$.

$$V_{ij} = \sum_{h=1}^{H} \alpha^h \boldsymbol{D_{ij}} Z_j^h$$

Specifically, $\boldsymbol{D_{ij}}$ is a vector of four dummy variables indicating the quartile of distance which $i - j$ pair falls into from the distribution of distances of all pairs. Z_j^h contains information on hospital characteristic h, such as indicators for whether hospital j is for profit, a teaching hospital, a specialty hospital, and the tercile of total hospital beds.

From equation 3, W(.) is a nonparametric function of the interaction between individual i and hospital j's characteristics:

$$W_{ij} = \sum_{h=1}^{H} \boldsymbol{X_i} Z_j^h \gamma^h$$

where Z_j^h are as defined above, and the vector $\boldsymbol{X_i}$ includes age categories (grouped by five years), gender, race (white, black, other), ethnicity and illness severity. Note that individual characteristics $\boldsymbol{X_i}$ are fully interacted with the binary hospital characteristics Z_j^h.

I estimate the patient-level multinomial logit hospital choice model in equation (3) using maximum likelihood, deriving estimates of parameters γ^h and α^h for $h = 1, ..., H$. McFadden (1973) shows that the probability of individual i choosing hospital j, is given by:

$$\pi_{ij} = Pr(Y_{ij} = 1) = \frac{exp(V_{ij} + W_{ij})}{\sum_{j \in J_i} exp(V_{ij} + W_{ij})} \tag{4}$$

where Y_{ij} =1 if individual i is treated at hospital j and =0 otherwise, and J_i is the set of hospitals within 50 mile radius from patient i. To allow for differences in preferences over time and across medical conditions, I estimate hospital choice separately for different years, for different specialties (cardiac or orthopedic), and for those who do and do not obtain surgical procedures.[33]

Following McFadden (1973), the expected market demand for hospital j in region k is given by:

$$\hat{d}_{jk} = \sum_{i \in k} \hat{\pi}_{ij}$$

As such, the market share of specialty hospitals in region k is:

had 23 hospitals to choose from and chose a hospital that was 7.80 miles from the centroid of her zip code.

[33]In total, the model is estimated separately four times for each year.

$$S\hat{MKS}_k = \frac{\sum\limits_{j \in SPC_k} \hat{d}_{jk}}{\sum\limits_{j \in J_k} \hat{d}_{jk}} \tag{5}$$

where SPC_k is the set of all specialty hospitals within 50 mile radius from each patient residing in market k; J_k is the set of all hospitals (specialty and incumbent) within 50 mile radius from each patient in market k. The actual market share of specialty hospitals in region k is: $SMKS_k = S\hat{MKS}_k + \hat{u}_k$, where $\hat{u}_k$ is the estimated residual of the specialty hospital market share in k.

The distribution of predicted versus actual specialty hospital market share is shown in Figure 4. As can be seen, the distribution of specialty hospital market shares is highly skewed to the right, with the average share being heavily driven by those markets with very high specialty hospital penetration. My model somewhat overpredicts specialty hospital market share at the lower end of the distribution. However, overall, it does a very good job of predicting the specialty hospital market share throughout the distribution. In my sample period, the average specialty hospital market share has increased from 0.90% to 3.75% between 1999 and 2007. This is driven by increases in the specialty shares of both cardiac and orthopedic care, with the average cardiac share increasing from 0.97% to 2.89% and the average orthopedic share increasing from 0.64% to 5.78%.[34]

4.3 Uncontested Medical Treatment

After having obtained the predicted market share and the estimated residual, I can then determine how incumbent hospitals respond to a change in their profits from specialty services. I employ a control function approach, namely the method of two-stage residual inclusion, which provides consistent estimates for both linear and non-linear relationships (see Terza et al. (2008)).[35] That is, rather than using predicted market share of specialty hospitals as a covariate, both the actual market share and the estimated residual are included. Unobserved factors affecting specialty hospital market shares are controlled for in the estimated market share residual.

4.3.1 Patient-Level Analysis

I use individual patient-level data to analyze how hospital respond on the intensive margin and whether they differentiate treatment by payer type. The advantage of the patient-level

[34] These figures are shown in the Appendix.

[35] With a main relationship that is nonlinear, two-stage predictor substitution (2SPS) (i.e. putting in the predicted market share values) will not be consistent. The reason is that part of the error term that leads to endogeneity cannot be eliminated by moving it outside of the expectation due to nonlinearity. See Terza et al. (2008) for a discussion.

analysis is that individuals' demographic and clinical characteristics are included as controls in the analysis. This is particularly important to take into account when examining differences across payer types.

The primary estimating equation for the patient-level analysis is:

$$Y_{ikjt} = \alpha_k I(HSA_k) + \alpha_t I(Year_t) + \theta_k[I(HSA_k)\cdot t] + \gamma SMKS_{kt} + \sigma\hat{u}_{kt} + \boldsymbol{X_{it}}\beta + \boldsymbol{Z_{jt}}\eta + \epsilon_{ikjt} \quad (6)$$

where Y_{ikjt} is the medical treatment of individual i from HSA k at hospital j and time t; $SMKS_{kt}$ is the specialty hospital market share in k at time t; $\hat{u}_{kt}$ is the estimated residual of the specialty hospital market share in k at time t; $\boldsymbol{X_{it}}$ are characteristics of individual i at time t (dummies for gender, five year age group, race, Hispanic, urban, primary payor, zip code characteristics); and $\boldsymbol{Z_{jt}}$ are characteristics of hospital j at time t (dummies for tercile of total beds, teaching hospital, and for profit). Hospital department fixed effects are included in the analysis. The parameter of interest is γ, the coefficient on specialty hospital market share. As discussed, equation (6) includes market-specific linear trends, allowing for different market trends. Standard errors are clustered by HSA to account for any within market correlation.

4.3.2 Hospital Level Analysis

To analyze hospital responses on the extensive margin, I use hospital-year information as the unit of analysis. In particular, I aggregate the number of patients in a hospital who have particular types of hospital admissions in a given year. Since the distribution of hospital admissions is heavily skewed to the right due to the presence of very large hospitals, I take the log of admissions for the dependent variables.

I assign the specialty hospital market share to hospitals based on the HSA which they are located. Specifically, I use the predicted specialty hospital market shares derived for patients in a given HSA and assign these shares to all hospitals located in the same HSA. In some cases, there are very few hospitals in an HSA. As such, identifying HSA fixed effects and HSA time trends is demanding for estimation. Instead, I control for time varying HSA demographic characteristics to capture factors that may be correlated with specialty hospital market shares and hospital admissions, such as the HSA per capita income and the proportion of resident who are: 65 years or older, White, Black, Hispanic, high school graduates, urban, below the federal poverty, and native born. Additionally, I add fixed effects for the Hospital Referral Region (HRR) in which the hospital is located as well as HRR time trends.[36]

[36] Each HRR is formed from various HSAs. HRRs are regional health care markets for tertiary medical care that needs a major referral center. Dartmouth Atlas define the boundaries of HRRs by determining where patients were referred for major cardiovascular surgical procedures and for neurosurgery. There are 24 HRRs in Texas.

The primary estimating equation for the hospital-level analysis is given by:

$$Y_{rkjt} = \alpha_r I(HRR_r) + \alpha_t I(Year_t) + \theta_r[I(HRR_r) \cdot t] + \gamma SMKS_{kt} + \sigma \hat{u}_{kt} + HSA_{kt}\beta + Z_{jt}\eta + \epsilon_{rkjt} \quad (7)$$

where Y_{rkjt} is the hospital level outcome of hospital j, in HSA k and HRR r at time t; $SMKS_{kt}$ is the specialty hospital market share in HSA k at time t; $\hat{u}_{kt}$ is the estimated residual of the specialty hospital market in HSA k at time t; $\boldsymbol{HSA_{kt}}$ are time-varying characteristics of HSA k at time t; and $\boldsymbol{Z_{jt}}$ are characteristics of hospital j at time t. HRR fixed effects, year fixed effects, and HRR time trends are also included. Regressions are weighted by the total number of hospital beds in the first year the hospital appears in the sample. Standard errors are clustered at the HRR level. Again, the parameter of interest is γ, the coefficient on specialty hospital market share.

5 Empirical Results

5.1 The Extensive Margin: Volume of Admissions

I first turn to the hospital level regressions to examine if specialty hospitals affect the volume of admissions at incumbent hospitals. To understand the direct impact that increased competition for specialty services has on incumbent hospitals' line of contested services, I estimate their change in admissions. Table 4 shows evidence of a sizeable decline, with a 1 percentage point change in specialty hospital market shares leading to a 1.071% change in contested admissions. While the results are somewhat imprecise, they are sizeable and are statistically significant at the 10% threshold. This finding suggests a shift in volume of contested services from incumbents to specialty hospitals, a phenomenon referred to as business stealing.[37]

Next, I test if specialty hospitals caused incumbents to shrink services across the board due to the negative budget shock (column 2 of Table 4). I find no evidence that this occurred. There is, however, heterogeneity across the types of uncontested admissions. Columns 3 and 4 show the impact on uncontested elective (i.e. scheduled) and non-elective (i.e. urgent) admissions. There is a large increase in uncontested elective admissions, with a 1 percentage point increase in specialty hospital market share causing a 2.648% increase in admissions. This offsets a decline in non-elective admissions, which is in the order of 1.051%. This is consistent with the findings of David et al. (2011), who also find a decline in trauma care due to specialty hospital entry. These results suggest that hospitals are admitting fewer patients from the emergency department and are replacing these visits with more elective care. It is possible that some of this is a temporal shift in care (i.e. those who would have been admitted from the emergency department are being admitted later and are coded as an elective visit).

[37]See Mankiw and Whinston (1986) and Li and Dor (2013) on possible effects increased specialty hospitals can exert on incumbents' contested service line.

My data do not include readmissions, so I cannot test for this directly. However, subsequent findings suggest that this is unlikely the whole story and that hospitals are strategically cutting back on unprofitable care and replacing it with higher profit, discretionary procedures.

As discussed, one way in which hospitals can try to make up lost revenue from the decline in contested admissions is to increase admissions in the remaining profitable procedures, which are primarily surgeries. First, I test if there is a change in the total volume of surgeries performed at hospitals. Column 1 of Table 5 shows that there is no significant evidence of a change in total surgeries. Next, I examine which types of uncontested surgeries are most affected. I find a significant increase in the number of general surgery admissions, with a 1 percentage point increase in specialty hospital share causing a 0.97% increase in general surgery admissions (column 2). I find no significant evidence of changes in other types of surgeries. These results are aligned with general surgeries having more clinical grey areas than other types of surgeries.

To understand the nature of the increase in general surgical admissions, I analyze what types of surgical procedures are driving these results. There is some evidence that the volume of non-elective general surgeries have decreased (column 1), which is consistent with hospitals cutting back on unprofitable care. However, this result is not statistically significant. I find evidence that elective general surgical procedures increase in the order of 2.855% (column 2 of Table 6). Columns 3 and 4 provide some evidence on the exact types of general surgeries that have increased. Obesity and stomach procedures are arguably the most discretionary types of procedures in the general surgery department.[38] I measure the impact on these surgeries to get a sense of just how elective are the procedures driving the increase in general surgeries. I find a sizeable increase in these types of procedures. Stomach procedures increase by 2.668% and obesity procedures by 4.427% with a 1 percentage point increase in specialty hospital market share.

5.2 The Intensive Margin: Intensity of Treatment and Differences by Payer Type

Next, I turn to the patient-level analysis to test whether hospital spillovers also occur on the intensive margin of patient treatment. Additionally, I estimate whether there is heterogeneity across payer types in the effects. Table 7 shows the impact of specialty hospital market shares on the share of patients with an uncontested surgery. I first analyze surgeries as a whole (columns 1 and 2), and add in department fixed effects to test within individual hospital departments (columns 3 and 4). The first column shows that there is a slight increase in the share of patients with a surgical procedure. However, this effect isn't statistically significant.

[38]Stomach procedures include a range of surgeries, both obesity related and not. This DRG has been found to be notoriously wrongly coded by hospital administrators.

I add in specialty hospital market shares and payer interactions to test for differences across payer types (column 2). I find no effect for Medicare patients (the base category), Medicaid, and uninsured patients. However, I find that a 1 percentage point increase in specialty hospital market share leads to a 0.211 percentage point increase in HMO patients receiving a surgery and a 0.137 percentage point increase for FFS patients.

These results show an overall increase in the share of private payers with an uncontested surgical procedure. I next test whether, on average, there is a differential increase in surgeries within an individual hospital department. This is to better understand if the overall results are being driven by a subset of departments or if hospitals are increasing intensity of treatment within individual departments. I find no overall effect in the share of patients with a surgery in a department (column 3). However, I find there is heterogeneity across different payers. In particular, the intensity of treatment increases for private payers, with a greater proportion having a surgery, but no effects are found for other types of payers. Specifically, a 1 percentage point increase in specialty hospital market share causes a 0.088 percentage point increase in the share of HMO patients with a surgery in a department and a 0.080 percentage point increase in the share of FFS patients.

To understand the nature of surgeries being affected among the private payers, I analyze different types of surgeries in Table 8. First I estimate changes in the DRG weight for the sample of individuals with a surgery (column 1). Department fixed effects are included so these represent average changes within a department. I find evidence there is a decline in the average DRG weight for private payers, in the order of approximately 0.02 of a standard deviation with a 10 percentage point increase in specialty hospital market shares. This suggests that hospital departments are performing more marginal surgeries on healthier private payers.

I next analyze the effects on the proportion of individuals with an elective surgery. I find that there is a significant increase in the share of private payers with an elective surgery (column 2), where a 1 percentage point increase in specialty hospital market share increases elective surgeries in departments by 0.128 percentage points for HMO patients and 0.128 percentage points for FFS. These findings also support the evidence that hospital departments are performing relatively more discretionary surgeries amongst private payers. There is also evidence of a decline in the share of uninsured patients with an elective procedure, in the order of 0.065 percentage points, suggesting that that hospitals are cutting back on unprofitable care.

Columns 3-5 of Table 8 provide evidence on which departments are driving these changes. Most noticeable is the large increase in the share of private payers with general surgeries (column 3). A 1 percentage point increase in specialty hospital market share increases the share of private payers with a surgery in the general surgery department by 0.141 percentage points for HMO patients and 0.118 percentage points for FFS patients. The evidence for other types of surgeries, such as in gynecology, neurosurgery, and urology being impacted is more limited. As discussed previously, general surgeries tend to have more clinical grey areas than other surgeries.

The evidence thus far suggests that hospitals respond to the loss of admissions in their profitable service lines by increasing profitable procedures among the most profitable patients. I next test for differential effects in the intensity of treatment across payer types. To measure intensity of treatment, I use the length of stay (in days). Table 9 shows a small increase in the average length of stay in a hospital (columns 1). Specifically, a 10 percentage point increase in specialty hospital market share increases length of stay by 0.129 days, or 0.012 of a standard deviation. This effect is driven by private payers (column 2), where a 10 percentage point increase specialty hospital market share increases the length of stay by 0.271 days (or 0.029 of a standard deviation) for HMO patients and 0.222 days (0.0241 of a standard deviation) for FFS patients.

These findings may be driven by an increase in the share of private payers with surgeries. Columns 3-6 demonstrate whether this is the case. I first add department fixed effects to the analysis to see if the increase in length of stay persists, on average, within a department. I find the overall increase in length of stay remains (column 3), and that the differential increase among private payers still holds (column 4). Next, I condition on a patient's DRG. If surgeries are completely driving the increased length of stay among private payers, then we should see the effect disappear. However, columns 6 shows that this isn't the case. There is still a significant differential increase in private payers' length of stay. In particular, conditional on patients' DRG, HMO patients experience an increase of 0.176 days (0.019 standard deviations) and FFS patients an increase of 0.126 (0.013 standard deviations) from a 10 percentage point increase in specialty hospital market share. As noted previously, only private payers reimburse for extra hospital days. These findings suggest hospitals are trying to make up for lost revenue.

Finally, I examine if increased specialty hospital market share has an impact on patients' death rate. There is an increase in the average death rate of patients (column 1 of Table 10). However, this could be due to composition effects in terms of the types of patients being admitted. Testing for heterogeneity across payers, I find the effect is primarily concentrated among uninsured, where a 1 percentage point increase in specialty hospital market share increases the proportion of uninsured who die by 0.0003 percentage points). These results still hold when estimating changes within departments (columns 3-4). As shown previously, however, there is a decline in the share of uninsured patients with an elective visit, suggesting that this result is driven, at least in part, by uninsured patients who are admitted having higher severity.

5.3 Discussion

My findings suggest that hospitals respond to the loss of a profitable service line by increasing surgical procedures with lower marginal benefit. Hospitals might have previously been constrained in performing such procedures, but now have the opportunity with freed resources from contested services. However, it is unlikely the effects are all driven by pent up demand because the increase is concentrated solely among the private payers, whose insurance reimburses more generously. This suggests that hospitals are strategically targeting profitable procedures to profitable patients. This is further supported by the increase in the length of stay only among private payers, even when taking into account the increased share of patients with surgeries.

Furthermore, the decline in non-elective procedures and the smaller share of uninsured patients with elective surgeries suggests that hospitals are trying to both make up for lost revenue and cut back on unprofitable care. It could be that some individuals are no longer getting necessary care. However, there is a range of treatment options that are consistent with acceptable medical practices so this may not be a concern.

From a welfare point of view, it is unclear to what extent an expansion of lower marginal benefit procedures is a concern. If social marginal costs are now greater than social marginal benefits, then specialty hospitals can be welfare reducing. However, two important considerations are that i) private patients are not paying the full cost of additional services, since they have insurance, and ii) patients do not know the expected benefit due to asymmetric information between the physician and the patient (the principle-agent problem). One argument put forth to ban specialty hospitals is that they are responsible for increasing health care costs among specialty services in a market. My findings suggest that they may also be driving up costs in non-specialty services, by increasing the volume of elective and general surgeries amongst private payers. One implication of my findings is that specialty hospitals are not only if hospitals are able to differentiate treatment by payer type then the ACA and potential reductions in premiums may be less cost-saving than once thought. Since my findings show that hospitals target high profitable treatment to private payers, the increase in private payers will raise costs in hospital markets.

6 Conclusion

It is widely believed that hospital departments do not operate independently and that cross-subsidization occurs within hospitals. At the same time, much of the existing literature ignores hospital spillovers when examining policy changes and shocks to profits in specific service lines. Few empirical studies to date have analyzed the extent to which hospitals adjust other margins of care. Even less attention has been given to just how nuanced are hospitals' responses to these shocks. Not only can hospitals adjust on the extensive margins, by changing the volume of department admissions, but they can also adjust on the intensive margin by changing treatment intensity. They may also differentiate medical treatment across types of payers, which has received little attention in the literature to date.

This paper finds strong evidence that hospitals cross-subsidize and differentiate medical treatment across payer types. It contributes to the existing literature by providing a more complete picture of hospital spillovers. I use the entry of specialty hospitals in Texas as a shock to incumbent hospitals' most profitable procedures in order to analyze the impact on other service lines. I find that the hospital response is very sophisticated. Hospitals practice both revenue augmenting and cost-cutting behavior, targeting specific procedures and payers according to their profitability. Specifically, they increase the number of surgical procedures in other departments and perform more surgeries on marginal patients. This varies with the service line and the payer type. The effects are concentrated in medical specialties where there are more discretionary surgeries and higher profit margins, such as the department of general surgery. In addition, hospitals increase the intensity of treatment among private payers, by increasing their length of stay. Furthermore, hospitals cut back on unprofitable treatment by reducing non-elective admissions and uninsured elective care.

The findings of this paper suggest that hospital responses to financial shocks are sophisticated and targeted. Hospitals are able to adjust their mix of services and are able to differentiate treatment by payer type. My findings suggest that focusing only on substitution within a service line, as much of the existing literature has done, ignores important hospital responses and leads to incomplete welfare implications, particularly among different payer groups.

Appendix

A Specialty Hospital Designation

Specialty hospitals were identified following the definition outlined in the Medicare Payment Advisory Commission (2005)'s Report to the Congress. A hospital was designated as a specialty hospital if at least 45 percent of the hospitals discharges were cardiac, orthopedic or surgical in nature, or at least 66 percent of the hospitals discharges fell into two major diagnosis-related categories (MDC), with the primary one being either cardiac or orthopedic. This definition is the most widespread and is used in numerous other governmental reports, including those by the Secretary of the Department of Health and Human Services (HHS) and the Center for Medicaid and Medicare Services (CMS). This designation is also aligned with the description of a specialty hospital provided in Section 507 of the Medicare Prescription Drug, Improvement, and Modernization Act of 2003 (MMA) as well as the one outlined in Texas Senate Bill 872. The MMAs definition only considers physician-owned hospitals to be specialty hospitals, while the Texas Senate Bill excludes public hospitals as well as those hospitals for which the majority of inpatient claims are for major diagnosis-related groups relating to rehabilitation, psychiatry, alcohol and drug treatment, or children or newborns. Additionally, it should be noted that the Texas Senate Bill only classifies specialty hospitals using the higher threshold of two thirds (roughly 0.66 as used above) for the top two MDCs or surgical cases. Thus, while my approach will capture all hospitals designated as specialty using the Texas Senate Bill, it will also include additional hospitals since the Medicare Payment Advisory Commission (MedPAC) definition is somewhat less stringent.

The steps I take to identify specialty hospitals are as follows. I first derived the total discharges in a year for each hospital. Then, to isolate the concentration of services offered in the hospital, I examined the distribution of medical diagnoses. Specifically, I constructed three specialty indices for each hospital for each year based on the definition of specialty hospital above:

Specialty Index 1 is the proportion of total hospital discharges that fall in the most common Major Diagnostic Category (MDC) in the year. This index only considers hospitals with top MDCs being cardiac or orthopedic and is missing for all others. A hospital was classified as a cardiac specialty hospital in the year if its most common MDC was Diseases and Disorders of the Circulatory System (MDC 5) and if 45% of its cases fell into this category. Similarly, orthopedic hospitals must have its most common MDC being Diseases and Disorders of the Musculoskeletal System and Connective Tissue (MDC 8), with 45% of its cases in this group. Hospitals with Specialty Index 1 of 0.45 or greater are consequently designated as being specialty.

Specialty Index 2 is the proportion of total hospital discharges with surgical DRGs in the year (as identified using the CMSs annual list of DRGs). A hospital was classified as a surgical specialty hospital in the year if this index was 0.45 or greater (i.e. 45% or more of discharges involved a surgical procedure) and if it was not identified as a particular type of specialty using Specialty Index 1.

Specialty Index 3 is the proportion of total hospital discharges that that the top two MDCs make up in the year. It only considers those with the most common MDC being either Cardiac (MDC 5) or Orthopedic (MDC 8). A hospital was classified as a specialty hospital in the year if the specialty index was 0.66 or greater. Again, it was identified as a particular type (cardiac or orthopedic) based on the most common MDC. Although all three indices were used to determine which hospitals were specialty hospitals, there were no hospitals identified as a specialty using Index 3 that were not already identified using Indices 1 and 2. Thus, the main criteria effectively used to determine specialty hospitals was whether at least 45 percent of a hospitals discharges were in cardiac, orthopedic, or surgical.

All hospitals that were identified as a specialty were then examined thoroughly. If the hospital was publicly owned, it was removed from the list of specialty hospitals. I used question B1 from the Annual Hospital Survey to establish the type of organization that is responsible for controlling the operation of the hospital. Any reporting to be government operated (codes 12-16 and 41-48) were removed from the specialty list. Additionally, a hospital had the majority of inpatient claims being for discharges relating to rehabilitation, psychiatry, alcohol and drug treatment, or children or newborns, was removed from the list of specialty hospitals and excluded from analysis. Hospitals whose primary focus was on surgeries not covered by Medicare (such as bariatric surgery) were also removed. Specifically, I used the question on AHA Annual Survey of Hospitals that asks hospitals to indicate the type of services that best what is provided to the majority of their patients. Hospitals were excluded from the analysis if they identified as being either psychiatric (code 22), an institute for the mentally retarded (code 62), tuberculosis or other respiratory diseases (code 33), cancer (41), rehabilitation (46), chronic diseases (48), acute long-term care (80 and 90), or alcoholism/other chemical dependency (82). Additionally, I examined the share of DRGs in each hospital in a year that fell into rehabilitation, psychiatry, alcohol/drug treatment, children/newborns, and bariatric surgery. This was done primarily to validate the AHA information and also to examine hospitals that were not in the AHA Annual Survey. Those with very high shares in the excluded categories were removed from the analysis.

Additionally, there were a number of hospitals that were on the margin of being a specialty hospital, meeting the threshold in some years but not others. For these hospitals, I followed the approach taken by Chollet et al. (2006), using a case by case basis. A hospital was designated as specialty if it was just under the threshold in earlier years but was well above it in later years. Conversely, if a hospital was above the threshold in the earlier years but the specialty index gradually fell over time to below the threshold, it was classified as a specialty hospital only in those earlier years where it met the specialty criteria.

Another challenge was that the Texas IPUDFs do not include hospitals with fewer than 50 inpatient discharges per quarter or those that report with other facilities. In such cases, I used discharge information for the quarters whenever available as well as in-depth web searches and AHA information to establish if a hospital was a specialty. If the hospital was clearly above the threshold in the periods it was in the discharge data files, it was considered to be a specialty throughout the sample. The AHA data had detailed information on the characteristics of most Texan hospitals, including those that were not in the PUDF, which was also quite useful in identifying specialty hospitals not appearing in the discharge data. I ran a probit model to obtain a propensity score for being a specialty hospital using AHA variables, such as total beds, physician ownership, total births, as the explanatory variables and an indicator for being a (non borderline) specialty hospital as the dependent variable. This helped identify some hospitals missing in the PUDF data as well as borderline hospitals as being specialty. Additionally, I spent considerable time looking up individual hospitals through web searches to see if it self-identified as a specialty or whether there was strong qualitative evidence to indicate it was a specialty hospital.

Upon developing a preliminary list of specialty hospitals, I compared it to those produced by other organizations. In particular, I examined the lists provided in the 2006 Senate Hearings on Physician-Owned Specialty Hospitals to ensure I was not missing any specialty hospitals (US Congress (2006)). All hospitals listed in the report as specialty (i.e. specialty) were on my list; although, my list also included hospitals that were not owned by physicians (i.e. other investor-owned and in one case non-profit). Additionally, I obtained a list of existing hospitals that identified as specialty in 2012 from the Regulatory Licensing Unit of the Texas Department of State Health Services. Reassuringly, I had classified all hospitals on that list as specialty hospitals. Although the Chollet et al. (2006) study does not provide a list of specialty hospitals and uses only the somewhat more stringent Texas Senate Bill definition of specialty hospital, I compared the number of specialty hospitals and their general location (i.e. county) for the time period of their study using only the Texas Senate Bill criteria. Again, my approach produced very similar results in terms of the quantity and location of specialty hospitals in Texas.

B Obtaining Patient to Hospital Distances

B.1 Hospital Location

The location of hospitals was obtained using information from the American Hospital Associations (AHA) Annual Survey of Hospitals, the Texas Health Care Information Collection (THCIC) database, and researcher collected data. The AHA Annual Survey of Hospitals and the THCIC information were kindly provided by the Texas Department of State Health Services (DSHS). Both data sources contain annual information on all licensed hospitals in Texas, including the physical address of hospitals. It is mandatory for all licensed hospitals to respond to the AHA Annual Survey. As such, the bulk of the hospital addresses were obtained from the AHA Annual Survey. In the case where a hospital is licensed as part of a main hospital, only the main hospital reports to the AHA. As such, I used data from the THCIC database to fill in addresses for these hospitals whenever possible. A small subset of hospitals did not appear in either the AHA Annual Survey or the THCIC data files, so I performed thorough internet searches for these hospitals to obtain an address. The majority of hospitals appeared in both the AHA Annual Survey and the THCIC data files, so I cross-checked the AHA information against the THCIC information. If the addresses differed across sources, I verified the correct address through rigorous internet searches. It should be noted that in a small number of cases, hospitals changed location over the sample period, either moving into a brand new structure (largely in rural areas) or moving into an existing building that had previously housed a hospital (more common in urban areas). In these cases, the year the hospital moved was noted, with the old and new location being used in the appropriate time period. Once the hospital locations were verified and collected, GIS software was used to convert the addresses into longitudinal coordinates. The software used was ArcGIS 10.1 developed by ESRI. ArcGIS can be used to manage attribute data, in this case addresses, and display them geographically by geocoding. Specifically, the hospital addresses were geocoded in ArcGIS 10.1 using the 10.0 North America Address Locator. This locator is based on NAVTEQ Q3 2011 reference data for North America and was last updated in June 2012. In almost all cases, the hospital addresses matched correctly to the points plotted by ArcGIS. In some cases, however, the address had to be slightly altered prior to geocoding for ArcGIS to correctly identify the location (i.e. giving a street name adjacent to the actual street or slightly changing the street number). Many robustness checks were done to ensure that the location obtained correctly matched the hospitals address, such as comparing the address and coordinates generated by ArcGIS to those in Google Maps.

B.2 Patient Location

The analysis is restricted to patients living in Texas. This was determined using information collected by hospitals on patients listed state of residence and zip codes. Individuals denoted as residing outside of Texas were excluded from the analysis (132,336 inpatient visits). The full five digit zip code was recorded for 94.19% of Texan patients. In order to preserve patient confidentiality, the DSHS suppressed the last two digits of a zip code if there were fewer than thirty patients in the zip code in a discharge quarter. The entire zip code was suppressed if a hospital had less than 50 discharges a quarter or if the ICD-9 code indicated sensitive medical conditions (i.e. alcohol or drug abuse or an HIV diagnosis). Although some patients with missing zip codes had county of residence, I only included patients with a full five digit zip code in the analysis to ensure a high level of precision in patient residence.

The location of patients residences were approximated with longitudinal coordinates that were derived in ArcGIS using the centroid of the zip code for those patients with full five digit zip codes. Zip Codes are not geographic features but are instead a collection of mail delivery routes for the US Postal Service. As such, to obtain a geographic representation of the zip codes to match to the patient-level data, ZCTA area shapefiles for all of Texas were obtained from the US Census Bureau for the years 2000 and 2010. ZCTA regions are geographical areas produced by the US Census Bureau based on the most prevalent postal zipcode within a fixed geographic area. As such, while the match between ZCTA areas and zip codes is not exact, there is significant overlap. In order to calculate the centroids of the ZTCA boundaries, I used the Feature to Point tool in ArcGIS which creates a feature class containing centroid points generated from the boundary polygon line of the ZCTA area.

B.3 Patient to Hospital Distance

To derive distances between patients' residences and hospitals, the centroids of the ZCTAs and the hospital locations were projected using a UTM Projected Coordinates System (NAD 1983 HARN UTM Zone 14N). The distances were calculated using the Point Distance tool in ArcGIS, which provides Euclidean distances (i.e. as the crow flies). Non-teaching hospitals that were more than 50 miles from the patient residence were dropped from her choice set. Teaching hospitals that were more than 100 miles from the patient were also dropped.

C Supplemental Figures and Tables

Figure A1: Hospital Service Areas in Texas

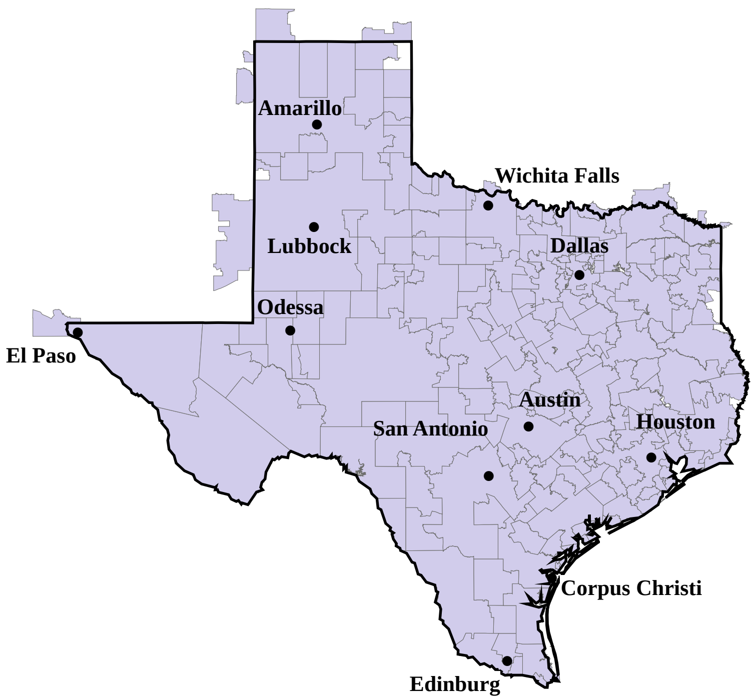

Table A1: The Distribution of Predicted and Actual Specialty Market Shares

Year		Mean	Std. Dev	25th Percentile	Median	75th Percentile	OLS Coefficient	R squared
				Actual Specialty Market Share				
1999	All	0.009	0.031	0	0	0		
	Cardiac	0.010	0.043	0	0	0		
	Orthopedic	0.006	0.019	0	0	0		
2003	All	0.027	0.049	0	0.005	0.032		
	Cardiac	0.020	0.054	0	0	0.003		
	Orthopedic	0.034	0.070	0	0	0.045		
2007	All	0.037	0.056	0	0.013	0.056		
	Cardiac	0.024	0.060	0	0	0.009		
	Orthopedic	0.058	0.092	0	0.019	0.095		
Overall	All	0.029	0.057	0	0	0.033		
	Cardiac	0.022	0.064	0	0	0.001		
	Orthopedic	0.036	0.075	0	0	0.047		
				Predicted Specialty Market Share				
1999	All	0.007	0.015	0	0	0.008	1.348	0.457
	Cardiac	0.006	0.016	0	0	0.004	1.772	0.404
	Orthopedic	0.009	0.016	0	0	0.011	0.594	0.253
2003	All	0.025	0.044	0	0.010	0.030	0.621	0.311
	Cardiac	0.020	0.041	0	0.004	0.020	0.458	0.122
	Orthopedic	0.034	0.054	0	0.013	0.042	0.704	0.296
2007	All	0.041	0.057	0	0.024	0.064	0.743	0.564
	Cardiac	0.033	0.051	0	0.017	0.050	0.734	0.399
	Orthopedic	0.053	0.067	0	0.027	0.086	0.792	0.336
Overall	All	0.029	0.050	0	0.005	0.036	0.748	0.442
	Cardiac	0.025	0.048	0	0.002	0.029	0.682	0.266
	Orthopedic	0.035	0.058	0	0.006	0.046	0.798	0.371

Notes: The specialty market share is defined as the proportion of patients in the HSA that are admitted to specialty hospitals. The predicted specialty market shares are estimated using maximum likelihood and are derived from a patient-level multinomial hospital choice model for patients seeking care in specialty services (i.e. MDC=5 or MDC=8). The choice set includes all hospitals within a 50 mile radius from the patient (or 100 miles for teaching hospitals). A patient's indirect utility function is specified as a non-parametric function of hospital-patient distance quartiles, fully interacted with patient and hospital characteristics. Estimation was done separately across years and across type of care (cardiac surgical, cardiac non-surgical, orthopedic surgical, and orthopedic non-surgical). The coefficient and the R-squared from an OLS regression of actual market share on predicted market share are shown in the last two columns.

Table A2: The Distribution of Predicted and Actual Specialty Market Shares using Distance Squared

Year		Mean	Std. Dev	25th Percentile	Median	75th Percentile	OLS Coefficient	R squared
				Actual Specialty Market Share				
1999	All	0.009	0.031	0	0	0		
	Cardiac	0.010	0.043	0	0	0		
	Orthopedic	0.006	0.019	0	0	0		
2003	All	0.027	0.049	0	0.005	0.032		
	Cardiac	0.020	0.054	0	0	0.003		
	Orthopedic	0.034	0.070	0	0	0.045		
2007	All	0.037	0.056	0	0.013	0.056		
	Cardiac	0.024	0.060	0	0	0.009		
	Orthopedic	0.058	0.092	0	0.019	0.095		
Overall	All	0.029	0.057	0	0	0.033		
	Cardiac	0.022	0.064	0	0	0.001		
	Orthopedic	0.036	0.075	0	0	0.047		
				Predicted Specialty Market Share				
1999	All	0.008	0.017	0	0	0.008	1.169	0.442
	Cardiac	0.006	0.018	0	0	0.004	1.555	0.403
	Orthopedic	0.009	0.018	0	0	0.010	0.451	0.183
2003	All	0.024	0.045	0	0.007	0.026	0.598	0.292
	Cardiac	0.020	0.043	0	0.003	0.019	0.417	0.111
	Orthopedic	0.032	0.052	0	0.011	0.039	0.789	0.341
2007	All	0.039	0.053	0	0.023	0.060	0.799	0.574
	Cardiac	0.031	0.049	0	0.016	0.047	0.843	0.476
	Orthopedic	0.050	0.061	0	0.025	0.091	0.808	0.295
Overall	All	0.027	0.049	0	0.004	0.034	0.771	0.438
	Cardiac	0.024	0.047	0	0.002	0.027	0.705	0.268
	Orthopedic	0.033	0.055	0	0.004	0.045	0.850	0.378

Notes: The specialty market share is defined as the proportion of patients in the HSA that are admitted to specialty hospitals. The predicted specialty market shares are estimated using maximum likelihood and are derived from a patient-level multinomial hospital choice model for patients seeking care in specialty services (i.e. MDC=5 or MDC=8). The choice set includes all hospitals within a 50 mile radius from the patient (or 100 miles for teaching hospitals). A patient's indirect utility function is specified as a non-parametric function of hospital-patient distance (distance and distance squared), fully interacted with patient and hospital characteristics. Estimation was done separately across years and across type of care (cardiac surgical, cardiac non-surgical, orthopedic surgical, and orthopedic non-surgical). The coefficient and the R-squared from an OLS regression of actual market share on predicted market share are shown in the last two columns.

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Figure 1: Number of Specialty Hospitals per county in Texas for 1999

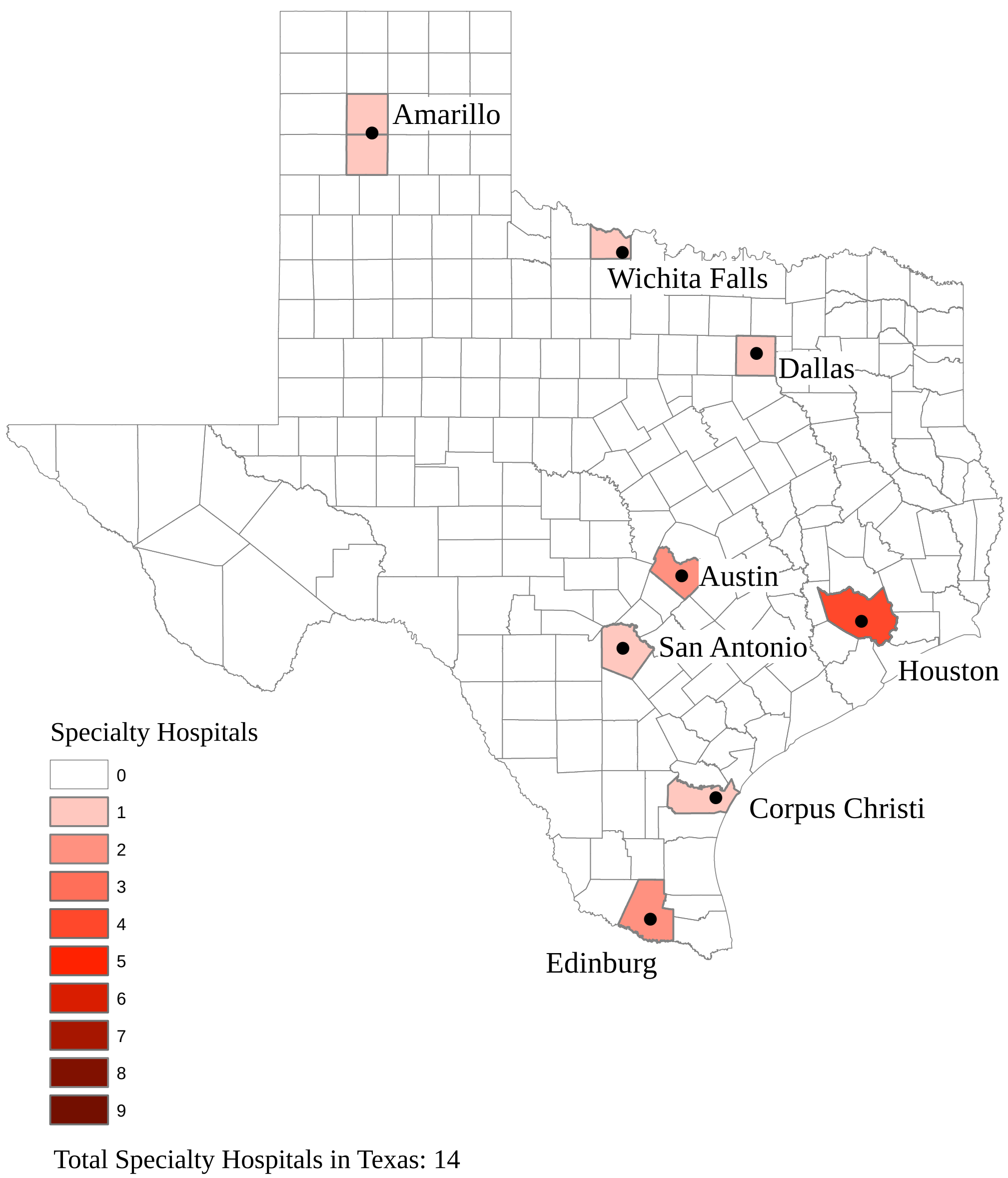

Figure 2: Number of Specialty Hospitals per county in Texas for 2003

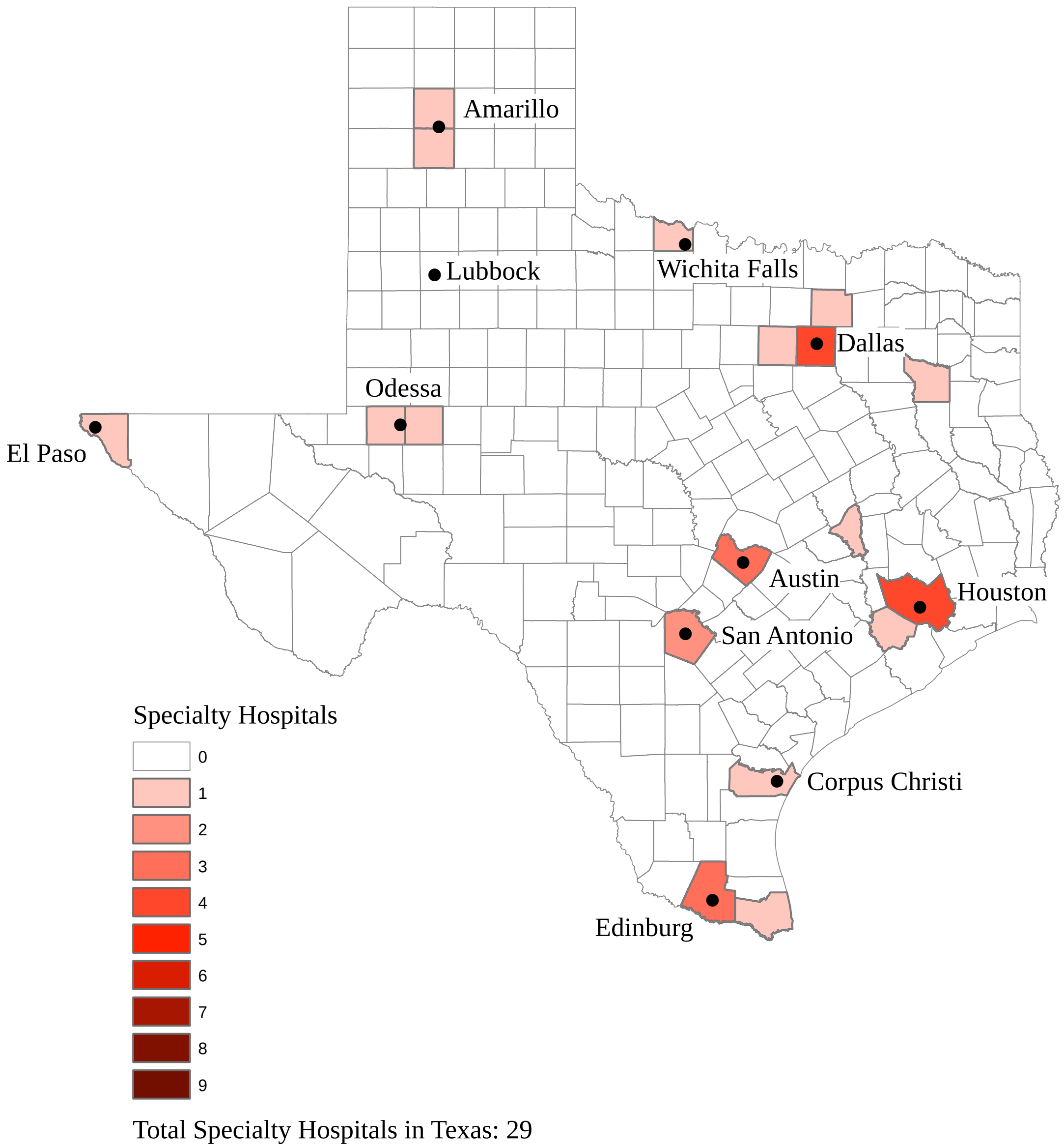

Figure 3: Number of Specialty Hospitals per county in Texas for 2007

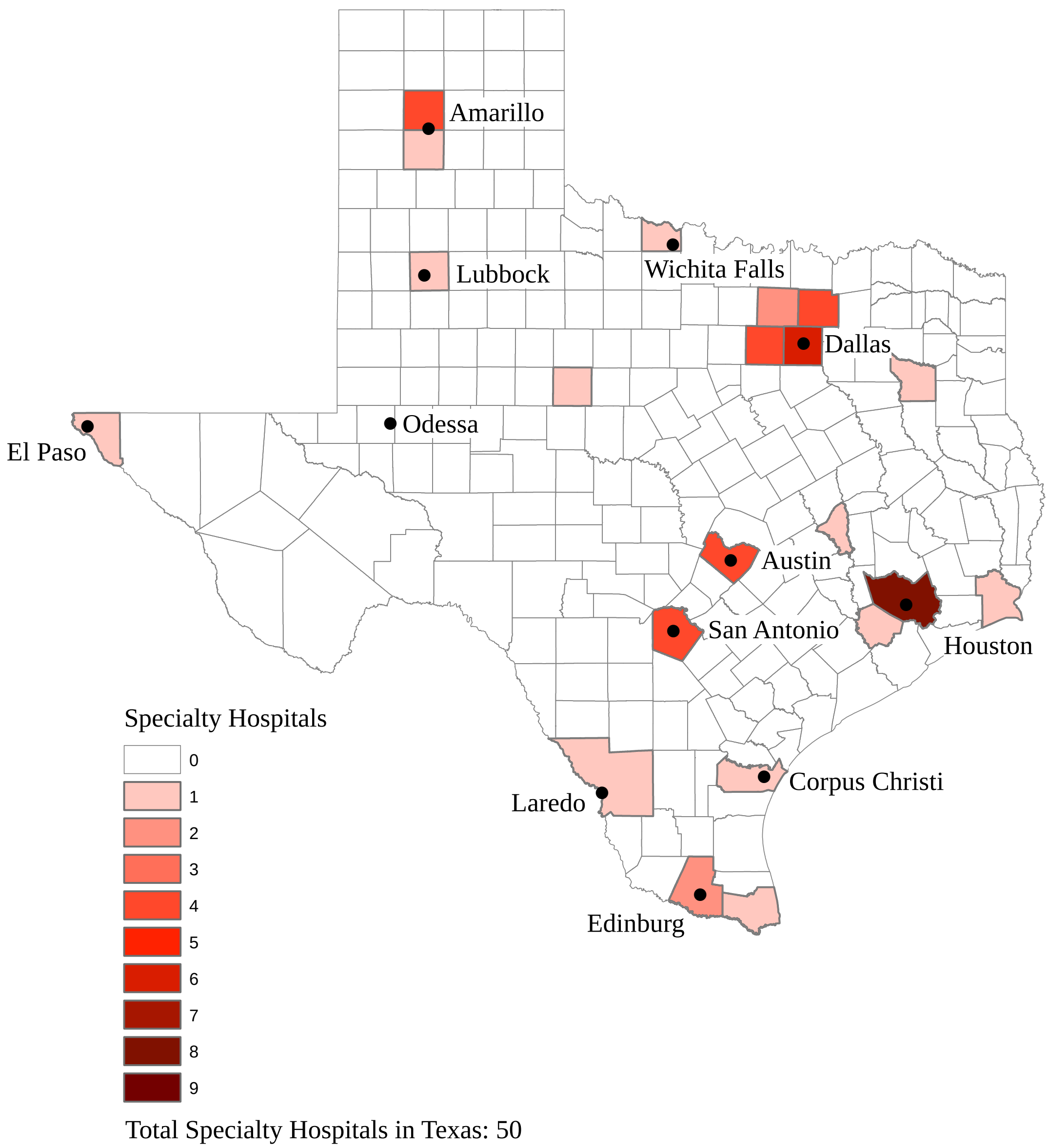

Figure 4: Distribution of Actual and Predicted Specialty Hospital Market Shares

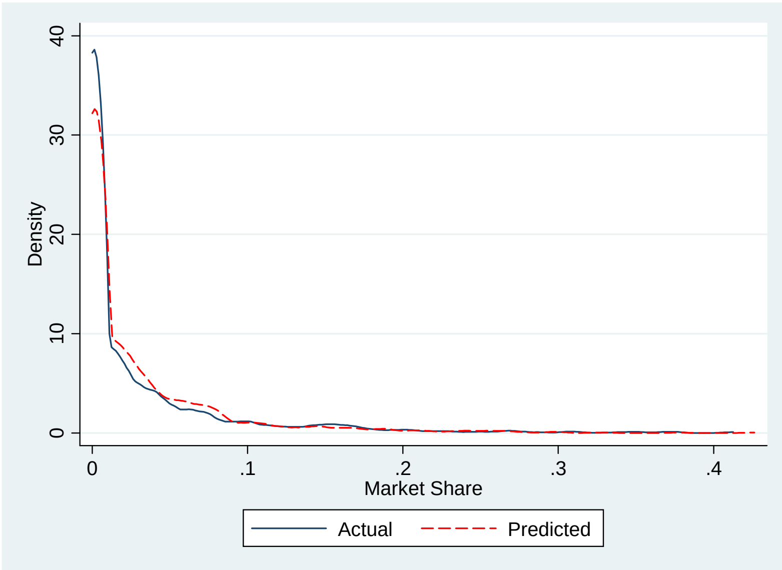

Table 1: Hospital Profitability by Medical Specialty

Most Profitable
Thoracic Surgery
Cardiovascular Surgery
Neurosurgery
General Surgery
Profitable
Surgical Orthopedics
Urology
Oncology
Gynecology
General Medicine
Less Profitable
Pulmonology
Gastroenterology
Nephrology
Otolaryngology
Cardiology
Neurology
Medical Orthopedics
Unprofitable
Emergency Department
Hospice Care
Psychiatry

Notes: Profitability status was assigned by compiling information from Lindrooth et al. (2013), Horwitz (2005), and Resnick et al. (2005). Lindrooth et al. (2013) calculate Medicare markups to assign specialty profitability. Horwitz (2005) determines profitability using information from peer-reviewed medical and social science literature, government reports, and interviews with hospital administrators and doctors. Resnick et al. (2005) use hospital finance department data to determine the profitability of surgical specialties.

Table 2: Admissions by Hospital Type

	General Hospital	Specialty Hospital
	% in Contested Services	
MDC=5 (Cardiac) or 8 (Orthopedic)	21.89	67.39
	% by Medical Specialty	
Cardiology	12.3	27.8
Dentistry	0.1	0.04
Dermatology	0.22	0.13
Endocrine	2.59	1.13
Gastroenterology	6.09	2.84
General medicine	4.23	1.84
General surgery	7.94	7.65
Gynecology	3.01	5.25
Hematology	0.97	0.37
Neonatology	15.19	0.4
Nephrology	2.58	1.07
Neurology	3.64	1.59
Neurosurgery	1.14	2.42
Obstetrics	16.49	0.5
Oncology	1.46	0.51
Ophthalmology	0.13	0.07
Orthopedics	6.87	29.96
Otolaryngology	0.75	0.62
Psychiatry	1.53	0.05
Pulmonary	7.82	3.31
Rheumatology	0.27	0.87
Thoracic surgery	1.69	5.41
Transplants	0.06	0
Urology	1.59	1.91
Vascular surgery	1.32	4.29
Total	**100**	**100**
Observations	5,180,523	64,498

Notes: Data come from the Texas Inpatient Public Use Data Files, years 1999-2007. Contested services are defined as a hospital admission with principle diagnosis/procedure (DRG) falling into Major Diagnostic Categories (MDC) of 5 (Cardiac) or 8 (Orthopedic). Data from the Massachusetts Health Data Consortium were used to map DRGs into specific medical specialties.

Table 3: Descriptive Statistics: Uncontested medical treatment by Insurance Type

Insurance Type	Obs	% of sample	Surgery	Length of Stay	Elective	DRG Weight	Died
Medicare	1,077,754	44.62	0.187	6.414	0.265	1.167	0.046
			(0.39)	(7.088)	(0.441)	(0.863)	(0.209)
Medicaid	270,938	11.22	0.173	5.067	0.254	0.969	0.014
			(0.378)	(7.424)	(0.435)	(0.897)	(0.119)
Private: HMO	203,164	8.41	0.401	4.263	0.391	1.101	0.017
			(0.49)	(5.854)	(0.488)	(0.845)	(0.129)
Private: FFS	565,226	23.40	0.395	4.243	0.371	1.102	0.019
			(0.489)	(14.454)	(0.483)	(0.896)	(0.135)
Uninsured	217,022	8.99	0.289	4.765	0.149	1.108	0.023
			(0.453)	(8.057)	(0.357)	(0.968)	(0.15)
Other	81,267	3.36	0.332	4.989	0.293	1.147	0.022
			(0.471)	(6.844)	(0.455)	(1.049)	(0.148)
Total	2,415,371	100	0.266	5.378	0.290	1.117	0.031
			(0.442)	(9.419)	(0.454)	(0.892)	(0.173)

Notes: Data come from the Texas Inpatient Public Use Data Files, years 1999-2007. This table shows descriptive statistics of the main outcome variables, by payer type. Means are shown with standard deviations in parentheses. Surgery, elective, and died are proportions of the relevant payer type. Length of stay is measured in days. DRG weight is as described in the text. The sample consists only of patients with uncontested admissions.

Table 4: Total Contested and Uncontested Hospital Admissions

	Log Contested Admissions	Log Uncontested Admissions	Log Uncontested Elective	Log Uncontested Non-Elective
SMKS	-1.071*	0.133	2.648**	-1.051*
	(0.571)	(0.351)	(1.197)	(0.532)
Observations	2353	2353	2241	2340
Mean	5.495	6.448	4.889	6.086
St. Dev	1.321	1.088	1.624	1.137

Notes: This table shows the change in contested and uncontested admissions at incumbent hospitals due to specialty hospital market share (SMKS). The coefficient on SMKS is estimated with OLS using the method of two-stage residual inclusion. Hospitals are weighted by the total number of beds in their first year. Hospital controls include indicators for the tercile of beds in first year; for profit; and teaching hospital. Annual HSA controls are also included (per capital income as well as the proportion of the population: 65+, White, Black, Hispanic, rural, high school graduate, native born, below federal poverty line). Year fixed effects, HRR fixed effects, and HRR time trends are included. Standard errors are clustered by HRR. * p<0.10, ** p<0.05, *** p<0.01.

Table 5: Total Hospital Admissions by Surgery Type

	Contested + Uncontested	Uncontested		
	Log Surgical Admissions	Log General Surgeries	Log Other Surgeries	Log Non-Surgical Admissions
SMKS	0.153	0.970**	0.171	0.156
	(0.723)	(0.466)	(0.692)	(0.330)
Observations	2240	2225	2154	2353
Mean	5.138	4.343	4.192	6.193
St. Dev	1.592	1.337	1.512	1.017

Notes: This table shows the change in surgical admissions at incumbent hospitals due to specialty hospital market share (SMKS). The coefficient on SMKS is estimated with OLS using the method of two-stage residual inclusion. Hospitals are weighted by the total number of beds in their first year. Hospital controls include indicators for the tercile of beds in first year; for profit; and teaching hospital. Annual HSA controls are also included (per capital income as well as the proportion of the population: 65+, White, Black, Hispanic, rural, high school graduate, native born, below federal poverty line). Year fixed effects, HRR fixed effects, and HRR time trends are included. Standard errors are clustered by HRR. * p<0.10, ** p<0.05, *** p<0.01.

Table 6: Total General Surgery Admissions by Surgery Type

	Log Non-Elective	Log Elective	Log Stomach Procedures	Log Obesity Procedures
SMKS	-0.244	2.855**	2.668**	4.427*
	(0.556)	(1.103)	(0.954)	(2.307)
Observations	2192	2021	1583	717
Mean	3.877	3.384	1.347	1.953
St. Dev	1.280	1.401	0.972	1.459

Notes: This table shows the change in general surgical admissions at incumbent hospitals due to specialty hospital market share (SMKS). The coefficient on SMKS is estimated with OLS using the method of two-stage residual inclusion. Hospitals are weighted by the total number of beds in their first year. Hospital controls include indicators for the tercile of beds in first year; for profit; and teaching hospital. Annual HSA controls are also included (per capital income as well as the proportion of the population: 65+, White, Black, Hispanic, rural, high school graduate, native born, below federal poverty line). Year fixed effects, HRR fixed effects, and HRR time trends are included. Standard errors are clustered by HRR. * p<0.10, ** p<0.05, *** p<0.01.

Table 7: Impact of Increased Specialty Competition on Share of Surgical Patients

	Overall		Within Department	
	Surgery	Surgery	Surgery	Surgery
SMKS	0.0117	-0.0313	0.00983	-0.0140
	(0.0323)	(0.0468)	(0.0136)	(0.0163)
SMKS x Medicaid		0.0149		0.0162
		(0.0673)		(0.0169)
SMKS x Private: HMO		0.211***		0.0878***
		(0.0745)		(0.0314)
SMKS x Private: FFS		0.137**		0.0804***
		(0.0569)		(0.0252)
SMKS x Uninsured		0.00137		0.00620
		(0.0855)		(0.0299)
N	2,295,202	2,295,202	2,275,625	2,275,625
Dept FE	No	No	Yes	Yes
Mean	0.266			
St. Dev	0.442			

Notes: This table shows the change in the proportion of patients with a surgical admission in a HSA due to specialty hospital market share (SMKS). The coefficient on SMKS is estimated with a linear probability model using the method of two-stage residual inclusion. The base category for payer type is Medicare. Patient demographic characteristics (gender dummy, five year age group dummies, race dummies, Hispanic dummy, urban dummy) and hospital characteristics (dummies for tercile of beds, for profit, teaching dummy) are included. Zip code characteristics are included (proportion of the population 65+, median household income). Year fixed effects, HSA fixed effects, and HSA time trends are included. Standard errors are clustered by HSA. * p<0.10, ** p<0.05, *** p<0.01.

Table 8: Impact of Increased Specialty Competition on Types of Uncontested Surgeries

	DRG Weight	Elective Surgery	General Surgery	Gynecology Surgery	Neuro-surgery	Urology Surgery
SMKS	0.909***	0.0470	-0.0485	-0.0016	-0.0002	-0.0023
	(0.228)	(0.0472)	(0.0299)	(0.0239)	(0.0099)	(0.0128)
SMKS x Medicaid	-0.309	-0.0003	0.0480	-0.0377	0.0037	0.0003
	(0.332)	(0.0269)	(0.0420)	(0.0231)	(0.0106)	(0.0117)
SMKS x Private: HMO	-1.200***	0.128**	0.141***	0.0331	0.0125	-0.0082
	(0.323)	(0.0547)	(0.0312)	(0.0470)	(0.0105)	(0.00969)
SMKS x Private: FFS	-1.199***	0.128***	0.118***	-0.0303	0.0212*	0.0155**
	(0.316)	(0.0419)	(0.0345)	(0.0287)	(0.0108)	(0.0070)
SMKS x Uninsured	-0.938**	-0.0650**	0.0758	-0.0568**	0.0078	0.0070
	(0.418)	(0.0271)	(0.0537)	(0.0282)	(0.0103)	(0.0083)
N	533,058	2,275,625	2,295,292	2,295,292	2,295,292	2,295,292
Sample	Surgical	All	All	All	All	All
Sample Mean	1.694	0.139	0.135	0.060	0.021	0.025
St. Dev	1.518	0.346	0.342	0.237	0.142	0.155

Notes: This table shows the change in the DRG weight for surgical admissions and the change in the proportion of patients with particular types of surgical admission in a HSA due to specialty hospital market share (SMKS). The coefficient on SMKS is estimated with a linear probability model using the method of two-stage residual inclusion. The base category for payer type is Medicare. Patient demographic characteristics (gender dummy, five year age group dummies, race dummies, Hispanic dummy, urban dummy) and hospital characteristics (dummies for tercile of beds, for profit, teaching dummy) are included. Department fixed effects are included when the DRG weight and elective surgeries are the dependent variable. Zip code characteristics are included (proportion of the population 65+, median household income). Year fixed effects, HSA fixed effects, and HSA time trends are included. Standard errors are clustered by HSA. * p<0.10, ** p<0.05, *** p<0.01.

Table 9: Impact of Increased Specialty Competition on Length of Stay (LOS)

	Overall		Within Department		Within DRG	
	LOS	LOS	LOS	LOS	LOS	LOS
SMKS	1.294*	0.497	1.168*	0.593	0.836	0.398
	(0.680)	(0.812)	(0.592)	(0.734)	(0.536)	(0.652)
SMKS x Medicaid		0.504		0.232		0.0646
		(0.974)		(0.922)		(0.838)
SMKS x Private: HMO		2.714***		2.112**		1.766**
		(0.841)		(0.834)		(0.714)
SMKS x Private: FFS		2.217***		1.641**		1.255**
		(0.816)		(0.712)		(0.579)
SMKS x Uninsured		1.385*		1.022		0.786
		(0.818)		(0.763)		(0.895)
N	2,295,290	2,295,290	2,275,623	2,275,623	2,295,200	2,295,200
Dept FE	No	No	Yes	Yes	No	No
DRG FE	No	No	No	No	Yes	Yes
Mean	5.376					
St. Dev	9.414					

Notes: This table shows the change in the length of stay in a HSA due to specialty hospital market share (SMKS). The coefficient on SMKS is estimated with OLS using the method of two-stage residual inclusion. The base category for payer type is Medicare. Patient demographic characteristics (gender dummy, five year age group dummies, race dummies, Hispanic dummy, urban dummy) and hospital characteristics (dummies for tercile of beds, for profit, teaching dummy) are included. Zip code characteristics are included (proportion of the population 65+, median household income). Year fixed effects, HSA fixed effects, and HSA time trends are included. Standard errors are clustered by HSA. * p<0.10, ** p<0.05, *** p<0.01.

Table 10: Impact of Increased Specialty Competition on Mortality Rate

	Overall		Within Department	
	Died	Died	Died	Died
SMKS	0.0177*	0.00753	0.0174*	0.0093
	(0.00989)	(0.0130)	(0.0100)	(0.0128)
SMKS x Medicaid		0.0152		0.0124
		(0.0114)		(0.0098)
SMKS x Private: HMO		0.0212		0.0194
		(0.0177)		(0.0182)
SMKS x Private: FFS		0.0178*		0.0136
		(0.0107)		(0.0107)
SMKS x Uninsured		0.0324**		0.0257*
		(0.0161)		(0.0142)
N	2,290,407	2,290,407	2,270,885	2,270,885
Sample	All	All	All	All
Dept FE	No	No	Yes	Yes
Mean	0.0307			
St. Dev	0.1724			

Notes: This table shows the change in deaths in a HSA due to specialty hospital market share (SMKS). The coefficient on SMKS is estimated with a linear probability model using the method of two-stage residual inclusion. The base category for payer type is Medicare. Patient demographic characteristics (gender dummy, five year age group dummies, race dummies, Hispanic dummy, urban dummy) and hospital characteristics (dummies for tercile of beds, for profit, teaching dummy) are included. Zip code characteristics are included (proportion of the population 65+, median household income). Year fixed effects, HSA fixed effects, and HSA time trends are included. Standard errors are clustered by HSA. * p<0.10, ** p<0.05, *** p<0.01.