Medicaid Expansion and Private Insurance: The Effect of Patients' Hospital Avoidance on Provider Reimbursement

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April 28, 2021

Submitted to the Department of Economics of Amherst College in partial fulfillment of the requirements for the degree of Bachelor of Arts with honors.

Abstract

The recent Medicaid expansion accompanying the Affordable Care Act has been successful in expanding access to care for millions of Americans but may have had unintended consequences for hospitals' bargaining positions vis-a-vis private insurers. In my thesis, I focus on one key way in which hospitals' bargaining positions can change due to Medicaid expansion: the avoidance by privately insured patients of hospitals with large Medicaid patient shares (patient crowd out).

I use 2009-2017 discharge data from Washington (using State Inpatient Databases (SID) from the Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality) to consider how an unanticipated increase in Medicaid enrollment has affected the prices for non-emergency services. To disentangle the effect through this "crowd out" channel, I estimate models to classify the degree to which hospitals meaningfully exposed to the privately insured patient market were vulnerable to patient crowd out. I find that hospitals most exposed to crowd out saw lowered reimbursement: a 1 standard deviation increase in these hospitals' Medicaid patient shares decreases the price for non-emergency services by between 0.24-0.31 standard deviations. I find little effect of Medicaid expansion on prices in the least vulnerable hospitals, implying that Medicaid patient shares affect reimbursement mainly through the crowd out channel.

The results suggest Medicaid expansion's effects on hospital finances are substantial in the short term after expansion. The further separation of hospitals into financial "winners" and "losers" may leave "losers" less likely to have the resources necessary to compete with "winners" and adapt to future public insurance expansions. These payment gaps may have effects on patient care quality and market structure that should be studied carefully in the future.

Keywords: Medicaid Expansion; Patient Choice; Hospital-Insurer Bargaining

JEL: I11, I13, I18, L13

Acknowledgements

Professor Ishii - I am grateful for all your guidance through this process. This project would not have been possible without your insight and encouragement. Thank you for your support through all the meetings, messages, and drafts that were essential to this thesis. Thank you also for introducing me to Economics as a first-year and believing in me every step of my college career.

Professor Reyes - Thank you for introducing me to the Health Economics literature and for your encouragement and enthusiasm during the Thesis Seminar and through the proposal process. I am grateful for your willingness to help me develop my ideas into a coherent thesis.

The Department - I am grateful to the Department for funding my research and giving me the opportunity to pursue my interests. Without your generosity, this thesis would not be possible.

Andrew Swenson and Crystal Zhou - Thank you for all the working sessions (in person and virtual), tea times, and messages that made the thesis process and senior year fun and rewarding. Writing a thesis with friends never felt so good.

Meredith King - Thank you for reading through my thesis and keeping me company in Converse. Your friendship has been one of the highlights of my time at Amherst.

Mom and Dad - Thank you for all the support and helping me get to where I am today. I am grateful for your encouragement and for your belief in me.

Contents

1 Introduction

Medicaid, public health insurance available to low income individuals and families, provides coverage for tens of millions of Americans, improving care quality and outcomes for disadvantaged populations. Its reimbursement rates for healthcare services, however, have long been a source of contention. Recent briefs from the American Hospital Association, a healthcare industry trade group, find that in 2019, aggregate Medicaid payments (including subsidies for hospitals with disproportionately high Medicaid patient populations) fell below costs: on average, hospitals received 90 cents for every dollar spent on the care of Medicaid patients (American Hospital Association, 2021). This shortfall makes treating Medicaid patients unattractive for hospitals in two ways. First, at the margin, the reimbursement for treating a Medicaid patient is likely to be below cost; second, given constraints like capacity, the opportunity cost of treating Medicaid patients is high if they are admitted in place of privately insured patients.

The impact of Medicaid patients on hospital finances and reimbursement from private insurers has been particularly salient in recent years. The Affordable Care Act (ACA), legislation altering many aspects of the healthcare market, included funding for Medicaid expansion beginning in 2014. While this expansion was optional, many states have taken advantage; to date, 38 states, plus Washington D.C, have implemented the expansion (Kaiser Family Foundation, 2021). This expansion differed from expansions in previous years, as it effectively extended eligibility to adults with incomes up to 138% of the federal poverty line; previous expansions were generally far more limited in scope.

Among the goals of the ACA's Medicaid expansion were improved access to health coverage and increased care utilization for previously disadvantaged populations. On those fronts, the policy seems to have been largely successful; many studies have discussed the gains in coverage and increased utilization of care among the newly enrolled (e.g. Kirby and Vistnes, 2016; Simon et al., 2016). There is also evidence that there are some financial benefits for hospitals, such as reduced uncompensated care costs and increased Medicaid revenue (e.g. Nikpay et al., 2015; Dranove et al., 2016). There has not been much discussion, however, on the effects of this expansion on the prices paid by private health insurers to hospitals. This is a gap in the literature that I seek to address. In this thesis, I investigate the impact of the ACA Medicaid expansion on the bargaining outcomes of private insurers and hospitals for non-emergency services, focusing particularly on the bargaining effect of changes in hospital attractiveness to privately insured patients (and thus insurers) and their hospital avoidance. Hospital attractiveness drives insurer demand for inclusion in provider networks, altering bargaining outcomes and hospital revenue. This mechanism is one relatively understudied in the literature, particularly in the context of public insurance expansion. These results carry significant implications for the success of the Medicaid expansion program, as previous research has identified the link between hospital finances and care quality and health outcomes; as might be expected, better financial status is associated with better patient care outcomes and quality and safety measures (e.g. Encinosa and Bernard, 2005).

Reimbursement from private insurers plays a large role in a hospital's financial health. As previously mentioned, hospitals frequently face losses when treating Medicaid patients. The same is true for Medicare, the other major public health insurance in the United States (American Hospital Association, 2021). The majority of hospital profits likely come from private insurance reimbursement; according to a recent research report from the RAND Corporation, the average price paid by private insurers was 241% of Medicare's average reimbursement rate in 2017 (White and Whaley, 2019). Thus, previous studies on the effect of Medicaid expansion on hospital finances that focus on reductions in uncompensated care costs omit a key determinant of hospital financial well-being.

The prices that private insurers pay to hospitals are determined by bargaining. The details of the actual bargaining process, including contract term length, vary by hospital and insurer. For example, contract lengths for one hospital in Connecticut with which I communicated ranged from 1 to 3 years. What is generally routine, however, is what each party offers during bargaining. In the current insurance landscape, most private insurers contract with hospitals to form networks. Patients covered by a particular insurer are incentivized to visit hospitals in their insurer's network; otherwise, they may face large copays and other out-of-pocket costs. During bargaining, insurers typically offer hospitals inclusion in their provider network, while hospitals propose "discounted" prices (reimbursement rates) that insurers would pay for care given to their enrollees.

Medicaid expansion can affect the bargaining outcomes (reimbursement rates) of hospitals by changing the bargaining position of hospitals vis-a-vis insurers or the overall surplus being allocated. My thesis explores the impact of one mechanism through which bargaining positions can be changed as a result of Medicaid expansion: privately insured patient avoidance ("crowd out") of hospitals with large Medicaid patient shares. I contribute to the general hospital-insurer bargaining literature by considering the impact of changes in patient perception of hospital quality resulting from public insurance expansion on bargaining dynamics, and hope to provide a starting point for a larger evaluation of Medicaid expansion's impact on long-term hospital financial status (and accordingly, patient health outcomes and care quality). The bargaining dynamics I study in this paper are derived from the standard bargaining models in the healthcare market literature, where prices reflect surplus allocation derived from the bargaining position and power of each party. Bargaining position and power for hospitals vis-a-vis insurers (and vice versa) are derived from hospital (and insurer) characteristics and market structure. Thus, any impact from Medicaid expansion on bargaining position would occur by altering either hospital or insurer characteristics, or market structure. There are two ways in which Medicaid expansion can alter these characteristics or market structure, both observable in a hospital's share (or percentage) of patients enrolled in Medicaid.

The first channel is insurance crowd out, where public insurance dollars substitute for private dollars that would otherwise be spent on health insurance (e.g. previously privately insured patients switching to Medicaid). This alters the size of the private insurance market. Previous studies have identified a sizable private insurance crowd out effect (different from the patient crowd out I mention above) that occurs after public insurance expansions (see Gruber and Simon, 2008). Privately insured patients enrolling in Medicaid would generally see the proportion of patients treated at a hospital enrolled in Medicaid increase and the proportion enrolled in private coverage decrease. This would also reduce the size of the patient population private insurers capture and leverage during bargaining. This change in market size alters the total surplus amount over which a hospital and insurer bargain. This is a consideration that largely impacts the side of the healthcare market other than the one at the focus of this thesis: the upstream market for insurance. Furthermore, changes in this dimension would mainly affect the relative surplus allocation if there is large variation between insurers' exposure to insurance crowd out, which would impact the market power of insurers competing for hospitals differently. Changes in this dimension may be attenuated in the ACA's Medicaid expansion due to the early implementation of the individual mandate, with previously uninsured patients buying private health insurance to satisfy coverage requirements.

Of course, there is also the opposite effect as well: enrollment in Medicaid by previously uninsured patients. This does not affect the size of the private insurance market. The effect of this enrollment is related to the second channel through which Medicaid expansion impacts bargaining: altering the relative attractiveness of hospitals, a hospital characteristic, to privately insured patients. This is the channel on which I focus in this thesis. Previous research has provided evidence that privately insured patients prefer hospitals with lower relative numbers of Medicaid patients (Sfekas, 2013). These preferences are observable in the share of a hospital's patient population enrolled in Medicaid: private patient avoidance would lower the proportion of patients treated at a hospital enrolled in private insurance and increase the proportion enrolled in Medicaid. The attractiveness of a hospital is reflective of the value that a hospital would bring to an insurer upon inclusion in the provider network. This is a hospital characteristic that is largely observable (or forecastable) for insurers who can differentiate between hospitals of high and low attractiveness in the absence of unanticipated shocks. Intuitively, if an insurer's patients avoid a certain hospital, there is not much point in including it in their provider network. As its willingness to pay to include the hospital in its network is low, the insurer has more leverage in negotiation. That hospital's inclusion in the network would be contingent on large discounts offered by the hospital to offset the low value that it brings. This is likely more salient for non-emergency services, the sector on which I focus in this thesis. Thus, changes in a hospital's Medicaid patient population post-Medicaid expansion would change the hospital's bargaining position. Variation across hospitals in Medicaid patient share gains or decreases post-expansion would then affect hospital bargaining positions differently. I hypothesize that after Medicaid expansion, hospitals that see larger privately insured patient avoidance will receive lower surplus allocation during bargaining, resulting in lower observed non-emergency service prices paid by insurers. I define this privately insured patient avoidance of hospitals with high Medicaid patient shares as patient crowd out (different from insurance crowd out).

To study this effect, the increase in a hospital's Medicaid patient percentage must not accounted for by the hospital. The impetus for changes in the hospital characteristics that determine a hospital's Medicaid patient share should thus be exogenous. If a hospital's increase in its Medicaid patient population post-Medicaid expansion were to be predicted accurately, the hospital could take adaptive measures, such as increasing capacity. The effect of the increase in Medicaid patients on privately insured patient hospital choice would then be attenuated: it is important to not conflate the effect of a hospital's Medicaid patient share with other actions that the hospital might take to improve reimbursement outcomes. To that end, I study this effect using data from Washington, a state in which the number of new enrollees in Medicaid from the expansion greatly exceeded projections. Hospital forecasts of their post-expansion Medicaid patient shares were then likely inaccurate. Accordingly, the increase in hospitals' Medicaid patient shares were likely not accompanied by proportional adaptive measures by hospitals.

I specify a regression model that estimates the relationship between observed prices and Medicaid expansion effects. In the model, I separate out the patient crowd out effect of Medicaid expansion. To do so, I need to determine the effect of Medicaid expansion on hospital attractiveness. Accordingly, I estimate a patient choice model that captures the change in the likelihood a privately insured patient would choose a particular hospital after Medicaid expansion, and use this model to categorize hospitals by their level of patient crowd out. I focus only on prices for non-emergency services, as crowd out in emergency services is hard to observe: often emergency patients do not choose hospitals themselves, or choose only contingent on distance.

I find that Medicaid patient shares have a significantly negative effect on the prices for non-emergency services paid to hospitals meaningfully exposed to bargaining only for those hospitals with the largest amounts of patient crowd out. This implies that the effect of Medicaid patient shares on prices can be attributed mainly to patient crowd out. That hospitals with high patient crowd out see decreases in bargained price is not surprising and supports my hypothesis; the extent to which this effect is attenuated in hospitals with increased attractiveness, however, is of great interest. These results may speak to the nature of provider network construction: hospitals do not need to be the most attractive to patients, they only need to not be greatly unattractive. As insurers networks seem to have a minimum size threshold, as long as a hospital's crowd out ranking among its rivals is high enough, it will not face a penalty. These are relatively short-term results, given the recency of the expansion, and it remains to be seen if hospitals may leverage these short-term advantages against adaptive measures by high crowd out hospitals.

This paper proceeds as follows. In Section 2, I provide some background and a literature review. In Section 3, I present the data and some key variables. In Section 4, I describe the methodology. In Section 5, I present the results. In Section 6, I perform supplementary analyses and address some limitations. Section 7 concludes the paper.

2 Background and Literature Review

2.1 Background

The market for hospital services in the United States includes several actors, notably hospitals, private insurers, patients, and the government. Generally, private insurers and hospitals negotiate prices that are paid for services, while patients pay premiums to private insurers for coverage (there may also be copays, additional fees patients pay hospitals for certain services). There are several types of private insurance plans: large group, small group, and individual. Large and small group insurers generally engage with employers, who can provide health insurance to employees and their families as a benefit, while individual insurance can be bought by individual patients on the market.

Most private health insurance plans are managed care plans, where insurers contract with healthcare providers to form networks. Patients in these plans are incentivized to go to in-network providers as, depending on the plan, most patients pay little to no copays for those hospitals and may not be covered for care at providers outside the network. In return, contracted hospitals give discounts to the insurer. As of 2019, around 68% of the population of the United States is covered by private health insurance (Keisler-Starkey and Bunch, 2020); this form of insurer-hospital interaction is the dominant price determining procedure in the hospital services market.

The government, in addition to policy-making and regulatory duties, also provides public insurance to qualifying patient populations. Created in the Social Security Amendments of 1965, the two major plans are Medicare, serving the elderly (65 years or older) population, and Medicaid, serving low income and limited resource patient populations. Medicaid is a joint federal and state program but administered at the state level. Each state sets its own eligibility requirements for enrollment (after some baseline requirements by the federal government) and prices for hospital reimbursement. Thus while the federal government does provide some matching funds for Medicaid, there is large variation across states in Medicaid spending and patient populations. As of 2019, around 20% of the population is enrolled in Medicaid, but the distribution of those patients and their benefits are not equal across the states (Keisler-Starkey and Bunch, 2020).

Medicaid has undergone many changes since its inception. In particular, there have been several voluntary "Medicaid expansions," where states can opt to receive funding to expand eligibility of Medicaid programs with the goal of expanding coverage to more patients. Under the Affordable Care Act, states were allowed to opt into, starting in 2014, Medicaid expansion that extended eligibility to adults under the age of 65 with incomes up to 138% of the federal poverty line (FPL); as of November 2020, 38 states and the District of Columbia have adopted this expansion. The federal government is providing most of the funds needed to finance this program.

The 2014 expansion provided funds for the coverage of childless, able-bodied adults, a group previously not generally eligible for Medicaid. Among the states that have adopted this expansion is Washington. Washington was one of seven states that adopted "early expansion," accepting a waiver to receive federal funding starting in 2010 to cover adults with incomes up to 133% of the FPL. Despite this, the majority of the new Medicaid enrollment occurred after 2014, as early enrollment was capped with a target of 43,000 enrollees per year (Kaiser Family Foundation, 2014). As of June 2019, total enrollment in Medicaid in the state has reached over 1.7 million patients, up from an average of around 1.1 million patients from July to September of 2013 (Kaiser Family Foundation, 2019). These enrollment figures are extraordinary when viewed in conjunction with the pre-expansion forecasts. The Health Policy Center of the Urban Institute projected in May 2012 using their Health Insurance Policy Simulation Model that 330,000 new enrollees would be added to the state's Medicaid rolls (Buettgens et al., 2012). The Kaiser Family Foundation reported in 2014 that, as of March 31, 2014, the state had met its 2018 goal of a quarter million new enrollees (Kaiser Family Foundation, 2014). As of June 2019, the expansion has increased Medicaid enrollment in Washington by 549,700 (Kaiser

Family Foundation, 2019). The shattering of forecasts by new enrollment provides an opportunity to investigate a unanticipated shock to the state healthcare markets.

2.2 Literature Review

The effects of Medicaid expansion on access to care and utilization among newly enrolled patients have been well studied. Among others, Kirby and Vistnes (2016) find that at the national level, individuals who gained health insurance coverage through Medicaid or the ACA Marketplace in 2014 were much more likely to have access to preventative care than individuals uninsured both before and after expansion. Simon et al. (2016) also find Medicaid expansion increased access to care and coverage among the target population. An intuitive follow up question is the impact of the increased Medicaid patient population and their care utilization on financial outcomes.

The impact of this increased utilization on hospital financial outcomes is narrowly studied. Previous studies have focused mainly on uncompensated care costs and Medicaid revenue after expansion. Few studies have explicitly studied the effect on reimbursement from private insurers, or even total revenue. Among these studies, Moghtaderi et al. (2019) do not find any significant relative gains in total revenue or operating margins when comparing hospitals in expansion and non-expansion states. That study does not, however, identify and test specific channels for the effect. In contrast, my thesis investigates specific channels through which expansion may impact bargaining.

The hospital-insurer bargaining models studied in the literature analyze the distribution of surplus; improving one's bargaining position or power tends to result in a surplus distribution more favorable for that party. Medicaid expansion and Medicaid patient shares can affect surplus allocation through bargaining power and position. The net effect of Medicaid patient shares on private insurance reimbursement is demonstrated by Lewis and Pflum (2017). They find that an increase in the proportion of patients at a hospital enrolled in Medicaid results in a lower price. This can be partly attributed to the fact that their construction of price does not separate out privately insured and Medicaid patients, but I confirm their results in this thesis without that limitation.

Medicaid expansion affects both the surplus size and allocation of surplus in hospital-insurer bargaining. The literature on Medicaid expansion explicitly addresses issues of insurance crowd out in private insurance enrollment. Cutler and Gruber (1996), examining expansions from 1987 to 1992 increasing coverage for pregnant women and children, find that there is substantial insurance crowd out associated with these expansions. Subsequent research on the topic has produced mixed results on the intensity (Gruber and Simon, 2007). Some insurers may see more crowd out than others, altering their bargaining positions; a larger consideration is the overall decrease in private insurance enrollment and thus size of the surplus available in bargaining. The effect of this phenomenon on bargaining outcomes may be tempered, however, by the other provisions of the ACA that incentivize insurance enrollment, such as the individual mandate and exchanges.

Thus, the more significant effect of Medicaid expansion seems to be the crowd out of privately insured patients from hospitals. Pines et al. (2016) find relative decreases in admissions of privately insured patients in emergency departments after Medicaid expansion, but only investigate aggregate measures and not differences among specific hospitals. More general evidence on hospital choice supports this theory as well. Estimating a discrete choice model, Sfekas (2013) finds that in the Tampa area, privately insured patients are less likely to choose a hospital if it admitted a relatively larger number of Medicaid patients in the emergency department over a recent time period. Given the scope of Medicaid expansion, I extend these results and test the permeation of these effects to the non emergency population. To my knowledge, there are no direct studies on this expansion's patient crowd out; I seek to provide a novel evaluation of its effects.

Medicaid expansion induced bargaining position differences between hospitals, and potential subsequent profit disparities are of great importance to both patients seeking care and policy makers seeking to address care quality disparities. A rich literature has linked hospital finances with care quality, finding strong financial performance associated with greater safety and better reported care experiences (e.g. Encinosa and Bernard, 2005). Given a major goal of Medicaid expansion was to improve the access by underserved patient populations to quality care, it is important to examine the effects of Medicaid expansion on relative hospital changes in bargaining outcomes.

3 Data

I construct a data set across the years 2009 to 2017. The main datasets used in this construction are the yearly State Inpatient Databases (SIDs) for the state of Washington from 2009-2017, compiled by the Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality (AHRQ). Each database is a file containing the inpatient care records for all community hospitals in the state for a particular year: over 600,000 discharges per year (around 35%-40% with private insurance) from approximately 160 hospitals and hospital specialty units. These datasets contain information commonly found on discharge sheets, including basic patient demographics, diagnoses, total charges for the visit, and the insurance type (e.g. commercial, Medicare, Medicaid, self-pay). There are also accompanying cost to charge ratio (CCR) files provided by the HCUP. These were used to calculate the estimated cost for each inpatient discharge.

Table 1: Summary Statistics for Key Hospital Characteristics (Pre-Expansion Average)

Variable	N	Mean	SD	P25	P50	P75	Min	Max
Medicaid patient share	383	0.203	0.144	0.094	0.176	0.265	0.017	0.842
Private insurance patient share	385	0.312	0.165	0.174	0.307	0.408	0.013	0.913
Medicaire patient share	381	0.432	0.199	0.286	0.406	0.520	0.001	0.983
Uninsured patient share	350	0.039	0.025	0.024	0.036	0.049	0.185	0.000

Notes : Table 1 reports statistics for patient shares by insurer at the hospital-year level for pre-expansion years. All shares displayed as decimals.

In addition, the percentage of patients at each hospital in every year with a particular insurance type (Medicare, Medicaid, private insurance, uninsured) were calculated as the ratio of non-emergency discharges at a hospital with each insurance type listed as the

Table 2: Summary Statistics for Key Hospital Characteristics (Post-Expansion Average)

Variable	N	Mean	SD	P25	P50	P75	Min	Max
Medicaid patient share	383	0.220	0.151	0.113	0.200	0.296	0.002	0.809
Private insurance patient share	391	0.287	0.158	0.163	0.271	0.380	0.024	0.913
Medicaire patient share	386	0.463	0.201	0.333	0.438	0.575	0.001	1.000
Uninsured patient share	350	0.021	0.021	0.010	0.017	0.026	0.000	0.203

Notes : Table 2 reports statistics for patient shares by insurer at the hospital-year level for post-expansion years. All shares displayed as decimals

primary expected payer to the total number of non-emergency discharges at the hospital. Summary statistics for the patient shares by insurance type pre- and post-expansion are shown in Tables 1 and 2. The composition of patients at hospitals differ pre- and post-expansion. The share of uninsured patients and privately insured patients dropped, and the shares of Medicaid and Medicare patients increased. The almost 2% increase in the mean hospital Medicaid patient share represents an increase of almost 10% in a hospital's actual Medicaid patient population, which may have significant implications for reimbursement. Similarly, there was an almost 8% decrease in the average hospital's privately insured patient share; as privately insured patients make up the majority of hospital profits, this decrease may likely be a source of financial strain.

I supplement this data set with other data. For hospital characteristic data, I use the American Hospital Association's (AHA) Annual Survey of Hospitals. This survey collects responses from over 6,200 American hospitals on information such as system membership, ownership, and size. The data were matched to the hospital of each discharge observation in the SIDs. Unique hospitals were defined by their AHA identification number. Many hospital departments and subsections (such as psychiatric units) were presented separately from the main institution in the SIDs. These were grouped into the full hospital using AHA identification numbers. I use data on the Washington private insurance market from the Kaiser Family Foundation; they provide yearly HHIs for the small group, large group, and individual insurance markets at the state level. For construction of geographic markets, I use ZIP code to hospital referral region (HRR) crosswalks from the Dartmouth Atlas Data website, part of the Dartmouth Atlas Project.

While the discharges include diagnoses and disease resource groups (DRG), they do not provide any information on the relative intensity of resource use for each diagnosis. To address this, I use DRG weight data from the Centers for Medicare and Medicaid Services (CMS). These weights are diagnosis specific measures of mean resource use in treatment of a condition and the foundation of Medicare payments to hospitals. In addition, I supplement the discharge data with ZIP code distance data from the National Bureau of Economic Research (NBER), where the distances are great-circle distances based on internal points. These distances are for ZIP code tabulation areas (ZCTAs); in most cases, however, ZIP codes do match with the corresponding ZCTA. In either case, I use a crosswalk created by the Health Resources and Services Administration (HRSA), John Snow, Inc., and the American Academy of Family Physicians using data from the Uniform Data System (UDS), to map ZIP codes to ZCTAs.

Since the charges in my data are at the discharge level, they are specific to diagnosis, patient, and hospital characteristics. I thus cannot directly compare between hospitals the charges billed at the discharge level. I need to aggregate the charges to the hospital-year level. So, following Gowrisankaran et al. (2015), I construct base prices for each hospital. Base prices reflect the outcome of bargaining between hospitals and private insurers and differ by hospital and year. The price paid for treatment of a disease d is assumed to be the base price p multiplied by the "disease weight" w_d, which reflects differences in prices due to treatment of a particular disease, such as resource usage intensity. As in Gowrisankaran et al. (2015), I use DRG weights as disease weights and regress the total charges divided by DRG weight on age, gender dummies, and hospital dummies for each discharge and then calculate the base price for each hospital-year as the average fitted value for all observations at the hospital in a particular year with private insurance listed as the primary payer (labeled "GNT"). I also repeat this procedure for a second specification, regressing total charges divided by DRG weight on the above parameters and the patient's race (labeled "Modified GNT"). Since I focus only on non-emergency services, I construct these prices using only non-emergency discharges. The resulting base prices are very similar and are shown in Table 3. Due to the slightly richer construction of the "Modified GNT" value, I use this as my base price in my analyses.

Table 3: Summary Statistics for Base Price Constructions

Construction	N	Mean	SD	P25	P50	P75	Min	Max
GNT	768	23994.25	13857.80	15422.01	21557.93	28316.01	590.01	134914.60
Modified GNT	733	24560.67	14263.93	16215.63	21949.23	28902.19	2456.41	140454.00

Notes : Table 3 reports statistics for both base price constructions, as defined in the Data section.

While Gowrisanakaran et al. (2015) observe the identity of the insurer for each patient and are able to create payer specific base price estimates for each hospital-year, I only observe a general classification of the primary payer for each discharge (e.g. Medicare, Medicaid, private insurance, self-pay, etc...). This limitation is reflected in the wide variation seen in the base prices. Insurer specific prices are likely to be more precise as some of the variation here can be attributed to insurer variation by hospital. The set of insurers with which each hospital bargains may differ. Thus, my estimates of base price reflect the average outcome of each hospital's bargaining process with its own set of insurers. While I am unable to identify insurer specific factors that impact bargaining, I assume that the set of insurers (and their characteristics) that each hospital faces stays mostly stable throughout the years of the sample. If there are changes, I assume that they largely impact the state as a whole. With the implementation of the ACA in 2014, new private insurance options have become available, particularly through the exchanges. Again, I assume that most of these changes are applicable statewide.

4 Methodology

My thesis seeks to investigate the impact of the recent Medicaid expansion on the prices for non-emergency services bargained between hospitals and insurers. Specifically, I am interested in the effect of privately insured patient crowd out, the avoidance of hospitals with higher Medicaid patient populations by privately insured patients seeking non-emergency care. Hereafter, "crowd out" refers to my definition of patient crowd out; I will refer to insurance crowd out explicitly. To separately identify the effect of this channel, I estimate a series of interrelated models that build to a direct estimation of the effect of this channel on observed hospital prices. To separate out the effect of patient crowd out, I estimate a patient choice model to categorize hospitals by the difference in attractiveness after Medicaid expansion and use these categorizations to separately estimate the effect of Medicaid patient shares on bargained price for each group.

Bargaining between hospitals and insurers is inherently tied to competition. There is no need for insurers to include every hospital in their networks; indeed, including hospitals that are rarely used by their patients reduces insurer surplus, as wasteful administrative costs may supersede any marginal benefits from low patient utilization. Thus, hospitals must compete among rivals to be included in limited provider networks. The intensity of competition hinges on the substitutability of hospitals in the eyes of patients and insurers. Patients choose between hospitals that are substitutes; if a patient is unlikely to, barring extreme circumstances, choose one hospital over another, the two hospitals are not substitutes. If a hospital has few substitutes in the eyes of privately insured patients, the marginal effect of Medicaid patient shares at that hospital may be smaller. Privately insured patients may be less responsive to changes in that hospital characteristic if there are other characteristics whose effects dominate. Therefore, it does not make sense to compare the effect of Medicaid expansion on attractiveness to privately insured patients at one particular hospital to all hospitals in the state. That would likely attenuate the effect, as the overall effect of patient crowd out on a particular hospital will be estimated from a collection of different patient choice sets that may not include that hospital.

What collection of hospitals constitutes a choice set? It can be difficult to define *a priori* markets among which hospitals compete and patients choose options. A method common in the reduced form literature is to define geographic markets explicitly (e.g.

Lewis and Pflum, 2017). Studies can also be limited to investigating hospital markets in a particular metropolitan region or across several adjacent counties (e.g. Town and Vistnes, 2001; Sfekas, 2013). Geographic and distance based market definitions are useful not only because they are easily defined, but also because there is much evidence in the literature of distance and travel time being among the most important factors in patient hospital choices; patient preferences for hospitals that minimize travel time are strong (e.g. McGuirk and Porell, 1984; Beukers et al., 2014).

The geographic market definitions I use in this thesis are hospital referral regions (HRRs). HRRs are geographic bounds created by the Dartmouth Atlas of Health Care to study healthcare markets, and are defined so that residents in each HRR received a high percentage of their hospitalizations within the HRR. This definition thus captures a patient choice set that is relatively well defined and bounded. I consider hospitals "rivals" in the same market if they are in the same HRR and meet certain market share thresholds. This creates a relatively clear distinction between markets. Yearly hospital market shares were calculated as the number of privately insured patients that were discharged from a particular hospital in a year divided by the total number of privately insured patients discharged by all hospitals within their HRR in that year. Other research has also used this market definition (e.g. Moghtaderi et al., 2019). One potential issue with this formulation is that some HRRs span across state borders. As I only observe discharges from hospitals within Washington, I may not have the full picture of these HRR markets if patients from Washington go to hospitals in other states, or patients from other states go to hospitals in Washington. This does not seem to be a large concern, however; for each year from 2010 to 2017, out-of-state patient discharges accounted for less than 4% of all discharges in Washington.

To guarantee access for their patients at preferred hospitals, insurers compete as well. I do not address this competition explicitly. Given that I only observe patient insurance categories and not individual insurers, I am unable to accurately characterize insurer competition outside of statewide HHI values. Furthermore, given that this thesis focuses on the effect of Medicaid expansion on hospital characteristics, I focus on hospital competition. This is not a huge concern if insurers' shares of a hospital's privately insured patient population stays largely constant pre-and post-expansion or if any changes occur consistently across hospitals and markets. Then comparisons between pre- and post-expansion base prices are not conditional on the "average insurer." Otherwise, variation in the average base price a hospital receives pre- and post-expansion may also be a function of variation in insurers' shares of its patient populations pre- and post-expansion. In this case, I still estimate the average effect of Medicaid expansion on bargaining outcomes, but am comparing instead prices conditional on changing insurer importance. Finally, as previously mentioned, I examine only non-emergency admissions; given that hospital choice in emergency contexts can be largely skewed by distance or not chosen by the patient themselves, patient crowd out in the emergency context is likely small.

4.1 Baseline Model

Before separating out the effect of patient crowd out from Medicaid patient shares on reimbursement outcomes, it is prudent to ask whether Medicaid patient shares seem to affect bargaining outcomes at all? I thus first estimate a baseline regression model that seeks to establish support for this overall effect. To estimate the impact of Medicaid patient percentage and the ACA on bargaining outcomes, I estimate the following model:

$$\begin{aligned} Price_{ht} = \beta_1 Cost_{ht} + \beta_2 Med\%_{ht} + \beta_3 ACA_t + \beta_4 MarketShare_{ht} + \beta_5 NumHospitals_{ht} \\ + \beta_6 MarketShare_{ht} * NumHospitals_{ht} + \beta_7 RivalMed\%_{ht} \\ + H_t^{'}\delta_1 + X_{ht}^{'}\delta_2 + Z_h^{'}\delta_3 + \gamma_{ht} + \tau_t + \epsilon_{ht} \quad (1) \end{aligned}$$

where $Price_{ht}$ is the base price for hospital h in year t, $Cost_{ht}$ is the calculated average cost for a hospital h in year t, $Med\%_{ht}$ the percentage (share) of patients at hospital

h in year t whose primary payer is Medicaid, and ACA_t is an indicator that is 1 if the major programs of the ACA have been implemented (2014 onwards) and 0 otherwise. As bargaining is generally modeled as a distribution of surplus, the estimation of price without consideration of cost may not accurately reflect bargaining outcomes and is commonly included as a covariate (e.g. Lewis and Pflum, 2017; Town and Vistnes, 2001). It is important to note that cost here is an estimate of average variable cost, not marginal cost, but is still a useful proxy. The surplus is the difference between the marginal value of the buyer and the marginal cost of the seller; the bargained price is between those values and determines how the surplus is split between the two parties. Differences in price then capture the extent to which bargaining positions of hospitals differ. This price regression then ultimately models prices as a function of cost, as well as other hospital and market characteristics that determine the markup, or how much greater than marginal cost price is.

$MarketShare_{ht}$ is hospital h's share of the privately insured patient market in their HRR in year t and $NumHospitals_{ht}$ is the number of hospitals in the HRR. The variable $MarketShare_{ht} * NumHospitals_{ht}$ is equivalent to $\frac{MarketShare_{ht}}{\frac{1}{NumHospitals_{ht}}}$, which measures the ratio of hospital h's market share to the market share it would have if market shares were spread evenly among hospitals in the market. These covariates account for differences in bargaining position due to market power, which previous research has identified as significant (e.g. Gowrisankaran et al., 2015; Lewis and Pflum, 2017). While a hospital's own Medicaid percentage can affect bargaining outcomes, its rivals' can as well. $RivalMed\%_{ht}$ is the average Medicaid patient share at hospitals in the same HRR market. This accounts for the average level of Medicaid patient shares across the market, and is thus useful in controlling for market level patient population demographics. It accounts for different initial bargaining positions for hospitals across markets.

There are three sets of control variables that account for other determinants of markup and cost structure differences. Following Moghtaderi et al. (2019), $H_t^{'}$ represents a vector of HHI values for the statewide individual, small group, and large group insurance markets. This controls for year to year statewide changes in the market structure of the insurance marketplace that would affect hospital markup. Omission of these controls would mean the model does not account for any changes in the competitiveness of the insurance marketplace, which is a key determinant of insurers' bargaining position (Dafny et al., 2012). The vector X'_{ht} is a vector of hospital characteristics that vary in time, including the percentage of patients at a hospital who are uninsured or on Medicare and the number of beds available at the hospital; these controls largely follow the literature (e.g. Lewis and Pflum, 2017). These characteristics can create differences in hospital bargaining positions as well by affecting the attractiveness of hospitals (e.g. hospitals with more beds are likely to be associated with lower wait times) or differences in cost structure (high shares of Medicare or uninsured patients may mean more financial pressure).

The vector Z'_h is a vector of largely time invariant hospital characteristics such as teaching hospital status, ownership, and primary service type that may also influence a hospital's attractiveness to patients and insurers. Teaching hospital status may reflect higher resource accessibility and care quality, while hospitals with different ownership types may respond to profit incentives differently (e.g. nonprofit vs for profit). Hospitals with different primary service types may serve subsets of patients with particular conditions and thus be reimbursed at different rates than general hospitals. I also include γ_{ht} as hospital system fixed effects and τ_t as year fixed effects. Hospital system membership and system characteristics have been shown to have effects on bargaining outcomes (Lewis and Pflum, 2015). Time fixed effects are common in the literature (e.g. Town and Vistnes, 2001; Gowrisankaran et al., 2015).

The effect of Medicaid expansion on prices is captured by changes in the value of $Med\%_{ht}$ pre- and post-expansion. This implies an average treatment effect of a hospital's Medicaid patient share that is the same pre-and post-expansion. The identifying assumptions here are twofold. First, the effect of the Medicaid expansion on prices occurs only through its impact on the Medicaid patient shares at a hospital (and also that the ACA does not affect prices in Washington through the Medicaid patient percentage at a hospital by any means other than the Medicaid expansion). Second, there are no unobserved and systematic changes over time that lead to changes in bargaining outcomes. Bargaining position is derived from observable market and party characteristics; in this case, a hospital's Medicaid patient share is a hospital characteristic which hospitals and insurers can both observe. Given that the ACA is the major systematic change in the healthcare landscape during this period, controlling for the other effects of the ACA is highly significant. Furthermore, I assume that the implementation of Medicaid expansion led to an unanticipated shock in the Medicaid patient populations at hospitals. If this were not true, hospitals would be able to anticipate changes to hospital attractiveness and take adaptive measures, such as increasing capacity at a hospital or facilitating mergers to increase market power. While the ACA was passed in 2010 and Washington was expected to implement the Medicaid expansion from very early on (reflected in their early expansion waiver), the actual number of new enrollees in Medicaid greatly exceeded many of the forecasts (Buettgens et al., 2012; Kaiser Family Foundation, 2014).

Negotiations between hospitals and insurers determine prices in advance. Accordingly, contracts are crafted with observable data from previous periods. To that end, the model was estimated with lagged continuous variables as well, simulating the practical bargaining process. While actual contract term lengths may vary by hospital and insurer, there is anecdotal evidence that one year contracts are not uncommon. In one sense, the estimation with lagged covariate values represents bargaining relying on historical trends, while estimation with contemporaneous covariate values captures more forecast heavy bargaining processes. The true effect may lie somewhere in between.

4.2 Hospital Categorization

What I estimate in the previous model is the aggregate effect of Medicaid patient shares (and thus Medicaid expansion) on reimbursement outcomes. To separately estimate the effect of patient crowd out, I need to develop a categorization of hospitals that identifies hospitals' intensity of exposure to private patient crowd out. I do so by estimating the likelihood of a privately insured patient choosing a particular hospital conditional on, among other factors, its Medicaid patient share. This method has been previously used to demonstrate privately insured patient avoidance of hospitals with high numbers of emergency department admissions by Medicaid patients (Sfekas, 2013). I summarize below the option-demand model of Capps et al. (2003), through which patient hospital choice can be modeled. The model provides an intuitive construction of patient utility that is easily estimable in discrete choice form.

Consider a patient i who, through a managed care health insurance plan, has access to a network of hospitals, of which hospital h is one. There are many factors that can affect the attractiveness of a particular hospital. Some factors are patient based, such as income or the health condition. Other factors are hospital based, such as size or ownership type. Interactions of these factors, such as proximity and diagnosis-hospital specialty complementarities, are also important.

Let patient i's *ex post* utility of treatment at hospital h when sick be

$$U_{ih} = \alpha R_h + H_h' \Gamma X_i + \tau_1 T_{ih} + \tau_2 T_{ih} \cdot X_i + \tau_3 T_{ih} \cdot R_h - \gamma(I_i, Z_i) P_h(Z_i) + \varepsilon_{ih}. \quad (2)$$

R_h is a vector of hospital characteristics that are constant across patients and health conditions, and H_h is a vector of hospital characteristics that include both R_h and characteristics whose importance vary by patient or health condition (such as being a Level I Trauma Center). The vector X_i is a vector of patient characteristics consisting of I_i, the patient's socioeconomic characteristics, and Z_i, the patient's health condition and other clinical information. To account for distance, T_{ih} is the (approximate) travel time from the patient to the hospital. The function $P_h(Z_i)$ represents the copay or personal cost, and $\gamma(Y_i, Z_i)$ is a function converting that monetary amount to utils. Lastly, ε_{ih} reflects the unobserved section of the patient's utility from choosing a particular hospital.

Capps et al. (2003) select patients who face no meaningful differences in price between hospitals in their health insurance plans. To this end, I assume that in my model, patients face the same copay and out-of-pocket costs for all hospitals so that I may ignore the $\gamma(Y_i, Z_i)P_h(Z_i)$ term. Then, a patient i will choose a particular hospital h if, for all $k \neq h$, we have that the utility from hospital h is greater than the utility from hospital k:

$$\alpha(R_h - R_k) + (H_h^{'} - H_k^{'})\Gamma X_i + \tau_1(T_{ih} - T_{ik}) + \tau_2(T_{ih} - T_{ik}) \cdot X_i + \tau_3(T_{ih} \cdot R_h - T_{ik} \cdot R_k) > \varepsilon_{ih} - \varepsilon_{ik}, \tag{3}$$

with ε_{ih} and ε_{ik} identically and independently distributed standard double exponential.

This formulation has some important implications. The probability that a patient i chooses hospital h is given by the logit model:

$$s_{ih} = \frac{exp(U_{ih})}{\sum\limits_{k \in G} exp(U_{ik})}. \tag{4}$$

One of the factors that may impact patient utility is the percentage of Medicaid patients at the hospital, which would be an element of H_h. There are several reasons why this may be the case. First, as Dranove and Sfekas (2008) show, the response of patients to available hospital quality information is low relative to actual differences in mortality outcomes; quality measures may be hard for patients to interpret. As Sfekas (2013) suggests, Medicaid patient percentage may then act as a signal for the perceived quality of the hospital. While this depends on the visibility of Medicaid patients at hospitals, the ACA's Medicaid expansion increased Medicaid enrollment substantially, and its coverage in the media would have likely heightened public awareness of new Medicaid patients.

Secondly, since hospitals have a somewhat fixed short-term capacity, the sharp increase in Medicaid patients may reveal capacity constraints (e.g. bed shortages, longer wait times), which also likely affects privately insured patients' hospital choices. Accordingly, Sfekas (2013) finds that patients are less likely to choose a hospital if it served a larger number of Medicaid patients through the emergency department in a recent period, which he describes as perhaps the most visible hospital patient population. I test here instead the effect of the Medicaid patient share of the entire hospital, as given the visibility of the ACA, patients may be more responsive to any increase in Medicaid patients, having been primed by Medicaid expansion, but I still only consider non-emergency patient choices.

To study the impact of a hospital's Medicaid patient percentage on a privately insured patient's hospital choice, I estimate a conditional logit model of patient choice that is based on the Capps et al. (2003) model (equation (2)). While differences in patient utility from different hospitals are unobservable, the observed hospital choices of patients are leverageable in this framework. I estimate the following model for each geographic market separately, as the markets are defined to clearly distinguish patient choice sets:

$$\begin{aligned} Y^*_{iht} = {} & \beta_1 Med\%_{ht} + \beta_2 Dist_{ih} + \beta_3 Dist^2_{ih} + \beta_4 Med\%_{ht} * Dist_{ih} \\ & + \beta_5 Med\%_{ht} * Dist^2_{ih} + \beta_6 Beds_{ht} + P'_{it}\alpha + \gamma_t + \epsilon_{iht} \end{aligned} \tag{5}$$

where Y^*_{iht} is the propensity to choose hospital h by patient i at time t. This model will be known as Model 1. This is a specific version of equation (2): Y^*_{iht} is thus also the *ex post* utility of treatment of patient i at hospital h. The covariates in this model are derived from the parameters in equation (2): they are hospital characteristics, patient characteristics, or interactions of hospital and patient characteristics.

The variable $Med\%_{ht}$ is the percentage of patients at hospital h whose primary payer is Medicaid, $Dist_{ih}$ represents the distance between patient i and hospital h, $Dist^2_{ih}$ the same distance squared, and $Beds_{ht}$ is the number of beds available at hospital h in time period t. Finally, the vector P'_{it} represents a vector of patient characteristics: age, sex, white or nonwhite, disease severity measured by DRG weight, and the state quartile of the patient's ZIP code's median income, while γ_t is an indicator that is 1 when the ACA is in effect and 0 otherwise. The $Med\%_{ht}$ represents the percentage of all patients at the hospital on Medicaid, not just non-emergency populations. Privately insured patients may observe this value from previous trips to the ED or hear from others, and aggregate information about Medicaid patients from all areas of the hospital in their decision-making, even if they are only seeking non-emergency care.

The inclusion of $Dist$, $Dist^2$, and their interactions with Medicaid patient percentage reflect the importance of distance when patients consider hospital choices. It is well documented in the literature that travel time and hospital proximity are among the strongest determinants of hospital choice (e.g. McGuirk and Porell, 1984; Gowrisankaran et al., 2015). Distance is particularly salient in my market definitions here, as many of the HRRs span large land areas. Given the model of Capps et. al (2003) described above, the ideal specification would include interactions between most patient characteristics and hospital characteristics. Data and computational limitations make that very difficult. The sparsity of this model is of some concern. As a refinement on the base choice model above, I estimate a modified model where age and severity mean effects are removed from the equation; instead, these variables are interacted with two hospital characteristics, the number of hospital beds and an indicator for the hospital's nonprofit status, as well as $Dist$ and $Dist^2$. This model will be known as Model 2.

The model was not estimated for the full set of patients in the dataset. As I only study the non-emergency services market, I exclude emergency patients. In line with Sfekas (2013), I restrict the patient population to those aged 18 and older, as younger patients are likely to have both different hospital preferences and choice sets than those of adults and remove from consideration privately insured patients who are insured under health maintenance organization (HMO) plans, as HMO plan networks are generally more restrictive than other types of private insurance. These patients may face a different (limited) choice set when compared to other privately insured patients, making it hard to compare choice probabilities between patient groups. In addition, I only consider patients from Washington. Patients from outside the state may face different hospital choice sets (depending on the state in which they live) and insurers. As they represent a small percentage of Washington hospital discharges and their insurers are unlikely to compete as directly with Washington insurers, this seems appropriate.

Finally, I also omit from consideration hospitals that do not reach a 2.5% market share of the privately insured market, with the conditions above, in their respective geographic markets for each year of the data; accordingly, the patients who chose these hospitals are also removed from the population of interest. There are two reasons for this: the small nature of these hospitals suggests that they may not be true competitors with larger hospitals, and as such, may not be in private insurers' choice set when contracting among comparable hospitals. Also, given the small market share, the patients who go to these hospitals may differ from the general population of patients in a systematic way. The smaller set of hospitals also makes the model computationally easier to estimate. From these conditions, I take a size 1000 random sample of patients for each market in each year, for computational ease, and estimate the model.

4.3 Crowd Out Measures

The previous choice models were estimated in order to calculate choice probabilities for hospitals pre- and post-Medicaid expansion. This is important for the categorization of hospitals; I am using these *ex post* probability changes to reflect the extent to which some hospital is susceptible to patient crowd out. Crowd out is an otherwise latent hospital characteristic that is revealed by Medicaid expansion. I use these estimates of crowd out to classify hospitals by their level of exposure. Ultimately, I am only concerned with discrete categorizations of hospitals according to this crowd out exposure measure and not the actual (continuous) estimated choice probability differences. What matters is that some hospitals are similar in this dimension; discrete categorizations smooth inter-hospital variation that may obscure similarities between groups of hospitals.

Since crowd out represents the decline in the attractiveness of a hospital to privately insured patients, I define a measure of crowd out for a hospital h by calculating the difference between the probability of a privately insured patient choosing hospital h pre- and post-expansion. This requires the creation of counterfactual probabilities; calculating choice probabilities for the post-expansion period using actual values and patients from the post-expansion period is not appropriate as the underlying population of patients with private insurance may have shifted after Medicaid expansion and the ACA. For example, some privately insured patients may have qualified for and enrolled in Medicaid, or uninsured patients may have bought private insurance as a result of the ACA. The comparison would then be along two dimensions: the change in Medicaid patient percentage induced by both Medicaid expansion and the changing populations of privately insured patients. The counterfactual should keep all hospital and patient characteristics constant except for Medicaid patient shares (and the ACA indicator). Thus a sample from the pre- expansion period is needed to calculate probabilities for both periods.

The choice model was estimated for individual patients with varying patient characteristics; just taking one patient to calculate a choice probability for a particular hospital is thus not appropriate. To arrive at representative hospital level choice probabilities, I first stratify patients by gender (male and female), race (white and nonwhite), and age quartile. I sample patients from the 2010 patient sample used for the estimation of the patient choice model, sampling 30% of the patients from each strata in each market to be used in the calculation of counterfactual probabilities. The crowd out measure captures changes in choice probability; given that patient characteristics are held constant, changes in choice probability pre- and post-expansion are driven by changes in hospital Medicaid patient share. I compute two estimates of representative pre- and post-expansion Medicaid patient percentages at each hospital for use in the counterfactual. In the first case, I use the average Medicaid patient percentage for a hospital from 2010-2013 as the pre-expansion value and the average from 2014-2017 as the post-expansion value (defined as "full years" crowd out). This method captures the "long-term" effect of crowd out and smooths out year to year fluctuations in Medicaid patient percentages due to short-term shocks and unexpected changes in the market. If Medicaid patient shares jump quickly at the beginning of the expansion but decline towards the original equilibrium after, this method may underestimate the actual change in Medicaid patient shares. Alternatively, this is appropriate if hospitals are able to quickly adapt and privately insured patients are responsive only to long-term changes. In the second case, I use the Medicaid patient percentage from the year immediately before the expansion (2013) as the pre-expansion value and the year immediately after (2014) as the post-expansion value. This method captures the unanticipated increase in Medicaid patient population at the immediate onset of the expansion. It is the "short-term" effect, and assumes that privately insured patients are immediately sensitive to changes in Medicaid patient shares, and that information about the immediate change persists. This method is more accurate than the former if patients who observe changes in Medicaid patient shares at hospitals immediately after expansion are able to quickly disseminate information to other patients, who remember and apply these categorizations when they make hospital choices in succeeding years. In the absence of immediate patient substitution effects and information dissemination among patients, the short and long-term effect dichotomy is also important when considering contract term lengths. The shorter contract terms are, the more important immediate changes at the onset of the ACA are for insurers. In long-term contracts, insurers and hospitals can see the extent of crowd out over a long period, and base future bargaining on data from several years after expansion. As I cannot identify insurers and thus specific contract lengths in this study, I analyze the effect of both of these scenarios.

I calculate the pre- and post-expansion choice probabilities for each member of my counterfactual sample. To aggregate these probabilities to the hospital level, individual patient choice probabilities were multipled by the strata proportion and summed. This was done for both choice models estimated (Model 1 and Model 2) and both time periods. The difference, defined as the post-expansion minus the pre- expansion aggregate choice probability, is my measure of crowd out. By construction, these choice probabilities attempt to control for the effect of age quartile, gender (male and female), and race (white and nonwhite). Sampling with replacement in each strata also helps ensure that patient distances and income quartiles are representative within market. The resulting crowd out measures will be driven by changes in Medicaid patient percentages.

4.4 Full Model

As the purpose of the choice probability calculations is to create hospital categorizations, I group hospitals by their crowd out measure value. I create bins, CO_i, that correspond to the values of the crowd out measure. The exact construction of the bins and the number of bins used will be determined after examining the distribution of the crowd out measures. I interpret these bins as time invariant hospital characteristics whose values were revealed through Medicaid expansion.

The full model investigating the impact of privately insured patient crowd out on prices hospitals receive from private insurers is based on the baseline model (equation (1)). The only modifications are the inclusion of interactions between $Med\%_{ht}$ and indicators for which crowd out bin a hospital is in: CO_{i_h}. The full model is then:

$$\begin{aligned} Price_{ht} = \beta_1 Cost_{ht} + \beta_2 Med\%_{ht} + \alpha_i Med\% * CO_{i_h} + \beta_3 ACA_t + \beta_4 MarketShare_{ht} \\ + \beta_5 NumHospitals_{ht} + \beta_6 MarketShare_{ht} * NumHospitals_{ht} \\ + \beta_7 RivalMed\% + H_t^{'}\delta_1 + X_{ht}^{'}\delta_2 + Z_h^{'}\delta_3 + \gamma_{ht} + \tau_t + \epsilon_{ht} \end{aligned} \tag{6}$$

where all other variables are defined as before. The main coefficients of interest are β_2

and the set of α_i, the coefficients before each interaction of Medicaid patient share and a bin. Each α_i captures the difference in effect of a hospital's percentage of Medicaid patients for hospitals in one particular bin, relative to being in the base level bin. Due to the definition of the crowd out measure as the post-expansion choice probability minus the pre-expansion choice probability, if the the hypothesized effect of privately insured patient crowd out were true, the coefficients α_i would be increasing monotonically as crowd out decreases and positive choice differential bins have a price premium. Since the effect of this channel is being separated out from the overall effect of Medicaid expansion on prices, the coefficient β_2 may be impacted in both sign and significance as well.

I include the crowd out categorizations in the model as interactions with $Med\%$ and not as separate predictors by themselves. This is because I am interested only in the effect of the categorizations to the extent that they impact reimbursement through Medicaid patient shares differently. Including these categorizations separately may dilute this effect. If there are other underlying reasons why hospital attractiveness, a hospital characteristic, may impact bargaining, adding it as a predictor would include that effect as well. Estimates of coefficients of categorization covariates may also be biased if there are other factors that affect both hospital attractiveness and price. For instance, if being a "brand name" hospital increases separately both attractiveness to patients and negotiated prices, the effects may be confounded. As in the baseline model, this model is estimated for both contemporaneous and lagged covariates to capture forward looking and historically based bargaining procedures.

5 Results

5.1 Baseline Model

The full results of the baseline model can be seen in Table 4. For ease of interpretation across the different scales and units of the covariates, I estimated the baseline model with standardized prices and the covariates. I also estimated the model for both the full set of hospitals and the sample of hospitals used in the choice model. As mentioned previously, I use the "Modified GNT" construction of base price as the dependent variable for all price regressions, and only consider non-emergency services.

Table 4: Effect of Medicaid Patient Shares on Bargained Price

	(1)	(2)	(3)	(4)
VARIABLES	All Hospitals	Choice Sample	All Hospitals (lagged)	Choice Sample (lagged)
Standardized cost	0.740***	0.628***	0.535***	0.499***
	(0.08)	(0.16)	(0.09)	(0.13)
Standardized Medicaid patient percentage	0.0078	-0.0789*	0.00912	-0.0924*
	(0.03)	(0.05)	(0.03)	(0.05)
ACA Indicator	0.134*	0.142*	0.0666	0.058
	(0.07)	(0.08)	(0.06)	(0.07)
Standardized privately insured patient market share	-0.0395*	-0.0144	-0.0449*	-0.0145
	(0.02)	(0.03)	(0.02)	(0.03)
Standardized number of hospitals in market	-0.0647***	-0.0218	-0.0726***	-0.0265
	(0.02)	(0.05)	(0.03)	(0.05)
Standardized market share * number of hospitals	0.0565	-0.0552	-0.00396	-0.0908*
	(0.04)	(0.05)	(0.04)	(0.05)
Standardized HHI of individual insurance market	-0.0662***	-0.0880***	-0.0999***	-0.0960***
	(0.02)	(0.03)	(0.03)	(0.03)
Standardized HHI of small group insurance market	0.0185	0.0253	0.033	0.0334
	(0.02)	(0.03)	(0.02)	(0.03)
Standardized HHI of large group insurance market	-0.0135	0.00215	-0.0146	-0.0155
	(0.02)	(0.03)	(0.02)	(0.02)
Standardized rival Medicaid patient percentage	-0.0768***	-0.0761***	-0.0675***	-0.0568**
	(0.02)	(0.02)	(0.02)	(0.02)
Standardized Medicare patient percentage	-0.107***	-0.0042	-0.0593	0.0434
	(0.04)	(0.08)	(0.04)	(0.08)
Standardized uninsured patient percentage	-0.00992	-0.0601***	-0.018	-0.0731***
	(0.02)	(0.02)	(0.03)	(0.02)
Standardized number of hospital beds	0.0666*	0.0832*	0.142***	0.122***
	(0.04)	(0.04)	(0.04)	(0.04)
Constant	-2.003***	-0.237	-1.291**	-0.0281
	(0.50)	(0.28)	(0.60)	(0.29)
Observations	533	234	533	235
R-squared	0.848	0.836	0.805	0.817
Year FE	YES	YES	YES	YES
System FE	YES	YES	YES	YES
Ownership FE	YES	YES	YES	YES
Service Type FE	YES	YES	YES	YES
Teaching Status Indicator	YES	YES	YES	YES

Notes : Columns 1 and 3 report estimates from estimation with all hospitals (column 1 with contemporaneous and column 3 with lagged values). Columns 2 and 4 report estimates from estimation with choice sample hospitals (column 2 with contemporanoues and column 4 with lagged values). Robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

The results, provide mixed support for the hypothesis that hospitals with larger Medicaid patient shares have lower reimbursement rates for non-emergency services. I find that when estimating the model with the full set of hospitals in the dataset, the effect of Medicaid patient shares is insignificant and small in both the contemporaneous and lagged estimations. When estimating the model with only the hospitals used in the choice model, however, the results are different. I find that there is a slightly significant negative effect of Medicaid patient shares on hospital reimbursement of non-emergency services; a 1 standard deviation increase in Medicaid patient shares results in an approximately 0.08 standard deviation decrease in the observed bargained price. The results are similar when estimating the model with those hospitals and lagged covariates. The effect size is slightly bigger: a 1 standard deviation increase in the Medicaid patient percentage decreases the observed price by just over 0.09 standard deviations.

That the effect is slightly significant and negative for hospitals that meet the criteria for inclusion in the choice model subset is telling. These are the hospitals that serve the majority of the privately insured patients in the dataset. They are then more characteristic of the bargaining process between private insurers and hospitals, and the estimations are likely to be more accurate when only considering these hospitals. Hospitals serving very small numbers of privately insured patients may have different revenue structures and goals that alter their bargaining with private insurers. It is also important to remember that this is the aggregate effect without separately identifying any mechanisms. To the extent that differences in patient crowd out drive the bargaining position of hospitals, this aggregate effect can be attenuated by the effect in hospitals with low crowd out. Still, this negative effect is an important starting point. The direction of the results from the estimation with choice model hospitals also seems to be in line with some previous results concerning Medicaid patient shares (Sfekas, 2013; Lewis and Pflum, 2017).

The coefficient of ACA is positive, though the significance of the effect varies across specifications. While I am unable to attribute this effect directly to the implementation of the ACA, I find that there is at least an increase in reimbursement associated with the years after 2014. What is notable, however, is this increase is of a similar order of magnitude to the absolute value of the effect size of Medicaid patient shares in the estimations with choice model hospitals. From these estimates, it is very possible a hospital could see either a net positive or negative reimbursement change after Medicaid expansion, depending on the exact change in the hospital's Medicaid patient share. In the most extreme case, the post-expansion years were associated with a 0.14 standard deviation increase in reimbursement; in this scenario, a hospital is only negatively affected in reimbursement rates if the Medicaid patient share increases by about 2 standard deviations. Otherwise, the decrease in reimbursement is offset by the post-2014 reimbursement premium. This suggests that the majority of hospitals may have seen better bargaining outcomes in the post-ACA years, despite the implementation of Medicaid expansion. While previous research has found increases in Medicaid revenue after the ACA, this provides evidence of likely increased private insurance revenue for many hospitals as well.

It is somewhat surprising that in the estimation with the choice model hospitals, the effect size of Medicaid patient share is larger than the (insignificant) reimbursement changes associated with Medicare patient share. Given that Medicaid and Medicare are both public insurance, it might be assumed that their effect on bargaining might be similar. One explanation for this difference may be the different patient populations served by each insurance. Since Medicare is available to all elderly adults, the services sought by Medicare patients may be very different and may not affect capacity constraints for services frequented by younger patients on either private insurance or Medicaid. There may also be less stigma placed by privately insured patients on Medicare as there is no income requirement for enrollment. On the other hand, the coefficient of Medicare patient shares is significant and negative for the estimation with all hospitals. This again suggests that the determinants of the bargaining process may be different when considering hospitals serving a small population of privately insured patients. I am unable to identify clear reasons behind the association here, but leave it for future consideration.

5.2 Hospital Categorization

The choice models were estimated separately for each market for the competition reasons outlined in the Methodology; the coefficients for Medicaid patient percentage for both specifications are shown in Table 5. The effect of Medicaid patient shares on the likelihood a hospital is chosen is negative for 6 of the 7 geographic markets. The significance of these results are mixed, but the significance, direction, and magnitude of the estimates for each market are generally consistent across models.

Table 5: Effect of Medicaid Patient Shares on Hospital Choice

MARKET	(1) Model 1	(2) Model 2
HRR 344	-7.44 (***)	-7.28 (***)
	(0.82)	(0.84)
HRR 437	6.20 (***)	5.98 (***)
	(1.65)	(1.64)
HRR 438	-2.94 (***)	-2.89 (***)
	(0.76)	(0.76)
HRR 439	-0.52	-0.76
	(1.66)	(1.65)
HRR 440	-1.61 (***)	-1.71 (***)
	(0.54)	(0.54)
HRR 441	-1.05	-0.48
	(1.77)	(1.74)
HRR 442	-9.52 (***)	-2.12
	(1.67)	(1.73)

Notes : The coefficients of Medicaid patient percentage in the choice models are reported for each market. Model 1 is as specificed in equation (5). Model 2 replaces age and severity fixed effects with interactions of those variables with distance, distance squared, total hospital beds, and nonprofit status. 1000 cases were used in the estimation of each coefficient. Robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1

The HRR with a highly positive effect of Medicaid patient shares on hospital choice is HRR 437, an HRR defined by Everett, WA. There may be underlying, market-specific explanations for this unusual result. This market is located right above Seattle; Everett itself is only 25 miles from Seattle. While HRRs are defined such that a large number of patients in the region seek care inside the region, they do not differentiate between patient types (insurance or demographic) and thus may not capture privately insured, patient-specific travel dynamics. Specifically, relatively large numbers of privately insured patients may be seeking care in nearby Seattle, so the choice model may be capturing only the choices of patients sufficiently far away from Seattle; the model may not be representative of the full patient population of the market. Intermarket spillovers are largely assumed away due to the construction of HRRs, careful consideration of this issue may be an important avenue of future research.

The variation in coefficients by market validates the separate estimation of this model by market. The market in the baseline model with the smallest (and insignificant) negative effect is HRR 439, the HRR centered on Seattle. This urban area, the market with the largest choice set of hospitals, may deemphasize selection on Medicaid patient percentage and instead elevate the effects of factors like distance. Given the potential disparities in population density in urban and suburban neighborhoods, along with potential disproportionate locating of privately insured patients in the suburbs and Medicaid patients in relatively poorer areas in the city, there may be confounding effects on hospital choice. If hospitals with lower Medicaid patient populations are located outside the city, then they may already be more attractive to privately insured patients due to their proximity; while Medicaid patient populations may be a factor, they are outweighed by distance. Indeed, there may even be some reverse causation: hospitals far from privately insured patients are chosen less often, which leaves them to serve Medicaid patients as a higher share of the patient population at that hospital. I do not test these hypotheses here, but leave them for future research. Whatever the reasons for these phenomena may be, I am interested in the model mainly for its predictive value in calculating choice probabilities.

5.3 Crowd Out Measures

Patient choice probabilities were calculated from the choice models described above. Table 6 provides a description of each strata level and its frequency in each market.

There are some general trends. Women make up a larger proportion of the privately insured patient discharges in each market, between 69 to 80 percent. The patients are also largely white, with white patients accounting for between 64 to 86 percent of the privately insured patient discharges in each market. These are somewhat wide disparities in demographics, which further validates the market by market approach to estimating patient choice. While I control for demographic information, any underlying structural considerations that impact both the demographic composition of the patient market and hospital characteristics would not be sufficiently accounted for in a larger estimation without market separation, as I am unable to include interactions between many patient demographics and hospital characteristics due to computational limitations.

Table 6: Strata Definitions and Frequency by Market

Strata	Sex	Race	Age Quartile	HRR 344 %	HRR 437 %	HRR 438 %	HRR 439 %	HRR 440 %	HRR 441 %	HRR 442 %
1	Male	Non white	1	0.003	0.010	0.006	0.008	0.002	0.005	0.002
2	Male	Non white	2	0.004	0.007	0.016	0.007	0.004	0.007	0.004
3	Male	Non white	3	0.019	0.014	0.033	0.028	0.013	0.018	0.013
4	Male	Non white	4	0.027	0.008	0.024	0.030	0.013	0.014	0.015
5	Male	White	1	0.008	0.028	0.019	0.015	0.010	0.008	0.005
6	Male	White	2	0.010	0.035	0.037	0.015	0.014	0.023	0.006
7	Male	White	3	0.060	0.099	0.082	0.071	0.084	0.086	0.042
8	Male	White	4	0.095	0.110	0.090	0.087	0.103	0.098	0.110
9	Female	Non white	1	0.082	0.040	0.082	0.109	0.097	0.066	0.115
10	Female	Non white	2	0.076	0.033	0.074	0.095	0.061	0.063	0.092
11	Female	Non white	3	0.042	0.014	0.047	0.048	0.026	0.023	0.062
12	Female	Non white	4	0.026	0.007	0.027	0.030	0.013	0.015	0.016
13	Female	White	1	0.176	0.186	0.159	0.120	0.155	0.175	0.135
14	Female	White	2	0.153	0.174	0.117	0.138	0.171	0.165	0.158
15	Female	White	3	0.118	0.120	0.103	0.115	0.137	0.129	0.120
16	Female	White	4	0.102	0.116	0.085	0.085	0.098	0.107	0.106

Notes: The strata definitions and frequency in each market are presented. The frequencies are in decimal form.

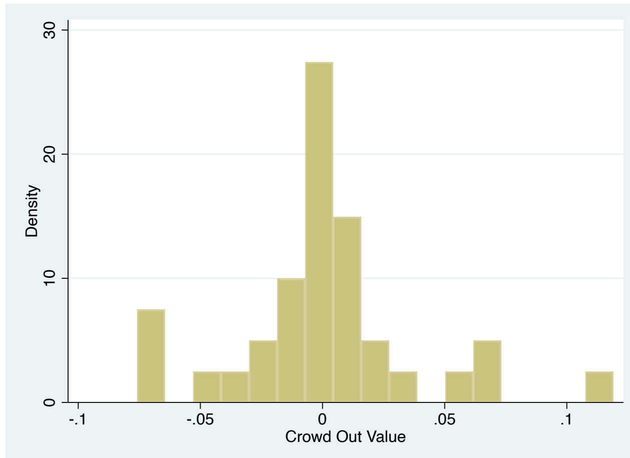
In both time period definitions from which I calculated average Medicaid patient shares, the pre- and post-expansion differences vary greatly by hospital. Some hospitals see declines in Medicaid patient shares after expansion, while the majority see increases. There do not seem to be any trends in these share differences between markets. There are large differences for some hospitals in Medicaid patient shares calculated using each method; the changes at the onset of the expansion are not the same as the longer term values, which supports the use of two methods to calculate crowd out.

Decreases in Medicaid patient share may reflect fluctuations where Medicaid patients shift hospitals within market. There could several reasons for this phenomenon, but it is not possible to identify them specifically in this thesis. Decreases in one hospital also largely correspond to increases in other hospitals in the market. The same is not true for increases; there are several markets where the Medicaid patient shares increased for every hospital in the market. Importantly, for no market is the aggregate difference across hospitals negative (all markets had an aggregate increase in the Medicaid patient shares). The magnitude of within hospital changes in Medicaid patient share also seem to be larger in markets with fewer hospitals. Larger markets may see smaller per hospital Medicaid patient increases due to distance considerations: it is less likely one particular hospital is closer to a particularly large region of newly enrolled Medicaid patients.

The crowd out measures for each hospital were calculated by subtracting the weighted (by strata level frequency) sum of post-expansion choice probabilities from the weighted sum of the pre-expansion choice probabilities. Given the fixed hospital choice sets for each market and the absence of an outside option, the aggregate choice probabilities of all hospitals in the same market totaled to 1. The hospitals with the largest positive and negative differences are generally spread out; there is not one HRR that occurs unusually frequently. The average crowd out of these most negative differences is a decrease in choice probability of about 6.4%; the average positive value is about 7.2%. These values are consistent with my construction of the crowd out measures; as there are no outside options, the sum of the choice probability differences for each market is 0.

The distribution of the crowd out measures calculated from Model 1 using the "full years" pre-expansion period and post-expansion period average Medicaid patient shares are shown in Figure 1; the results are very similar when calculating crowd out measures using the Medicaid patient shares from 2013 (pre-expansion) and 2014 (post-expansion) and Model 2. The distribution is unimodal and largely centered near 0. There are gaps in the histogram. While most of the hospitals experienced similar intensities of crowd out, there are some extreme winners and losers; the bins generally decrease in size quickly as the distribution moves away from the center. The overall crowd out measures are subtle for the majority of hospitals.

Figure 1: Distribution of Crowd Out Values from Model 1



Following these distributions, I create bins for the crowd out measures. Given that the majority of the hospitals are clustered around the center of the distribution, I create three bins. The first bin comprises those hospitals with crowd out measures in the 25th percentile and lower, the second the middle 50 percent, and the 3rd hospitals with crowd out measures in the 75th percentile and above. This means that the hospitals which experienced the most crowd out are in bin 1. These three groups, while unbalanced in size, accurately reflect classes of hospitals that are similar in this characteristic.

5.4 Full Model

The estimates of crowd out calculated from the baseline choice model were used in the estimation of the full model. Bins were created with the description provided above. The results of the full model are presented in Table 7. For brevity, I display only the coefficients of interest and the results using crowd out estimates from Model 1; results are similar for crowd out estimates from Model 2.

The coefficient of Medicaid patient share in this model should now be interpreted as the effect of Medicaid patient share on prices for hospitals in the first bin of crowd out (i.e. hospitals in the 25th percentile of crowd out, which corresponds to the hospitals with

Table 7: Effect of Crowd Out on Price

VARIABLES	(1) Full years crowd out	(2) 2013 to 2014 crowd out	(3) Full years crowd out (lagged)	(4) 2013 to 2014 crowd out (lagged)
Standardized cost	0.667***	0.679***	0.535***	0.540***
	(0.17)	(0.17)	(0.14)	(0.14)
Standardized Medicaid patient percentage	-0.236**	-0.242**	-0.305***	-0.303***
	(0.11)	(0.11)	(0.09)	(0.09)
* Bin 2	0.2	0.225	0.264**	0.294***
	(0.16)	(0.15)	(0.11)	(0.10)
* Bin 3	0.372**	0.410***	0.511***	0.503***
	(0.15)	(0.15)	(0.13)	(0.15)
ACA Indicator	0.155*	0.153*	0.057	0.0523
	(0.08)	(0.08)	(0.07)	(0.07)
Constant	0.000861	0.0356	0.388	0.418
	(0.35)	(0.35)	(0.31)	(0.31)
Observations	234	234	235	235
R-squared	0.844	0.845	0.829	0.827

Notes : For brevity, I present the coefficients of interest only from the estimation with crowd out estimates from Model 1. Columns 1 and 3 are estimated with crowd out measures calculated from the "full years" period definition. Columns 2 and 4 are estimated with crowd out measures calculated from the 2013 and 2014 Medicaid patient share values. All other covariates from the baseline model are included in the estimation but omitted here. Robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

the greatest amount of crowd out). The significance of the coefficient is preserved, and the magnitude of the effect is even larger now. A 1 standard deviation in the Medicaid patient share of hospitals with the largest crowd out estimates results in between a 0.24 to 0.31 standard deviation decrease in reimbursement price for non-emergency services. This effect is larger than the effect estimated in the baseline model, suggesting that the baseline effect was attenuated by hospitals with less crowd out. This effect persists over the contemporaneous and lagged estimations and both Models 1 and 2.

The estimates for other bins are positive. The significance of the estimates vary, but the estimates for bin 3 (hospitals with an increase in attractiveness after Medicaid expansion) are always significantly positive, and the estimates for both bins are significantly positive in the lagged specification. The monotonicity of the estimates from bin to bin is also noteworthy and in line with my hypothesis: hospitals in successively less patient crowd out bins are correspondingly compensated better.

The total effect of Medicaid patient share on prices for each bin is the base effect plus the coefficient for that bin. So, while the coefficient for bin 2 is positive, the total effect for that bin is still negative. The total effect for bin 3, however, is positive; increasing Medicaid patient shares at those hospitals actually results in higher prices for non-emergency services. This implies that the effect of Medicaid patient shares on reimbursement is driven mainly by crowd out. The reason behind the slightly significant negative effect of Medicaid patient percentage on prices in the baseline model is now clearer. That effect was driven primarily by hospitals who are highly exposed to crowd out, and somewhat muted by other hospitals with less crowd out. This also provides an explanation for the overall insignificant effect of Medicaid patient percentage in the baseline regression using the full set of hospitals. That set included hospitals that captured little of the privately insured patient market both before and after the expansion; given their consistently low privately insured patient populations, patient crowd out at these hospitals would not have been large as a result of Medicaid expansion. It is likely these hospitals attenuated the effect of Medicaid patient shares in the baseline regression.

The results also suggest the importance of crowd out as a factor in bargaining may not be continuous. Even if a hospital experiences some mild exposure to crowd out, the bargaining results may not be worse than some hospitals that are less exposed. It is more important to not be among the most highly exposed hospitals; the substitution of privately insured patients away from highly exposed hospitals and to other less exposed hospitals may be enough to offset influxes of Medicaid patients. Alternatively, since insurers presumably must have a certain number of hospitals in their networks to appeal to patients, not being one of the most highly exposed hospitals is enough to guarantee that bargaining position does not change too much. Once the bottom group of unattractive hospitals is removed, crowd out position within the rest of the hospital set may not be important for inclusion in the provider network.

That the coefficients are significant more often and greater in magnitude for the lagged specification also suggest that to the extent hospitals and insurers rely on historical data for projections for new contracts, the effect of high patient crowd out may be much larger. The true effect may very well lie somewhere between the estimated effects of the contemporaneous and lagged estimations. These lagged estimates assume that either bargaining occurs every year or insurers only assess the previous year's hospital and market characteristics when bargaining, but future research may incorporate different lag periods to capture the effect of longer contract lengths.

An intuitive question following these results is whether the estimated positive effect of crowd out for hospitals in bin 3 (hospitals experiencing the least crowd out) completely reverses the effect of Medicaid patient shares on bargaining. Is the total effect of Medicaid patient shares for hospitals in bin 3, the sum of the coefficients $\beta_2 + \alpha_3$ from equation (6), positive? I conduct an asymptotic test on whether the sum of these coefficients is greater than 0. When considering the estimates from the contemporaneous estimations, I do not find evidence that the sum of the coefficients differs from 0 in either time period definition (crowd out calculated using either the long-term or short-term time period definitions). In the lagged estimation, however, I find evidence that the sum of these coefficients differs from 0. The estimate of the sum of the coefficients when considering long-term crowd out values is significant at the $p = 0.05$ level and the estimate of the sum of the coefficients when considering short-term crowd out values is significant at the $p = 0.1$ level. In these cases, the estimated sum of the coefficients is around 0.2.

The significantly positive estimates of the sum of $\beta_2 + \alpha_3$ in the lagged estimation represent a complete reversal of the standard negative effect I find in the baseline model and in previous studies. One explanation for this result is that hospitals that experienced lower levels of patient crowd out were the ones that either prepared better or predicted more accurately the extent to which Medicaid expansion would increase the number of Medicaid patients at their hospitals. That these estimates are significant only when considering lagged hospital characteristic values also suggests that when hospital-insurer bargaining relies on historical reputation, price premiums from hospital attractiveness are enhanced. Whether these effects persist in longer contract terms is an open question.

It is important to remember that crowd out is an intrinsic hospital characteristic here; while it is present every year, it is only revealed post-expansion when new Medicaid patients are admitted to hospitals and privately insured patients make new hospital choices. An important consideration is then are there any other drivers that impact a hospital's intrinsic exposure to crowd out? Perhaps these values are really driven by underlying the demographics of each hospital's immediate location and hospitals and insurers have inherently been accounting for some of these features. I am unable to answer these questions in this thesis but leave them open for future research.

The results here support the hypothesis that crowd out of privately insured patients at hospitals as a result of Medicaid expansion resulted in decreased non-emergency service prices from private insurers. The impact of patient preferences in bargaining thus seems relatively salient in the short term. This result has some broader implications for the healthcare landscape post-Medicaid expansion. Given that a substantial percentage of hospitals lose money when treating public insured patients, private insurance payments are integral to the financial health of hospitals. The payment disparities found here suggest that Medicaid expansion may create financial "winners" and "losers" among hospitals. The literature has established a clear link between hospital finances and patient outcomes; will care quality diverge between these hospitals? As privately insured patients substitute away, "losers" will serve disproportionately many publicly insured patients; short-term gaps in care quality and overall health outcomes between patients of different insurance types due to the hospitals they visit are a worrying consequence to consider.

6 Discussion

In this thesis, I find evidence of a negative effect on non-emergency service prices by Medicaid patient shares for the hospitals most affected by privately insured patient crowd out, implying that much of the negative effect of Medicaid patient percentage on prices in the baseline model can be attributed to the patient crowd out channel. Here, I perform some supplementary analyses and address some limitations.

6.1 Crowd Out By Quartiles

The crowd out effects on reimbursement in the main analysis are estimated with hospitals grouped into three bins of differing crowd out exposure. I estimate here the full model with crowd out categorizations derived from quartiles of the calculated choice probability differences. This grouping method divides hospitals into smaller groups and may capture more group to group variation that is missed by larger groups. The trade-off of this grouping is that since the majority of hospitals have very similar values clustered around the mean, there may be some misgrouping of hospitals near the mean. Hospitals that are actually very similar in crowd out may be on different sides of the immediate quartile boundary at the 50^{th} percentile, and may be treated differently.

The results of this estimation are in Table 8. For brevity, I display only the results using crowd out estimates calculated using Model 1 but the results are similar when using Model 2. The results are similar to those of the main analysis. There is still a negative effect of Medicaid patient share on reimbursement for the hospitals in the first quartile, and each successive quartile has the effect attenuated. The significance of the estimates varies; the estimates for quartile 2 and 4 are significant, but those for quartile 3 are significant only with lagged covariates. The significance for quartile 4 is expected as it is in line with the main results from the earlier model. The differences in significance for quartiles 2 and 3 may result from the misgrouping of hospitals I mention earlier. Despite

Table 8: Effect of Quartile Crowd Out Definitions on Price

	(1)	(2)	(3)	(4)
VARIABLES	Full years crowd out	2013 to 2014 crowd out	Full years crowd out (lagged)	2013 to 2014 crowd out (lagged)
Standardized cost	0.701***	0.722***	0.541***	0.543***
	(0.193)	(0.196)	(0.144)	(0.147)
Standardized Medicaid patient percentage	-0.218*	-0.223*	-0.296***	-0.298***
	(0.117)	(0.114)	(0.087)	(0.087)
* 2nd Quartile	0.314*	0.367**	0.290**	0.310**
	(0.165)	(0.159)	(0.125)	(0.125)
* 3rd Quartile	0.0939	0.117	0.228*	0.278**
	(0.184)	(0.173)	(0.131)	(0.118)
* 4th Quartile	0.344**	0.360**	0.501***	0.497***
	(0.163)	(0.165)	(0.128)	(0.148)
ACA indicator	0.151*	0.144*	0.0568	0.0517
	(0.079)	(0.078)	(0.067)	(0.067)
Constant	0.105	0.148	0.398	0.423
	(0.317)	(0.303)	(0.304)	(0.300)
Observations	234	234	235	235
R-squared	0.847	0.849	0.829	0.827

Notes : For brevity, I present the coefficients of interest only from the estimation with crowd out estimates from Model 1. Columns 1 and 3 are estimated with crowd out measures calculated from the "full years" period definition. Columns 2 and 4 are estimated with crowd out measures calculated from the 2013 and 2014 Medicaid patient share values. All other covariates from the baseline model are included in the estimation but omitted here. Robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

that, the effects of the crowd out are clearly attenuated still in hospitals with less crowd out under this model; I thus do still find evidence that the negative effect of Medicaid patient percentage can be attributed to the patient crowd out channel.

6.2 Year to Year Effects

The full model only captures the overall impact of crowd out on prices, as it is a time invariant property by construction. It may mute effects of the crowd out that are more short-term (year to year). If patients adapt to changing Medicaid patient percentages at hospitals early on, crowd out effects may be most pronounced in the first few years.

Alternatively, the departure of privately insured patients from certain hospitals due to crowd out in the early years of the expansion and the resulting yearly increase in Medicaid patient percentage can compound crowd out effects by making hospitals less and less attractive year over year. In a third case, it may take time for patients to notice to and adjust to changing Medicaid patient populations at hospitals, suggesting that crowd out effects are driven primarily by later years after expansion.

I examine here the year to year effects of crowd out, estimating a modified version of the full model that interacts each Medicaid patient share measure (interacted with a bin or not) with an indicator for the year. Due to multicollinearity constraints, it is not possible to estimate year interactions with the ACA indicator; to still account for ACA related effects, the estimation is limited to the post-expansion years.

The results of this estimation are presented in Table 9. For brevity, I present only the estimates using the "long-term" crowd out values from Model 1; the results are similar with the "short-term" values and Model 2 values. What is surprising is that the estimates for hospitals in bin 2 are significantly positive for all years in the contemporaneous estimation when the overall effect was not significant in the full model. Similarly, the yearly effects for hospitals in bin 3 are not significant while the overall effect was significantly positive in the full model. This may be indicative of ACA effects that were not adequately controlled for, despite limiting the estimation to the post-expansion years. However, I find that the effect of Medicaid patient shares for hospitals with the most crowd out is largely concentrated at the onset in 2014; the estimates for the coefficient for 2014 are much larger than in the full model. There is some evidence that the negative effect of Medicaid patient shares in hospitals most exposed to crowd out are largely driven by effects at the onset of the expansion. A future study with longer-term data on Medicaid expansion may be necessary to see if the overall effect persists in the long run.

Table 9: Year to Year Effect of Crowd Out on Prices

VARIABLES	(1) Full year average crowd out	(2) Full year average crowd out (lagged)
Standardized cost	1.161***	1.119***
	(0.12)	(0.14)
Standardized Medicaid patient percentage	-0.425**	-0.505***
	(0.18)	(0.16)
* Bin 1 * 2015	-0.0809	-0.00954
	(0.25)	(0.22)
* Bin 1 * 2016	-0.263	-0.112
	(0.26)	(0.29)
* Bin 1 * 2017	0.455	-0.297
	(0.47)	(0.33)
* Bin 2 * 2014	0.517**	0.694***
	(0.24)	(0.22)
* Bin 2 * 2015	0.523**	0.594**
	(0.23)	(0.24)
* Bin 2 * 2016	0.485**	0.555**
	(0.23)	(0.23)
* Bin 2 * 2017	0.510**	0.614***
	(0.24)	(0.23)
* Bin 3 * 2014	0.198	0.569**
	(0.31)	(0.23)
* Bin 3 * 2015	0.202	0.669**
	(0.30)	(0.27)
* Bin 3 * 2016	0.141	0.621**
	(0.29)	(0.26)
* Bin 3 * 2017	0.16	0.610**
	(0.28)	(0.24)
Constant	0.331	0.739
	(0.39)	(0.45)
Observations	132	133
R-squared	0.855	0.849

Notes: For brevity, I present the coefficients of interest only. I present only the model estimated with "full year" crowd out defintion calculated from Model 1; results are similar with 2013 and 2014 crowd out values and Model 2 values. Column 1 is estimated with contemporaneous covariates. Columns 2 is estimated with lagged covariates. All other covariates from the baseline model are included in the estimation but omitted here. Robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

6.3 Limitations of Study

There are several limitations to this study. First, the analysis here is limited to modeling hospitals' bargaining positions with the "average" insurer in their insurer sets. That these insurer sets may differ across hospitals presents some difficulty in completely describing the bargaining process. There are other difficulties with unobserved insurer characteristics. Are the crowd out effects I find here driven by one particular form of private insurance (e.g. individual, small group, large group)? The introduction of new health insurance exchanges under the ACA may help those seeking to purchase individual health insurance; does this heighten the importance of the individual insurance market? On the other hand, are employers who give their employees group insurance responsive to patient preferences? These are open questions for future research. I also do not observe in the data physicians groups and private practices that may provide competition or complementarities in some specialty care services; since I do not focus on particular diagnostic groups, this limitation may not be as important, but future research in specific service submarkets may seek to quantify their effect more carefully.

This study also does not explicitly identify the insurance switching effects after Medicaid expansion. I decompose the Medicaid patient share effect at hospitals with different levels of crowd out. This does not address, however, if there are underlying differences in the Medicaid take up rates in the patient populations of different hospitals. One way to address this would be to construct *post hoc* Medicaid take up rates for each ZIP code and calculate the likelihood of a patient from a particular hospital enrolling in Medicaid. This analysis requires enrollment rates to have stabilized, as otherwise there is the risk of misidentifying the long run take up rate. If enrollment can be shown to have stabilized and the data is available, this would be an interesting opportunity for future research.

In addition, I do not observe the growth (or contraction) of the privately insured patient market, rather only patients who are admitted and discharged from hospitals. Insurers are involved in two markets: the market for insurance and for hospital services.

To maximize their total surplus across the two markets, insurers could very well leverage spillover effects from the insurance market, gaining surplus from patients and ceding some to hospitals in the hospital services market. This may very well be captured in the ACA indicator in the price regression, but it is unclear whether that is sufficient.

I assume in these analyses that the other provisions of the ACA do not confound the effects of Medicaid patient shares. I have previously mentioned that Washington received a federal waiver to begin early enrollment in Medicaid expansion beginning in 2010, but that the number of enrollees in this program was well known to be capped for each year and small compared to the eligible population and the enrollment numbers after the formal implementation in January of 2014. Other aspects of the ACA were implemented on a staggered timeline after the passage of the law in 2010. While there may be some questions as to whether these policy changes dramatically affected the bargaining outcomes studied in this paper, I believe that the event definition I provide is sufficient, as Medicaid expansion, the establishment of insurance exchanges, and the implementation of the individual mandate all began in 2014. These are the events that impact Medicaid patient shares and the bargaining studied in this thesis the most.

7 Conclusion

I have shown in this thesis evidence that suggests crowd out of privately insured patients negatively affects the non-emergency service reimbursement outcomes of hospitals in the four years after Medicaid expansion. The effect of Medicaid patient shares, and thus the effect of Medicaid expansion itself, seems attributable to the patient crowd out channel. These results provide an indication of some disparities that can arise with the implementation of new public insurance regulation.

A large contributor to Medicaid expansion's popularity has been federal funding. From 2014-2016, the federal government funded 100% of the cost of Medicaid expansion.

That has changed, however, with the percentage dropping yearly and settling at 90% from 2020 onwards. It remains to be seen whether the transferring of some costs to states may result in lowered average Medicaid reimbursement. Given that the scope of this study includes only the period where the federal government has been funding the full cost of expansion, the price effects of crowd out may shift after this period. In this case, persistently high Medicaid patient percentages at hospitals could have knock on effects on quality that reduce privately insured patient admissions and reimbursement. The disparities shown in this paper may in fact be even greater in the future.

Medicaid expansion under the ACA is also less than a decade old in Washington and other states early to implement it. The increase in Medicaid patients at Washington hospitals from 2014-2017 may reflect a short-term spike above the long-term trend as formerly uninsured or under-insured patients make up for previous under-utilization of the healthcare system. It remains to be seen if the effects of crowd out persist in a long-term equilibrium as hospitals identify new ways to appeal to insurers and patients.

There are also broader implications of these results for patient care and healthcare market structures. I have touched upon already the potential care disparities that may arise from reimbursement gaps. The creation of "winners" and "losers" among hospitals from Medicaid expansion may create a shift in the market structure, as losers fall behind, leaving opportunities for the winners to acquire them. Consolidation in hospital markets may be an unintentional consequence of this policy, and more research is needed on that front in the coming years. These concerns reflect the need for policy makers to consider more carefully the knock on effects of insurance and healthcare reform legislation.

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The HRR data set forth at Data Section of publication was obtained from Dartmouth Atlas Data website, which was funded by the Robert Wood Johnson Foundation, The Dartmouth Clinical and Translational Science Institute, under award number UL1TR001086 from the National Center for Advancing Translational Sciences (NCATS) of the National Institutes of Health (NIH), and in part, by the National Institute of Aging, under award number U01 AG046830.